Medical AI – HIV/AIDS Treatment Management System

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Abstract. Medical AI has established itself as a robust and fruitful field in the last 30 years. Most resource poor countries face the triple burden of malaria, tuberculosis and HIV. This coupled with the problems of lack of infrastructure, scarcity of clinical staff, and complex clinical guidelines, have encouraged the application of AI in healthcare specifically on practical issues of field medical data collection, mining, and better integration with healthcare workflow. One such application is an HIV/AIDS antiretroviral therapy management system that uses AI algorithm to predict drug resistance and the progression of the disease. Another serious problem is the scarcity of personnel with sufficient AI knowledge in the medical field. A distance education has shown its potential to remedy the problem.

Keywords: medical AI, medical informatics, data mining, knowledge discovery, medical data, medical AI education, HIV antiretroviral therapy, drug resistance

1 Brief History

Medical informatics is the field of study that applies computer science techniques to medicine and one such application regards the use of AI. The first AI applications in medicine date back to 1970s when researchers tried to emulate the reasoning strategy of clinicians. Well known is an expert system MYCIN [1], which was proven to outperform a cohort of infectious disease experts. Unfortunately, MYCIN was never used in practice because of ethical issues and lack of foresight into integration of MYCIN into clinical workflow. Nevertheless, researchers from all areas of AI found medical applications interesting and challenging [2] and in 1989 a new Artificial Intelligence in Medicine (AIM) journal was launched. Participants at a panel discussion, presented at a biennial conference AIME'07, arrived at a conclusion that "AI in medicine field is robust and there is a clear evidence of progress" [3].

In the middle of 1990s a back-propagation learning algorithm was published and personal computers became readily available. Many new AI technologies, like neural networks, fuzzy systems, decision trees, Bayesian networks, and evolutionary and swarm intelligence algorithms, were not purely theoretical inventions anymore. They were built into user friendly software packages that had the capability to be adequately used on commonly available desktops. A door to wide scale applications of AI in traditionally non-technical areas was opening [4], [5], [6], [7], [8], and [9]. The experimentation, implementation and use of AI in medicine were also positively influenced by the large amounts of data being collected by medical informaticians. This facilitated the process of using AI techniques to unveil hidden structures and relations in this data. This process came to be known as a data mining or a knowledge discovery process.

It is however unfortunate that AI in medicine is separate from medical informatics, bioinformatics, and telehealth. In order to truly take advantage of AI in medicine, there needs to be a mind shift and the field needs to be viewed as an essential component of health informatics. It must be integrated into the workflow and thus be identified as a methodology that can help to facilitate treatment of disease and solve other problems in healthcare on all levels [3], be it molecular and cell levels, organism level, health care level, or medical knowledge level.

2 Medical Data

Medical data are most rewarding and difficult to mine. Data are voluminous and heterogeneous (images, interviews, laboratory results, doctor observations and interpretations), contain unstructured free-text narrative written possibly in different languages, and many synonyms. Another reason that compounds the difficulty of mining medical data is the fact that there is no clear international standardization of the actual data itself and its representation. It is also imperative that researchers are cognizant of ethical, legal, and social constraints, like disclosure of private information and data ownership. On the other hand, a researcher can contribute to improving the quality and availability of medical care and thus save lives and/or improve their quality.

With the advent of digital pens, biosensing devices, portable data collection devices and better connectivity, there is an increase in the ability to gather new medical data but there is a much slower uptake in the advent of methods capable to deal with the resulting, gigantic data repositories [3]. It may be the case in genetics and drug development but not in field problems. Healthcare information systems frequently generate and maintain data necessary for daily operation but the data are not ready for data mining. There are two main reasons for that: the cost of an information system and scarcity of people who are aware of AI methods. Most medical information systems are not built with a data mining exercise in mind, which means that "field" knowledge is mostly lost.

Data collection and preparation for data mining is almost always the most difficult and time consuming part of data mining and knowledge discovery exercise. New intelligent data preparation techniques should be developed and built into health information systems.

3 Medical AI Technology Integration

AI researchers can be historically divided into two groups: pragmatists, for whom a system performance is more important than whether the system solves problems as human beings would, and formalists who argue that true AI requires modelling and insights into human intelligence [3]. In today's world, people who operate effectively between both extremes are needed. Future cognitive computers may possess unlike-human intelligence but at the same time they will have to communicate with human experts and other healthcare personnel.

The evaluations of present decision support systems that failed show that is was not usually because of flawed technology but because of underestimating human issues in the design and implementation process. Should future AI technologies have their artificial thinking it would be paramount to build into them solid human communication enhancement. On the other hand, humans will have to do their bit and embrace and understand AI technologies more extensively.

4 Medical AI Education

The American Medical Informatics Association has clearly demonstrated that there is a shortage of skilled medical informaticians. They suggest that effort and resources need to be invested into education. It is believed that strong interdisciplinary education programs should be further fostered to improve the quantity and quality of researchers and practitioners and to help the dissemination of AI methods and principles in the biomedical and health care informatics community [3]. This was the driving force of launching a Postgraduate Diploma, Masters and PhD medical informatics programs at our university. The programs include an AI in medicine module. The authors' experience with those programs shows that students are either existing IT people or medical enthusiasts who are spatially distributed across sub-Saharan Africa. Thus distance education is the easiest option in delivering necessary information to build capacity in medical AI. It can hardly be expected that all graduates will become medical AI specialists but they will form a base that is needed for successful diffusion of AI techniques at all levels of medical care and research.

5 HIV/AIDS Treatment Management System

The current trend in patient healthcare is personalized medicine where treatment is individualized. Thus access and interpretation of personal patient information is vital in order to provide a sustainable and useful medical service. This is becoming more evident in the treatment of HIV/AIDS. Our research aims at developing a physician-administered AI-based decision support system tool that facilitates the management of patients on antiretroviral therapy.

HIV/AIDS is the leading cause of death in sub-Saharan Africa [10] and is one of the fastest growing epidemics in South Africa; currently there are 5.7 million confirmed cases. HIV infection can be effectively managed with antiretroviral (ARV) drugs, usually in the form of a highly active antiretroviral therapy (HAART), which consists of a regimen of three drugs from at least two of the following five drug classes: reverse transcriptase inhibitors (RTI), non-reverse transcriptase inhibitors (NRTI), protease inhibitors (PI), integrase inhibitors (II), and fusion inhibitors (FI).

Factors that influence treatment of HIV/AIDS with antiretroviral drugs include a treatment regimen prescribed by a physician, the stage of the disease (the progression of the disease), levels of drug concentration achieved, a patient's adherence to the regimen, drug resistance, and toxic effects of the drug. The drug resistance is arguably the most critical aspect of treatment and three common reasons that lead to the development of the resistance are high replication rates, selective pressure, and initial infection by resistant strains of HIV. Thus it is inevitable that drug resistance becomes a reality in most patients.

The design of a decision support system for the management of an antiretroviral therapy involves:

1. Development of an AI algorithm that analyzes HIV drug resistance data and provides interpretable information for a physician, indicating which ARVs a patient will be resistant to.
2. Using the AI algorithm to predict current and future CD_4 count (from a genomic sequence and other data).
3. Integration of the above tool with an electronic medical record such that it facilitates the storage, acquisition, and management of patient information.

The preliminary results in the development of such a management system are promising. A classification model was built to determine changes in CD_4 cell count. The changes in CD_4 ($\varDelta CD_4$) cell count to be predicted were grouped into four categories as shown in Equation 1. Three different groups of inputs where created and each was fed into the machine learning algorithm separately. These input groups were: Input 1, consisted only of genome sequence; Input 2, consisted of genome sequence and current viral load; Input 3, consisted of genome sequence, current viral load and number of weeks from the current CD_4 count to baseline CD_4 count.

$$Classification = \begin{cases} Output\ 1 & \text{if} \quad \varDelta \mathrm{CD}_4 < 0 \\ Output\ 2 & \text{if} \quad 0 \leq \varDelta \mathrm{CD}_4 \leq 50 \\ Output\ 3 & \text{if} \quad 50 < \varDelta \mathrm{CD}_4 \leq 100 \\ Output\ 4 & \text{if} \quad \varDelta \mathrm{CD}_4 > 100 \end{cases} \tag{1}$$

The model was built using a support vector machine and linear, quadratic (polynomial with degree two) and radial base function (RBF) kernels were used. The radial base function kernel with the parameters $cost = 3$ and $\gamma = 0.2$, and the polynomial kernel with the parameters $cost = 10$, constant polynomial coefficient of 1 and $\gamma = 1$ were determined by a coarse grid search.

The accuracy of the machine learning models is shown in Table 1. Results indicate that for the RBF, and linear and quadratic SVMs there are no differences between the Input 1 and Input 2 models, but there are differences between Input 1 and Input 3 models as well as the Input 2 and Input 3 models. The Input 3 model is more accurate than the other two models. This result was expected due to the fact that the longer a patient is on an effective ARV therapy the more the immune system reconstitutes, resulting in a higher CD_4 count. Thus, the time component is a valuable predictor. There is no difference between the quadratic and linear SVM algorithms as shown in Table 1, while the RBF model outperforms both the quadratic and linear SVMs with Input 3. It was unlikely that the data would be linearly separable hence the poorer performance of the linear SVM models. The superior performance of the RBF kernel is due to its localized and finite responses across the entire range of predictors.

Table 1. Accuracies of the different models

Input space model	RBF %	Quadratic %	Linear %
Input 1	66	66	66
Input 2	68	68	66
Input 3	83	72	71

6 Conclusion

Medical AI is a matured field that has established itself in medical research. Its full practical potential can be unleashed by seamless integration of AI applications into medical care workflow. Current applications of AI methods focus mainly on answering well-posed questions and are an important part of decision support systems. New AI methods that focus on helping the user to uncover new knowledge (discovery support systems) are yet to be developed. HIV/AIDS personalized treatment management system is an important example of using AI technologies in medical care. It is thus evident that integrating AI into medical workflow is essential for better health care delivery.

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