AN OVERVIEW OF MATERNAL MORTALITY MONITORING MODEL USING KNOWLEDGE DISCOVERY IN DATABASES (KDD)

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ABSTRACT

An overview of maternal mortality monitoring model using knowledge discovery in databases (KDD)is an important indicator of a nation's health care delivery system and the level of the society's development. Previous efforts to meet the Millennium Development Goals (MDGs) on the reduction of maternal mortality in Nigeria have shown only marginal reductions in the last five years, making the MDGs targets by 2020 clearly unachievable using current strategies alone (Mid-Point Assessment Overview, MDGs Nigeria, 2008), hence this study; The methodology adopted for this study is Object-oriented analysis and design methodology that starts with understanding the domain, locating proper data sources, preparing the raw data, applying advanced analysis techniques, and extracting and validating the resulting knowledge from a quality registry for maternal mortality. The results will be to develop an integrated IT solution that is suitable for Nigeria, focused on the maternity care conditions and control the rate of maternal mortality in Nigeria using knowledge discovery in database (KDD).

Keywords: knowledge discovery in database (KDD; Maternal, Mortality, Model

Introduction

Nigeria has a population of 140 million people with women of child bearing age constituting about 31 million and children less than five years of age constituting 28 million (National Bureau of statistics, 2010). Women of child bearing age and children under five years of age therefore constitute a significant percentage of the nation's population. Nigeria, which constitutes just 1% of the world population, accounts for 10% of the world's maternal and under-five mortality rates. Nigeria ranks second in the world, after India, in the scale of maternal mortality with the rate of 800 deaths per 100000 live births (Pitterson, 2010). Annually, an estimated 52,900 Nigerian women die from pregnancy related complications out of a total of 529,000 global maternal deaths. A woman's chance of dying from pregnancy and childbirth in Nigeria is 1 in 13, compared with 1 in 35 in Ghana and 1 in 2800 in developed countries, and only about 40% of deliveries are attended to by skilled birth attendants. According to the World Health Organization (WHO)/United Nations Children Fund (UNICEF), in 1995, Nigeria had the third highest number of maternal deaths in the world (approximately 45000 deaths). By the year 2000, for every 100,000 live births, about 800 women died in the process of child birth. Out of the 27 million Nigerian women of reproductive age back then about 2 million did not survive either pregnancy or childbirth. In 2008, according to UN report, the figure stood at between 1000 and 1500 deaths per 100,000 live births. The State of the World Children Report 2009 stated that 1 out of 9 global maternal deaths occurred in Nigeria.

Till date, Nigeria is second on maternal mortality rate in the world with about 144 girls and women dying every day from complication of pregnancy and child birth. 1 in every 18 women die giving birth compared to 1 in 4800 in the US (Pitterson, 2010; Daily Independent, 2010). According to the survey conducted in February 2010, the record stands at between 165 per 100,000 live births in the South West and 1549 per 100,000 live births in the North East (Onumere, 2010).

Government can improve the health facilities to reduce maternal mortality if a control system is put in place to report mortality rate in the country. The neglect which results to a higher mortality rate may be attributed to the lack of information on the rate of death experienced in the country during child birth. More specifically rural areas are the ones lacking the high quality services needed to reduce maternal mortality in the whole region. According to a study, health services and human health resources (such as equipped hospitals and well trained personnel) are more valuable for rural communities (Jennett, Yeo, Scott, Hebert &Teo, 2015). Thus the delivery of these services remotely using accessible technology could help to level up the unequal access to health services. Electronic health records, risk assessment systems, and remote control are just some examples of how technology can be applied in the healthcare field.

The number and the size of databases recording medical data are increasing rapidly. Medical data, produced from measurements, examinations, prescriptions, etc., are stored in different databases on a continuous basis.

This enormous amount of data exceeds the ability of traditional methods to analyze and search for interesting patterns and information that is hidden in them. Therefore new techniques and tools for discovering useful information in these data depositories are becoming more demanding.

Universally childbirth is an event that attracts celebration, but this is not so for many women who experience childbirth as suffering and tragedy that may end in death. The state of maternal health is an important indicator of a nation's health care delivery system and the level of the society's development. Previous efforts to meet the Millennium Development Goals(MDGs) on the reduction of maternal mortality in Nigeria have shown only marginal reductions in the last five years, making the MDGs targets by 2020 clearly unachievable using current strategies alone (Mid-Point Assessment Overview, MDGs Nigeria, 2008).

RELATED WORK

There are many studies which focused on an overview of maternal mortality monitoring model using knowledge discovery in databases (KDD) all of them concentrate on how to reduce mortality rate.

The rest of this paper is organized as following: the related work for this research area, Materials and Methods and Finally, conclusion

THE RELATED WORKS

Knowledge Discovery in a Database

Knowledge Discovery in Databases (KDD) is an umbrella name for all those methods that aim to discover relationships and regularity among the observed data (Fayyad, 2006). KDD includes various stages, from the identification of initial business aims to the application decision rules.

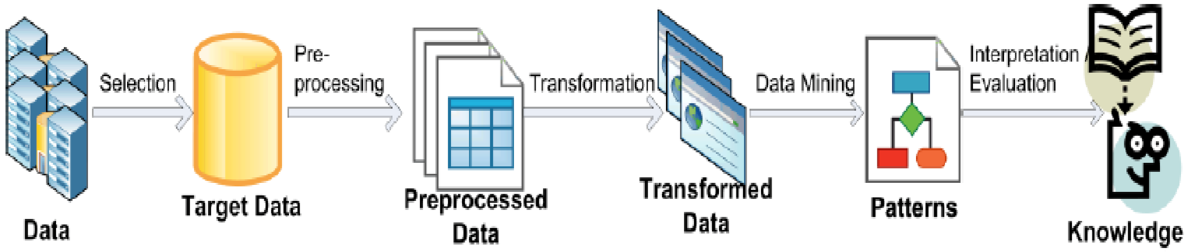

Fig. 2.1: Summarized KDD process steps (Fayyad et al., 2006)

Fayyad's process model shown in Fig. 2.1 includes nine steps:

1. Understanding the application domain: it involves pertinent prior knowledge and the objectives of the application.

2. Constructing a target dataset: consists of choosing a dataset or focusing on a subset of variables or samples of data on which the discovery is to be carried out.

3. Data clean-up and pre-processing: consists of basic operations, such as eliminating noise or outliers if necessary, gathering the necessary information to model or account for noise, coming to a decision on strategies for treating missing data fields, and accounting for time sequence information and changes known, as well as making a decision on DBMS issues, such as schema, data types and mapping of unknown and missing values.

4. Data trimming and projection: consists of finding practical features to represent the data, depending on the objective of the task, and using transformation methods or dimensionality reduction to decrease the effective number of variables that are being considered, or to get invariant representations for the data.

5. Selecting the function of data mining: involves choosing the purpose of the model derived by the algorithm of data mining (e.g., classification, summarization, clustering and regression).

6. Selecting the DM algorithm: involves choosing the method to be used for searching for patterns in the data, such as choosing which parameters and models may be appropriate, (e.g., the categorical data models are different from models on vectors over reals) and

matching a certain DM method with the general criteria of the KDD process (e.g., the user might be more interested in understanding the model than in its predictive capabilities).

7. Data mining: involves looking for patterns of interest in a certain representational form or a set of similar representations, including regression, classification rules or trees, clustering, dependency, sequence modeling, and line analysis.

8. Interpretation: involves interpreting the found patterns and possibly returning to any of the prior steps, as well as the possible visualization of the patterns extracted, removing the irrelevant or unnecessary patterns, and translating the useful ones into terms comprehensible by users.

9. Utilizing discovered knowledge: involves incorporating this knowledge into the system's performance, taking actions based on the knowledge, or merely documenting it and reporting it to the interested parties, as well as inspecting and resolving potential conflicts with previously supposed (or extracted) knowledge.

It is, therefore, the name for all the stages of finding and discovering knowledge from data, with data-mining being one of the stages as shown in Table 2.1.

According to Giudici (2003), "data mining is the process of selection, exploration, and modeling of large quantities of data to discover regularities or relations that are at first unknown with the aim of obtaining clear and useful results for the owner of the database."

Predictive data mining (PDM) works the same way as does a human handling data analysis for a small data set; however, PDM can be used for a large data set without the constraints that a human analyst has. PDM "learns" from past experience and applies this knowledge to present or future situations. Predictive data-mining tools are designed to help us understand what the "gold," or useful information looks like and what has happened during past "gold-mining" procedures. Therefore, the tools can use the description of the "gold" to find similar examples of hidden information in the database and use the information learned from the past to develop a predictive model of what will happen in the future.

Data Mining and Data Warehouse

In predictive models, the values or classes as researchers are predicting are called the response, dependent or target variables. The values used to make the prediction are called the predictor or independent variables. Predictive models are built, or trained, using data for which the value of the response variable is already known. This kind of training is sometimes referred to as supervised learning, because calculated or estimated values are compared with the known results. On the other hand, descriptive techniques are sometimes referred to as unsupervised learning because there is no already known result to guide the algorithms (Han &Kamber, 2006). The relevance of the field of databases to KDD is obvious from the name. Databases provide the necessary infrastructure to store, access, and manipulate the raw data. With parallel and distributed database management systems, they provide the essential layers to insulate the analysis for the extensive details of how the data is stored and retrieved. A strongly related term is online analytical processing (henceforth OLAP), which mainly concerns providing new ways of manipulating and analyzing data using multidimensional methods. This has been primarily driven by the need to overcome limitations posed by SQL and relational DBMS schemes for storing and accessing data (Sumathi, 2006).

Supporting operations from the DM perspective has an emerging research area in the database community. In the DM step itself, new approaches for functional dependency analysis and efficient methods for finding association rules directly from databases have emerged and are starting to appear as products. In addition, classical database techniques for query optimization and new object-oriented databases make the task of searching for patterns in databases much more reasonable (Sumathi&Sivanadam, 2006).

Data warehouses generalize and consolidate data in multidimensional space. The construction of data warehouses involves data cleaning, data integration and data transformation and can be viewed as an important preprocessing step for DM. Hence, the data warehouse has become an increasingly important platform for data analysis and OLAP and will provide an effective platform for DM (Berry and Linoff, 2012). Data warehousing provides architectures and tools for business executives to systematically organize, understand, and use their data to make strategic decisions. Data warehouse systems are valuable tools in today’s competitive, fast-evolving world. Many people feel that with competition mounting in every industry, data warehousing is the latest must-have marketing weapon-a way to retain customers by learning more about their needs (Sumathi&Sivanadam, 2006).

Moreover, data warehouses have been defined in many ways, making it difficult to formulate a rigorous definition. Loosely speaking, a data warehouse refers to a database that is maintained separately from an organization's operational databases. Data warehouse systems allow for the integration of a variety of application systems. They support information processing by providing a solid platform of consolidated historical data for analysis (Han &Kamber, 2006).

According to Immon (2006), a data warehouse is "an integrated collection of data about a collection of subjects (units), which is not volatile in time and can support decision taken by the management". The four keywords, subject-oriented, integrated, time-variant, and nonvolatile, distinguish data warehouses from other data repository systems, such as relational database systems, transaction processing systems, and file systems. In sum, a data warehouse is a semantically consistent data store that serves as a physical implementation of a decision support data model and stores the information on which an enterprise needs to make strategic decisions. A data warehouse is also often viewed as architecture, constructed by integrating data from multiple heterogeneous sources to support structured and/or ad hoc queries, analytical reporting, and decision making (Han &Kamber, 2006).

Data Mining Process

A process is represented by a sequence of steps executed in order to produce a certain result. A methodology is defined as an instance of a process, by specifying the tasks that should be executed, the inputs, the outputs and the way the tasks should be executed. In brief, a process gives the user the tasks that should be executed and a methodology tells the user also "how to" perform those tasks (Oprean, 2011).

Data Mining is one among the most important steps in the KDD process. It can be considered the heart of the KDD process. This is the area, which deals with the application of intelligent algorithms to get useful patterns from the dataset (Oprean, 2011). Nowadays, with the explosion of information, DM has become one of the top ten emerging technologies that will change the world (Oprean, 2011). There are two basic styles of DM: hypothesis testing and KD. Hypothesis testing is a top-down approach that is used when a confirmation or a rejection of an already defined hypothesis is needed. The other style is KD (relevant for this research study). It is a bottom-up approach and it is used when we want to find something that we do not know searching available data. It can be directed or undirected. There is no target field in undirected knowledge discovery. Instead, what the researcher wants from a computer is to recognize the schemes within the data that are of some importance (Glasnik, 2008). DM is a rather complicated process that has to be planned very carefully in order to be successful. It has to be organized within one of the proposed rigorous procedures.

According to Sumathi and Sivanadam (2006),"once a data warehouse has been developed, the DM process falls into four basic steps: data selection, data transformation, DM, and result interpretation" as shown in figure 2.3.

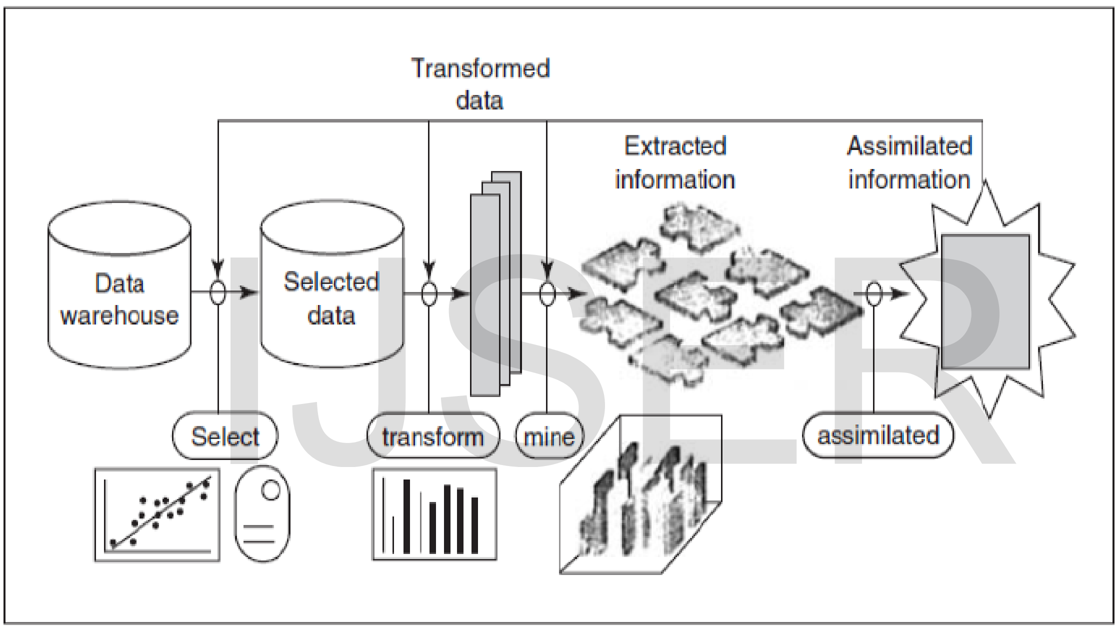

Fig. 2.2: Data Mining Process
Source: Sumathi and Sivanadam (2006)

The Data Mining process is iterative and interactive. The process is iterative, which means that sometimes it may be necessary to repeat the previous steps. The problem with this process, as with all the existing processes for DM, is the lack of user guidance.

Data Mining, Artificial Intelligence and Statistics

Data Mining takes advantage of advances in the fields of Artificial Intelligence (AI) and statistics. Both disciplines have been working on problems of pattern recognition and classification. AI techniques for reasoning, especially techniques form the uncertainty in AI community and graphical models for Bayesian modeling and reasoning provide a powerful alternative to classical density estimation in statistics (Sumathi&Sivanadam, 2006).

These techniques have the advantage of allowing prior knowledge about the domain and data to be included in a relatively easy and natural framework.

In addition to DM, techniques originating in AI have focused almost exclusively on dealing with data at the symbolic (categorical) level, with little attention paid to continuous variables. In machine learning and case-based reasoning, algorithms for classification and clustering have focused heavily on heuristic search and nonparametric models. Emphasis on mathematical rigor and analysis of results has not been as strong as in statistics or pattern recognition, with the exception of computational learning theory, which has focused on formal general worst-case bounds for a wide class of representations (Two Crows Corperation, 2005). Machine learning work contributes mainly to the DM step of the process, with some contributions in the area of representation and selection of variables through significant search. DM does not replace traditional statistical techniques. Rather, it is an extension of statistical methods that is in part the result of a major change in the statistics community. The development of most statistical techniques was, until recently, based on elegant theory and analytical methods that worked quite well on the modest amounts of data being analyzed. The increased power of computers and their lower cost, coupled with the need to analyze enormous data sets with millions of rows, have allowed the development of new techniques based on a brute-force exploration of possible solutions (Han &Kamber, 2006).

Statistics plays an important role primarily in data selection and sampling, DM, and evaluation of extracted knowledge steps. Historically, most statistics work has focused on evaluation of model fit to data land on hypothesis testing. These are clearly relevant to evaluation the results of DM to filter the good from the bad, as well as within the DM step itself in searching for, parameterizing, and fitting models to data (TCC, 2005).
On the limitations front, work in statistics has focused mostly on theoretical aspects of techniques and models. Thus, most work focuses on linear models, additive Gaussian noise

models, parameter estimation, and parametric methods for a restricted class of models. Search has received little emphasis, with emphasis on closed-form analytical solutions whenever possible. While the latter is very desirable both computationally and theoretically, in many practical situations a user might not have the necessary background statistics knowledge (which can often be substantial) to appropriately use and apply the methods. Furthermore, the typical require an a priori model and significant domain knowledge of the data as well as of the underlying mathematics for proper use and interpretation (TCC, 2005).

Finally, the key point is that DM is the application of these and other AI and statistical techniques to common business problems in a fashion that makes these techniques available to the skilled knowledge worker as well as the trained statistics professional. DM is a tool for increasing the productivity of people trying to build predictive models (TCC, 2005). Therefore, the researcher applied data mining in order to predict the pattern of mother to child mortality in Nigeria.

Health Informatics

Health care is a very research intensive field and the largest consumer of public funds in developed countries. With the emergence of computers and new algorithms, health care has seen an increase of computer tools and could no longer ignore these emerging tools. This resulted in the uniting of healthcare and computing to form health informatics. This is expected to create more efficiency and effectiveness in the health care system, while at the same time, improve the quality of health care and lower cost.

Health informatics is an emerging field. It is especially important as it deals with collection, organization, storage of health related data. With the growing number of patient and health care requirements, having an automated system will be better in organizing, retrieving and classifying of medical data. Physicians can input the patient data through electronic health forms and can run a decision support system on the data input to have an opinion about the patient's health and the care required. An example of the advances in health informatics can be the diagnosis of a patient's health by a doctor practicing in another part of the world. Thus, healthcare organizations can share information regarding a patient which will cut costs for communication and at the same time be more efficient in providing care to the patient (George, 2014).

There are other issues like data security and privacy, which is equally important when considering health related data. Thus, health informatics deals with "biomedical information, data, and knowledge with their storage, retrieval, and optimal use for solving problem and decision making process" (George, 2014). This is a highly interdisciplinary subject where fields in medicine, engineering, statistics, computer science and many more come together to form a single field. With the help of smart algorithms and machine intelligence we can provide the quality of healthcare by having, problem solving and decision-making systems. Information systems can help in supporting clinical care in addition to helping administrative tasks. Thus, the physicians will have more time to spend with the patients rather than filling up manual forms (George, 2014).

The applications of information and communications technologies in medicine are commonly referred to as telemedicine and medical informatics. Although these terms are often used together and confused with each other, they are separate and have their own definitions. The Institute of Medicine defines telemedicine as the use of electronic information and communications technology to provide health care when distance separates the participants. It includes all forms of electronic communication between patients and providers and among providers, starting from telephone to interactive video and web-based communication. Medical informatics is defined by The National Library of Medicine as the field of information science concerned with the analysis and dissemination of medical data through the application of computers to various aspects of health care and medicine.Medical informatics can also be referred to as the intersection of information science, computer science and health care. For example, medical informatics includes health care delivery processes that are supported by computers that help in analysing electronic data. (Christensen &Remler, 2007). Christensen&Remler(2007) have roughly categorized the different possible applications of ICT in chronic disease care in four group: technologies that support -

1) patient self-care and education,
2) communication between patients and providers or between providers,
3) electronic data storage and data sharing across providers, and
4) The technologies that combine all these three applications.

Successful management of chronic disease care is facilitated considerably by active involvement of the patient in his or her own treatment procedure. There is also increasing willingness from the patient side to be integrated in their own health care process, and health consumers are actively searching information independently (Detmer et al., 2013). The involvement is usually realized by patient education and information about his or her disease and information and communications technology can provide effective methods for patient participation.

This category includes medical devices for self-monitoring as well as interactive websites for education on the diseases. Moving towards more self-care and patient and health consumer inclusion is largely associated with new ICT technologies and has been noted by other commentators as well (Christensen,&Remler, 2007).

The ICT applications in electronic data storage and data sharing across providers - have probably received the most attention. It has been stated that shifting from paper based storing to electronic health records (HER), or electronic medical records (EMR) is associated with remarkable cost-savings (Hillestad et al., 2015) and faster access to information, which results in improved efficiency. Also unnecessary tests can be avoided, when information can be easily found from the data base by different users. Electronic process also enables storing bigger quantities of medical data (Haux, 2016). This is essential as the amount and complexity of health-related information and knowledge constantly increases and has already made information processing a major component of any health organization. Health ICT facilitates moving from decentralized and institution-based storage towards more global data storing (Haux, 2016). Having national health records can improve health care processes as different providers can access the same information fast and for example the duplication of tests could be prevented. In the European Union the long term goal is to have a system where all the clinicians in Europe can access health records from all countries (Andersen,Frogner, John & Reinhardt, 2006). This would improve conditions for treatment as the patient as well as the health care professional mobility is expected to increase. Without electronic records and communication technologies having wide databases would practically be impossible.

For instance, software that integrates and analyzes provider and self-monitored patient data combined with communication technology makes it possible to do certain monitoring tests at home and send the data to health care professionals to be analyzed. When there is need for intervention, it can be done inexpensively and without delay. These kind of technical solutions have already been used in continuous remote clinical monitoring and have brought significant benefits to both patients and payers. For instance in care of hypertension patients, remote monitoring has helped to drop the blood pressure of the test groups and reduce the costs of the care (Christensen &Remler, 2007). There is also a steady increase of new technologies such as ubiquitous computing environments and sensor-based technology for health monitoring from distance (Haux, 2016).

The Electronic Medical Record comprises health-related information that is created by health care providers on behalf of a patient, such as diagnostic tests or prescriptions for medications. The main objective of an EMR is to improve the ability of a care provider to document observations and findings and to provide more information on treatment of persons in his or her care. EMR can also provide the underlying patient information for functions such as drug-drug interactions, recommended care practices or interpretation of data to support and improve clinical decisions (The National Alliance for Health Information Alliance Technology, 2008). However, these functions are limited by the extent of the information available in a provider-focused EMR within a single health care organization, hence the need to document how EMR is utilized and supports medical services in centers that use EMR system. The EMR is expected to replace paper-based medical records as the primary source of medical history for each person seeking health care, while still complying with all clinical, legal and administrative requirements in developed countries (Janusz&Grzegorz, 2013).

To date, the digitization of health care typically has focused simply and solely on electronic records for patients. Most EMR systems are relational databases with a finite number of intra-enterprise applications and are limited to in-house use by health care facilities. Very few of these systems have realized fully functional, scalable, distribution capabilities, not to mention interoperability with external systems. This short-sighted tendency to build large-scale but restrictive automated systems that ignore the interactive nature of health care has resulted in limited operational success and acceptance (Wullianallur&Someswar, 2009). Electronic records have the potential to improve the quality of health care delivery and reduce costs (Hillestad et al., 2015). Accurate and up-to-date health information is critical. When an individual seeks health care, in order to provide effective and timely treatment, the provider needs to have information about the patient, including known allergies, chronic conditions, current medications and other pertinent health care data. However, such information is not always readily available. It may sometimes be available but incomplete or inaccurate, depending on whether the patient's records have been updated or not.

Though there have been challenges and failures in the implementation of EMR, their potential benefits are numerous. Some of the benefits are: complete and accurate information; universal and timely access to a patient's lifetime health information; knowledgeable sources to direct a patient to the appropriate care and substantially fewer medical errors. The EMR may exist in a distributed database, accessible from anywhere through a networked environment or a mobile smart card that a patient carries with him/her. If appropriate security measures are adopted, computerization also provides greater protection of confidential information via sophisticated keys and access controls. Additionally, the EMR system helps improve the quality of patient visit documentation and data, free up facility storage space, improve efficiency by eliminating time spent hunting down lost charts and provide immediate, simultaneous access to patient records (Janusz&Grzegorz, 2013).

Electronic Health Record Monitoring System

In the past 10 years Information technology (IT) has been used to improve the accuracy of patient records, and health monitoring. Benefits and challenging unsolved problems continue to be the outcomes of such attempts (Bates &Gawade, 2013), such as electronic health records, remote monitoring, tele-health, health data collection and processing, and clinical decision support systems, to name a few. Groups interested in the IT-Healthcare efforts have gathered and exchanged opinions to identify technological areas with the highest benefits. These groups integrated by members of the public, health care provider and private sectors selected tele-health and electronic health records, in this order, as the most valuable IT approaches. The groups of interest also identified as a disadvantage the changes in the current practices and processes in the delivery of health services (Jennet et al. 2015).

The use of electronic health records (EHR) is one of the most successful examples of the application of IT to support health care services. Research efforts state that EHR is a solution with great potential as EHR strengthens the collaboration between public and primary care (Calman,Nauser, Lurio, Wu &Pichardo, 2012). Electronic health records offer additional benefits such as improving public health surveillance by documenting patient data, real-time guiding of the physician interventions using statistical data to generate clinical alerts, improving surveillance and management of a communicable disease, etc. (Calman, et al., 2012).

In Ghana, a software solution was designed in response to the rapid expansion of community health workers in Africa and Asia. This was made taking as an advantage the proliferation of mobile devices. The Mobile Technology for Community Health (MoTeCH) offers features such as calculating the schedule for each patient; and notifying both patient and community workers when care is due. The system automates the delivery of information for routine reports and integrates with existing software applications for mobile data collection. The presented project is the initial part of an iterative process and still requires advanced software development skills, attention to standards and configurable design to make it more readily available to groups of interest within the research (Macleod, Philip, Stone, Walji&Awoonor-Williams, 2012).

From Brazil and Peru, a Windows-based application called “TeleConsult” proposes to reduce the high mortality on rural areas in Latin America. TeleConsults proposes the establishment of a medical network that communicates using satellite. The system acquires images from ultrasound examinations, electrocardiogram and blood imaging and pretends to cover disciplines such as cardiology, gynecology pediatrics and infections from the region (Sachpazidis, Rizou&Menary, 2008).

An effort in the maternity and prenatal care is the 'Prenatal Risk Calculation (PRC)’. PCR is a software solution based on a previously introduced system known as JOY. PCR and JOY work using chromosome data information (aneuploidies), through this analysis prenatal risk could detect symptoms such as Down syndrome and potential cancer cells on the product. The test performance between PCR and JOY gave higher significant results while detecting aneuploidies in the first trimester trial; testing alone, the test performance results of JOY were better than the results of PRC. PRC demonstrated to be a good tool to detect prenatal risk but it still needs to be improved (Hörmansdörfer et al., 2008).

A clinical decision support system (CDSS) on maternal care field was created and implemented for rural health care centers in Africa. The QUALMAT CDSS provides guidance for antenatal, delivery and post-delivery care. This guidance is possible by incorporating features such as an orientation process based on set of routine actions, algorithms to detect situations of concern, and electronic tracking of perinatal and postnatal care. CDSS is a java based application that incorporates the World Health Organization (WHO) guidelines for pregnancy and childbirth care. The CDSS was first developed in English for the use in Ghana and consist of four parts: a user interface; an XML-database for patient data, a set of algorithms to screen entered values; and a set of training documents.

Decision support is implemented by offering guidance through routine action in maternal and perinatal care, detection of critical situations using clinical data and electronic pictograph for observation on the progress of delivery up to 24 hours. This system requires an equipped site with a laptop computer. Staff members in charge receive general software and QUALMAT training and are left in charge of user administration. The implementation presented limitations in complex medical environments leading to a different conclusion than expected. Another challenging issue was the implementation of the system in a resource-poor environment, leading to hardware insufficiencies and user frustration (Blank et al., 2013).

One example of applying mobile and wireless computing in health remote health assistance is our previous work called ERPHA. ERPHA (Emergency Remote Pre-Hospital Assistance) is an example of an IT solution based on mobile technologies to improve remote monitoring under emergency situations like car accidents. ERPHA is an Information Technology solution that enables the continuous monitoring of a patient´s condition during the pre-hospital period.

ERPHA enhances the pre-hospital care quality by allowing early intervention of specialist physicians with key data such as video, audio and visualization of patient´s vital signs. ERPHA collects key health data form patient using body sensors that transfer their data to a mobile device (usually a smart phone) creating a body-sensor-network (BSN). The mobile device processes, displays and forwards the collected data to a hospital or medical center where a specialist physician can remotely assist paramedics in the diagnosis. Additionally, at the medical center the data sent by de mobile device is stored into a database for maintaining historical records of the patient. These records can be later used for identifying patterns for a more effective treatment or for classifying the severity of injuries. The mobile device can resend all collected data from the BSN plus video to a medical center where a physician can provide a better diagnostic of the patient being monitored. The BSN is built with Bluetooth-enabled sensors for vital signs such as ECG, stethoscope, pulse-oximeter, and blood glucose-meter. The mobile device has been implemented using smart phones running Windows Mobile and Android as operating systems. The mobile device currently transmits video, GPS location and data from the BSN to the hospital via Wi-Fi and 3G. Besides the smart phone a tablet can be used as alternate mobile device. At the hospital, the transmitted video, vital sign and patient information are stored and managed using dedicated database and video servers. The hospital front-end is implemented using Microsoft Visual Studio 2010 (ASP.NET) and Microsoft SQL Server 2008 R2. Further ERPHA details can be obtained at (Muñoz, Avila, Lavariega, Gonzolalez& Grote, 2012).

MATERIAL AND METHODS

Materials Required

Both secondary and primary data will be used to get facts on the subject where primary data will be collect from actual institutions and secondary data will be the data collect from literature review. Secondary data will also gathered information from a number of sources in order to carry out an investigation into the existing systems, its working procedures, and its mode of operation. Secondary data include: internet sources, journals, books and newspapers, manual auditing of maternal mortality rate monitoring.

Data Collection Tools

The researcher used the following methods during data collection: Observation and interviewing as our research methods. Through this the researcher was able to collect raw data on mother to child mortality rate at hospital where existing reports on the current system were obtained. Verbal interview techniques were used to interview employees in the hospital.

Observation

The researcher went to the hospital and observed their daily activities with regards to their current system and they were manually recording the mother to child mortality records. A follow up was made to determine the time it took to carry out the record management.

Interviewing

In this method, there was interaction between the researchers and the Staff. Interviews were conducted with the medical superintendent and some potential employees to find out what difficulties they encountered with the existing system. These interviews were held to verify the information collected since there was room to search for further information during the interview.

Methodology Adopted

Object-oriented analysis and design methodology (OOADM) which is adopted in this research work is a set of standards for system analysis and application design. It uses a formal methodical approach to the analysis and design of information system. Object-oriented design (OOD) elaborates the analysis models to produce implementation specifications. The main difference between object-oriented analysis and other forms of analysis is that by the object-oriented approach we organize requirements around objects, which integrate both behaviors (processes) and states (data) modeled after real world objects that the system interacts with. In other or traditional analysis methodologies, the two aspects: processes and data are considered separately. For example, data may be modeled by ER diagrams, and behaviors by flow charts or structure charts. The primary tasks in object-oriented analysis (OOA) are:

- Find the objects
- Organize the objects
- Describe how the objects interact
- Define the behavior of the objects
- Define the internals of the objects

Common models used in OOA are use cases and object models. Use cases describe scenarios for standard domain functions that the system must accomplish. Object models describe the names, class relations (e.g. Circle is a subclass of Shape), operations, and properties of the main objects. The OOADM presented the Data Flow Diagram (DFD), use case diagram, Interaction diagram, sequence diagram, activity diagram, collaboration diagram, package diagram for the proposed system.

CONCLUSION

The maternal mortality rate monitoring using KDD as developed in this paper is a work in progress that is expected to make a positive impact once it is implemented in any of the hospitals in Nigeria. Research demonstrates that the maternal mortality rate monitoring is a viable solution to the maternal-infant mortality problem that is currently present among the rural community areas in various states of Nigeria.

Also the use of electronic healthcare services makes possible to reduce attention issues associated with the main causes of death (hypertension, haemorrhages, and other complications of delivery) that are much higher in maternity-infant care. The mortality rate control system is a two-part system developed both for antenatal record assessment from any hospital terminal and maternal mortality rate monitoring reports.

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