Deep Learning in Medicine

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ABSTRACT

Spurred by advances in processing power, memory, storage, and an unprecedented wealth of data, computers are being asked to tackle increasingly complex learning tasks, often with astonishing success. Computers have now mastered a popular variant of poker, learned the laws of physics from experimental data, and become experts in video games – tasks which would have been deemed impossible not too long ago. In parallel, the number of companies centered on applying complex data analysis to varying industries has exploded, and it is thus unsurprising that some analytic companies are turning attention to problems in healthcare. The purpose of this review is to explore what problems in medicine might benefit from such learning approaches and use examples from the literature to introduce basic concepts in machine learning. It is important to note that seemingly large enough medical data sets and adequate learning algorithms have been available for many decades – and yet, although there are thousands of papers applying machine learning algorithms to medical data, very few have contributed meaningfully to clinical care. This lack of impact stands in stark contrast to the enormous relevance of machine learning to many other industries. Thus part of my effort will be to identify what obstacles there may be to changing the practice of medicine through statistical learning approaches, and discuss how these might be overcome.

Keywords: Computers; statistics; risk factor; prognosis; machine learning.

I INTRODUCTION

Today we are engaged in frequent enduring studies of the healthcare effects of numerous ingredients, the ultimate consequences of rival approaches of treatment, and decease irrefutable development of diseases. Huge databases on noteworthy inhabitants, focused on brain cancer, cardiovascular disease, arthritis, cancer and other major medicinal problems, are now being collected and used to clarify the true occurrence of diseases, to identify demographic influences and to measure salutary efficacy of drugs and procedures [6-8].

An enlightening review of the history of Al and the bouts between its supporters and challengers may be found in the recently published Machines Who Think [9]. According to Szolovits, P. [10], Medication is a field in which such help is judgmentally needed. Our cumulative expectations of the highest quality health care and the speedy evolution of ever more detailed remedial knowledge leave the physician without adequate time to devote to each case and besieged to keep up with the newest expansions in his field. For lack of time, most medicinal decisions must be based on fast decisions of the case relying on the physician's single-handed remembrance. Only in infrequent circumstances can a nonfiction search or other extended examination be undertaken to assure the doctor and the patient, that the modern knowledge is transported to accept on any particular case. Sustained training and recertification events encourage the surgeon to keep more of the pertinent evidence continuously in mind, but important confines of human recollection and remembrance attached with the growth of information assure that most of what is known cannot be known by most entities. It is the chance for new computer based tools: to help organize, store, and retrieve suitable medical knowledge needed by the consultant in dealing with each difficult case, and to recommend appropriate diagnostic, prognostic and therapeutic decisions and decision making techniques.

Artificial Intelligence is the study of thoughts which allow computers to do the things that make people seem intelligent ... The central goals of Artificial Intelligence are to make computers more useful and to understand the principles which make intelligence possible [11].

“Machine Learning is the discipline of getting computers to learn and act like humans do, and improve their learning over time in self-governing fashion, by feeding those data and information in the form of observations and real-world communications.”

In a 1970 review article, Schwartz speaks of -the possibility that the computer as an intelligent tool can redesign the present system of health care, basically alter the role of the doctor, and deeply change the nature of medical manpower employment and medical education--in short, the possibility that the healthcare system by the year 2000 will be basically different from what it is today [12].

According to the knowledge data discovery (KDD0 workshop of machine learning [3] Over the current ages, the decreasing cost of data acquisition and ready availability of data sources such as Smart card Based Health records, claims, administrative data and patient Based health data , as well as shapeless data, have controlled to an increased focus on data-driven and ML methods for medicinal and healthcare area. From the systems natural science point of view, large multimodal data typically including omics, clinical extents, and imaging data are now readily obtainable. Appreciated information for obtaining machine-like insight into the disease is also currently available in shapeless formats for example in the scientific works. The loading, incorporation, and examination of these data current noteworthy challenges for translational medication research and impact on the effective mistreatment of the data. Additionally, intellectual analysis of observational data from Smart card based record and patient based data sources and integration of insights generated from the same to the system natural science sphere can greatly improving longsuffering human involvement, consequence, and refining the complete health of the populace while reducing per capita cost of care. However, the black-box landscape, characteristic in some of the best performing ML methods, has widened the hole between how human and machines think and often unsuccessful to provide clarifications to make understandings tortious. In the novel era with users of "right aimed at explanation", this is detrimental to the acceptance in repetition. To drive the usage of such rich yet assorted datasets into actionable insights, we aim to bring together a wide array of investors, including doctors, biomedical and data science experts, and industry solution subject matter professionals. We will pursue to start deliberations in the area of precision medicine as well as the importance of interpretability of ML models towards the increased practical use of ML in drug and healthcare.

Artificial Intelligence is transforming the world of drug. AI can help doctors make quicker, more accurate diagnoses. It can forecast the risk of a disease in time to prevent it. It can help researchers understand how genetic disparities lead to disease. Although AI has been around for eras, new advances have ignited a prosperous in deep learning. The AI technique powers driver less cars, super-human image recognition, and life-changing, even life-saving, improvements in medicine.

Deep learning helps researchers examine medical data to treat diseases. It improves doctors' ability to analyze medical images. It's proceeding the future of personalized medicine. It even helps the blind "see."[5]

"Deep learning is transforming a wide range of scientific arenas," said Jensen Huang, NVIDIA CEO and co-founder. "There could be no more important application of this new capability than improving patient care." Three trends drive the deep learning revolution: further powerful GPUs, sophisticated neural network algorithms modeled on the human brain, and access to the explosion of data from the internet[5].

II REVIEW OF MACHINE LEARNING IN MEDICINE

Imagine physically as a young graduate student in Stanford's Artificial Intelligence lab, building a system to diagnose a common infectious disease. After years of sweat and toil, the day comes for the test: a head-to-head comparison with five of the top human experts in infectious disease. Over the first expert, system squeezes a narrow victory, winning by just 4%. It beats the second, third, and fourth doctors handily. Against the fifth, it wins by an astounding 52% [13].

Would you believe such a system exists already? Would you believe it existed in 1979? This was the MYCIN development, and in vindictiveness of the brilliant investigation outcomes, it certainly not through its way into scientific practice [14].

ML is routinely used in biological expansion and for evaluating and interpreting data in genomics, transcriptomics and proteomics pathways (e.g. [16, 17]), whereas in clinical laboratory medicine, it has been applied to classical biomarker testing of biological resources. Numerous "expert systems (ES)" have been newly labeled, original and commercialized for scientific workshop drives. Designed to appraise specific data in hematology, urinalysis or clinical chemistry, they are conventionally based on a predefined decision tree (DT) encompassing logic rules and checks to exclude diagnostic hypotheses or define them or propose additional examination to complete the diagnosis and support decision making (SDM). By contrast, ML is a totally different approach, where "rules" and everything are learned by the machine, or we can say machine intelligence. More often than not, speaking of obvious rules is unsuitable, as the forecast is somehow hidden in the model's non-linear restrictions that bend the decision boundaries around the data, literally. More specific queries using the search terms laboratory medicine, laboratory tests and machine learning in either the title or abstract identified 34 papers in Scopus and only three in PubMed, one of which was a research journal article [18]. We suppose that ML methods will become more broadly used in the analysis of research laboratory restrictions, and especially for data that can be easily grouped and compared across different groups. The application of ML in laboratory medicine should be supported as a means to enhance research laboratory association and expand the core skills set of research laboratory specialists, within a broader process of change and origination (e.g. [15, 19]). We entitlement this for a quantity of reasons. First, research laboratory are a foremost part of today's healthcare organizations. However, despite high throughput with low turnaround times, the capacity to screen data for results of special interest has decreased and few tests are directly diagnostic [20]. Second, technical improvements have enabled the integration of ES capabilities and software presentations, including automatic analyzers and modules of research laboratory information systems [21]. Since this kind of support is usually based on dichotomous thresholds or rigid mutual exclusion of data, it can be difficult if not impossible to obtain precise or personalized results [22], suggesting an obvious edge for development.

Third, because patients can now directly access their research laboratory test results of their investigative benefactor, there is an increasing demand for meaningful, possibly personalized reference limits and the need to interpret precision asterisks [20], the conventional signs indicating abnormal or borderline values. Finally, with the convergence of smartphones and innovative biosensors based on microfluidics and microelectronics, the vision of the lab-on-a-chip (LOC) and related models for laboratory medicine has opened opportunities, "in which a smartphone-enabled portable laboratory is brought to the patient instead of the patient being brought to the laboratory" [23]. In this context, apomediation refers to progressive disintermediation whereby traditional intermediaries, such as healthcare professionals who give "relevant" information to their patients, are functionally replaced by apomediaries, i.e. network/group/collaborative filtering processes [24]. ML systems can be seen as new and "smarter" apomediaries that act as gap fillers that analyze the increasing amount of diagnostic data a patient can access without mediation by a general practitioner or laboratory specialist, and then refer the patient to a specialist only in case of likely positive or anomalous results. This can be done by factoring together the diverse phenotypic attributes of a patient (i.e. in addition to body mass index [BMI], age, gender and ethnicity) or, better yet, of the patient's history of past basal values associated with a healthy condition. In this case, the very notion of reference limits would change, and ML, by leveraging and improving other statistical approaches, could help limit the misinterpretation of values outside of reference limits or of apparently normal data but also diagnostic for some conditions (e.g. [25]). Furthermore, some envision an ML-based clinical decision support that, by predicting correlated test results and enhancing the diagnostic value of multianalyte sets of test results, could help to reduce redundant laboratory testing [26] and, hence, lower healthcare costs, which are estimated to total $5 billion yearly in the United States alone [27]. Finally, the growing number of available and affordable types of diagnostic tests, different measurement methods and patient phenotypes (e.g. ethnic subtypes) has produced an unprecedented complexity of data interpretation and integration that calls for novel management technologies. In the following section, we report on research into the potential of ML models to address these challenges in laboratory medicine.

Hoong [4] summarized the potential of AI techniques in medicine as follows:

(a) Provides a research laboratory for the checkup, association, demonstration and classification of medical acquaintance.
(b) Harvests new tools to support medical decision-making, training and research.
(c) Participates happenings in medical, computer, cognitive and other disciplines.
(d) Propositions a content-rich discipline for forthcoming scientific medical area.

Many intelligent system have been developed for the purpose of enhancing health-care and provide a better health care facilities, reduce cost and etc. As express by many studies [28-33], intelligent system was developed to assist users and provide early diagnosis and prediction to prevent serious illness. Even though the system is equipped with "human" knowledge, the system will never replace human expertise as human are required to frequently monitor and update the system' s knowledge. Therefore, the role of medical specialist and doctors are important to ensure system validity.

Early studies in intelligent medical system such as MYCIN, CASNET, PIP and Internist-I have shown to out performs manual practice of diagnosis in several disease domain [34]. MYCIN was developed in the early 1970s to diagnose certain antimicrobial infections and recommends drug treatment. It has several facilities such as explanation facilities, knowledge acquisition facilities, teaching facilities and system building facilities. CASNET (Causal ASsociationalNETworks) was developed in early 1960s is a general tool for building expert system for the diagnosis and treatment of diseases[1-2].

CASNET major application was the diagnosis and recommendation of treatment for glaucoma. PIP an abbreviation for Present Illness Program was developed in 1970s to simulates the behaviour of an expert nephrologist in taking the history of the present illness of a patient with underlying renal disease. The work on Internist-I in early 1982s was concentrated on the investigation of heuristic methods for imposing differential diagnostic task structures on clinical decision making. It was applied in diagnoses of internal medicine.

In 1990s, the study in intelligent system was enhanced to utilize the system based on current needs. In several studies two or more techniques were combined and utilized the function of the system to ensure system performance. ICHT (An Intelligent Referral System for Primary Child Health Care) developed to reduce children mortality especially in rural areas [35]. The system success in catering common paediatric complaints, taking into consideration the important risk factors such as weight monitoring, immunization, development milestones and nutrition. ICHT utilized expert system in the process of taking the history data from patients. Other expert system have been developed such as HERMES (HEpathology Rule-based Medical Expert System) an expert system for prognosis of chronic liver diseases [36], Neo-Data expert system for clinical trails [37], SETH an expert system for the management on acute drug poisoning [38], PROVANES a hybrid expert system for critical patients in Anesthesiology [39] and ISS (Interactive STD Station) for diagnosis of sexually transmitted diseases [40].

Experienced Based Medical Diagnostics System an interactive medical diagnostic system is accessible through the Internet [29]. Case Based Reasoning (CBR) was employed to utilize the specific knowledge of previously experienced and concrete problem or cases. The system can be used by patients to diagnose them without having to make frequent visit to doctors and as well as medical practitioner to extend their knowledge in domain cases (breast cancer).

Data mining is an AI technique for discovery of knowledge in large databases, could be used to collect hidden information for medical purposes [41-43]. It could also be combined with neural network for classification of fuzzy pattern of HIV and AIDS using unsupervised learning [41]. Patients status life or dead was classified as training and testing pattern. Data mining was also used to generate a scatter diagram and a model of rules statement to enhance current rule base system [42]. Neves et al [43] developed information system that supports knowledge discovery and mining in medical imaging.

Fuzzy logic is another branch of artificial intelligence techniques. It deals with uncertainty in knowledge that simulates human reasoning in incomplete or fuzzy data. Meng [44] applied fuzzy relational inference in medical diagnosis. It was used within the medical knowledge based system, which is referred to as Clinaid. It deals with diagnostic activity, treatment recommendations and patient's administration.

Neural Network (NN) is one of the powerful AI techniques that has the capability to learn a set of data and constructs weight matrixes to represent the learning patterns. NN is a network of many simple processors or units [45]. It simulates the function of human brain to perform tasks as human does. As an example, a study on approximation and classification in medicine with incremental neural network shows superior generalization performance compared with other classification models [46]. NN has been employed in various medical applications such as coronary artery [47], Myocardial Infarction [48], cancer [49-50], pneumonia [51] and brain disorders [52]. In Karkanis et al [50] NN was implemented as a hybrid with textual description method to detect abnormalities within the same images with high accuracy.

Partridge et al [53] listed several potential of NN over conventional computation and manual analysis:

(i) Implementation using data instead of possibly ill-defined rules.
(ii) Noise and novel situations are handled automatically via data generalization.
(iii) Predictability of future indicator values based on past data and trend recognition.
(iv) Automated real-time analysis and diagnosis.
(v) Enables rapid identification and classification of input data.
(vi) Eliminates error associated with human fatigue and habituation.

III CENTRALIZED DATABASES AND WWW

For system using AI techniques, when the number of patients is high the system will produce more accurate results compared to the system with less number of patients. The patient's records are valuable information for the knowledge-based system. The current patients data would enhance and strengthen the validity of the system reasoning [29].

Current enhancements in information technology such as development of information superhighway inevitably encourage many organizations including government to develop electronic medical information and make it available on the Internet. The patients can use the information and monitor their risk level from their home or office without having to consult the physician [29]. The Internet supports two-ways communications between users around the world at minimum cost. In medical, communication is very important as new information or new discovery is the key for the future survival for example [54]. In addition, communications helps doctors sharing their knowledge or expertise [55].

IV WEB-BASED MEDICAL DIAGNOSIS AND PREDICTION

The model for Web-Based medical diagnosis and prediction consists of four components, they are databases, prediction module, diagnosis module and user interface. The databases consist of patient's database and patients-disease database. Patients database will be used to store patient's information such as name, addresses, and others particulars details. Patients-disease database stored all the information about patients and their illness. The information stored in the database includes types of diseases, the treatments and other details about the test and administering therapy. Patients information are separated in a different database to enhance the patients records storage, so that other departments could use the records when the patients are referred to them. This method could prevent other departments or unauthorized users from accessing the information about patient's diseases and provide a centralized information access for the patient's records.

Prediction module and diagnosis module are two of the main features in Web-Based Medical Diagnosis and Prediction. Prediction module utilizes neural networks techniques to predict patients illness or conditions based on the previous similar cases.

V APPLICATION OF MACHINE LEARNING IN MEDICINE

ML has made great advances in pharma and biotech efficiency. The following table 1 shows application of machine learning in medicine.

Table 1

Diagnose diseases	Correctly diagnosing diseases takes years of medical training. Even then, diagnostics is often an arduous, time-consuming process. In many fields, the demand for experts far exceeds the available supply. This puts doctors under strain and often delays life-saving patient diagnostics. ML – particularly Deep Learning algorithms – have recently made huge advances in automatically diagnosing diseases, making diagnostics cheaper and more accessible.
Develop drugs faster	Developing drugs is a notoriously expensive process. Many of the analytical processes involved in drug development can be made more efficient with Machine Learning. This has the potential to shave off years of work and hundreds of millions in investments.
Personalize treatment	Different patients respond to drugs and treatment schedules differently. So personalized treatment has enormous potential to increase patients' lifespans. But it's very hard to identify which factors should affect the choice of treatment. ML can automate this complicated statistical work – and help discover which characteristics indicate that a patient will have a particular response to a particular treatment. So the algorithm can predict a patient's probable response to a particular treatment. The system learns this by cross-referencing similar patients and comparing their treatments and outcomes. The resulting outcome predictions make it much easier for doctors to design the right treatment plan.
Improve gene editing	Clustered Regularly Interspaced Short Palindromic Repeats (CRISPR), specifically the CRISPR-Cas9 system for gene editing, is a big leap forward in our ability to edit DNA cost effectively – and precisely, like a surgeon. This technique relies on short guide RNAs (sgRNA) to target and edit a specific location on the DNA. But the guide RNA can fit multiple DNA locations – and that can lead to unintended side effects (off-target effects). The careful selection of guide RNA with the least dangerous side effects is a major bottleneck in the application of the CRISPR system. Machine Learning models have been proven to produce the best results when it comes to predicting the degree of both guide-target interactions and off-target effects for a given sgRNA. This can significantly speed up the development of guide RNA for every region of human DNA.

VI CONCLUSION

AI is already helping us more efficiently diagnose diseases, develop drugs, personalize treatments, and smooth oversee genetic factor. But this is **just the commencement**. The more we digitize and unify our medicinal data, the more we can use AI to help us find appreciated patterns – patterns we can use to make precise, cost-effective judgements in complex analytical processes. ML has the probable to meaningfully aid medical rehearsal. The future for medicine will be better and better. The use of computer and communication tools can change the medical practice into a better implementation. Consolidation in health-care provider will happen by focusing on cost and later on quality of services. Advancement in technology will form a platform for development a better design of telemedicine application. Telephone line and Internet will be the most important tools in medical applications. The main features in medical diagnosis and prediction using artificial intelligence techniques will make the consultation to be more interactive.

REFERENCES

[1] Harvey, J. 1986 Expert Systems: An Introduction. Electrical Communication. 60(2): 100-108.

[2] Kulikowski, C. A. and Weiss, S. M. "Representation of Expert Knowledge for Consultation: The CASNET and EXPERT Projects." Chapter 2 in Szolovits, P. (Ed.) Artificial Intelligence in Medicine. Westview Press, Boulder, Colorado. 1982.

[3] 2018 KDD Workshop on Machine Learning for Medicine and Healthcare, Location: London, United Kingdom, Workshop Date: August 20, 2018

[4] Hoong, N. K. (1988). Medical Information Science - Framework and Potential. International Seminar and Exhibition Computerization for Development-the Research Challenge, UniversitiPertanian Malaysia: Kuala Lumpur, pp. 191 - 198.

[5] Deep Learning,Advances In Medicine,Blog, Https://Www.Nvidia.Com/Object/Deep-Learning-In-Medicine.Html

[6] Mabry, J. C., Thompson. H. K., Hopwood, M.D., and Baker, W. R., "A Prototype Data Management and Analysis System--CLINFO: System description and user experience," MEDINFO 77, North-Holland, Amsterdam, (1977), 71-75.

[7] Rosati, R. D., McNeer, J. F., and Stead, E. A., pages 1017-1024. "A New Information System for Medical Practice," Archives of Internal Medicine 135, (1975).

[8] Weyl, S., Fries, J., Wiederhold, G., and Germano, F., "A modular self-describing clinical databank system," Comp. Biomed. Res. 8, (1975), 279-293.

[9] McCorduck, P., Computers Who Think, W. H. Freeman and Co., (1980).

[10] Szolovits, P. "Artificial Intelligence and Medicine." Chapter 1 in Szolovits, P. (Ed.) Artificial Intelligence in Medicine. Westview Press, Boulder, Colorado. 1982.

[11] Winston, P. W., Artificial Intelligence. Addison-Wesley, Reading, Mass., (1977).

[12] Schwartz, W. B., "Medicine and the Computer: The Promise and Problems of Change," New Engl. J. Med. 283, (1970), 1257-1264.

[13] Brandon Ballinger, Co-Founder @Cardiogram,Blog, Three Challenges for Artificial Intelligence in Medicine,Sep. 20,2016.

[14] An interesting snapshot of history can be found in the 1982 book Artificial Intelligence in Medicine, long out of print.

[15] Obermeyer Z, Emanuel EJ. Predicting the future – big data, machine learning, and clinical medicine. N Engl J Med 2016;375:1216.

[16] Camaggi CM, Zavatto E, Gramantieri L, Camaggi V, Strocchi E, Righini R, et al. Serum albumin-bound proteomic signature for early detection and staging of hepatocarcinoma: sample variability and data classification. ClinChem Lab Med 2010;48:1319–26.

[17] Madabhushi A, Doyle S, Lee G, Basavanhally A, Monaco J, Masters S, et al. Integrated diagnostics: a conceptual framework with examples. ClinChem Lab Med 2010;48:989–98.

[18] Demirci F, Akan P, Kume T, Sisman AR, Erbayraktar Z, Sevinc S. Artificial neural network approach in laboratory test reporting. Am J ClinPathol 2016;146:227–37.

[19] Forsting M. Machine learning will change medicine. J Nucl Med 2017;58:357–8.

[20] Horowitz GL. The power of asterisks. ClinChem 2015;61: 1009–11.

[21] Connelly DP. Embedding expert systems in laboratory information systems. Am J ClinPathol 1990;94(4 Suppl 1):S7–14.

[22] Lippi G, Bassi A, Bovo C. The future of laboratory medicine in the era of precision medicine. J Lab Precis Med 2016;1:7.

[23] Komatireddy R, Topol EJ. Medicine unplugged: the future of laboratory medicine. ClinChem 2012;58:1644–7.

[24] Eysenbach G. Medicine 2.0: social networking, collaboration, participation, apomediation, and openness. J Med Internet Res 2008;10:e22.

[25] Poole S, Schroeder LF, Shah N. An unsupervised learning method to identify reference intervals from a clinical database. J Biomed Inform 2016;59:276–84.

[26] Lindbury BA, Richardson AM, Badrick T. Assessment of machinelearning techniques on large pathology sets to address assay redundancy in routine liver function test profiles. Diagnosis 2015;2:41–51.

[27] Jha AK, Chan DC, Ridgway AB, Franz C, Bates DW. Improving safety and eliminating redundant tests: cutting costs in U.S. hospitals. Health Aff 2009;28:1475–84.

[28] Mahabala, H. N., Chandrasekhara, M. K., Baskar, S., Ramesh, S., and Somasundaram, M. S. (1992). ICHT: An Intelligent Referral System for Primary Child Health Care.

[29] Manickam, S., and Abidi, S. S. R. (1999). Experienced Based Medical Diagnostics System Over The World Wide Web (WWW), Proceedings of The First National Conference on Artificial Intelligence Application In Industry, Kuala Lumpur, pp. 47 - 56.

[30] Alexopoulos, E., Dounias, G. D., andVemmos, K. (1999). Medical Diagnosis of Stroke Using Inductive Machine Learning. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 20-23.

[31] Zelic, I., Lavrac, N., Najdenov, P., Rener-Primec, Z. (1999). Impact of machine Learning of the Diagnosis and Prognosis of First Cerebral Paroxysm. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 24-26.

[32] Ruseckaite, R. (1999). Computer Interactive System for Ascertainment of Visual Perception Disorders. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 27-29.

[33] Bourlas, P., Giakoumakis, E., and Papakonstantinou, G. (1999). A Knowledge Acquisition and management System for ECG Diagnosis. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 27-29.

[34] Shortliffe, E. H. (1987). Computer Programs to Support Clinical Decision Making. Journal of the American Medical Association, Vol. 258, No. 1.

[35] Mahabala, H. N., Chandrasekhara, M. K., Baskar, S., Ramesh, S., and Somasundaram, M. S. (1992). ICHT: An Intelligent Referral System for Primary Child Health Care. Proceedings SEARCC' 92: XI Conference of the South East Asia Regional Computer Confederation. Kuala Lumpur.

[36] Bonfa, I., Maioli, C., Sarti, F., Milandri, G. L., and Monte, P. R. D. (1993). HERMES: An Expert System for the Prognosis of Hepatic Diseases. Technical Report UBLCS-93-19, Universiti of Bologna.

[37] Theodorou, T., and Ketikidis, P. (1995). Neo-Dat An Expert System to Support the Designers of Clinical Trails. 5 th Hellenic Conference on Informatics.

[38] Droy, J. M., Darmoni, S. J., Massari, P., Blanc, T., Moritz, F., and Leroy, J. (1993). SETH: An Expert System for the Management on Acute Drug Poisoning. http://www.churousen.fr/dsii/publi/seth.htm

[39] Passold, Fs., Ojeda, R. G., and Mur, J. (1996). Hybrid Expert System in Anesthesiology for Critical Patients. In Proceedings of the 8 th IEEE Mediterranean Electrotecnical Conference - MELECON' 96 (ITALIA), Vol. III, pp. 1486-1489.

[40] Walker, N. J., and Kwon, O. (1997). ISS: An Expert System for the Diagnosis of Sexually Transmitted Diseases. 11 thAnnual Midwest Computer Conference (MCC' 97) March 21, Springfield, Illinois.

[41] SitiNurul Huda Sheikh Abdulah and MiswanSurip (1999). SatuMetodologiPerlombongan Data UntukPesakit AIDS. Proceedings of the First National Conference on Artificial Intelligence Application in Industry. Kuala Lumpur, pp. 57-71.

[42] Siti FatimahMdSaad and RogayahGhazali (1999). Data Mining for Medical Database.Proceedings of the First National Conference on Artificial Intelligence Application in Industry. Kuala Lumpur, pp. 72-79.

[43] Neves, J., Alves, V., Nelas, L., Romeu, A., and Basto, S. (1999). An Information System That Supports Knowledge Discovery and Data Mining in Medical Imaging. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 37-42.

[44] Meng, Y. K. (1996). Interval-Based Reasoning in Medical Diagnosis. Proceedings of National Conference on Research and Development in Computer Science and Its Applications (REDECS'96), UniversitiPertanian Malaysia: Kuala Lumpur, pp. 220 -224.

[45] Sarle, W. S. (1999). Neural Network FAQ, part 1 of 7: Introduction. Periodic posting to the Usenet Newsgroup comp.ai.neural-nets, ftp://ftp.sas.com/pub/neurl/FAQ.html

[46] Jankowski, N. (1999). Approximation and Classification in Medicine with IncNetNeuralNetworks. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 53-58.

[47] Lippmann, R. P., Kulkolich, L., Shahian, D. (1995). Predicting the Risk of Complications in Coronary Artery Bypass Operations Using Neural Networks. Advances in Neural Information Processing Systems 7, The MIT Press, Cambridge, pp. 1053-1062.

[48] Heden, B., Ohlsson, M., Rittner, R., Pahlm, O., Haisty, W. K., Peterson, C., and Edenbrandt, L. (1996). Agreement Between Artificial Neural Networks and Human Expert for the Electrocardiographic Diagnosis of Healed Myocardial Infarction. Journal of the American College of Cardiology, Vol. 28, pp. 1012-10s16.

[49] Street, W. N., Mangasarian, O. L., andWolberg, W. H. (1996). Individual and Collective Prognostic Prediction. Thirteenth International Conference on Machine Learning.

[50] Karkanis, S. A., Magoulas, G. D., Grigoriadou, M., and Schurr, M. (1999). Detecting Abnormalities inColonoscopic Images by Textual Description and Neural Networks. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 59-62.

[51] Caruana, R., Baluja, S., and Mitchell, T. (1996). Using the Future to “Sort Out” the Present: Rankrop and Multitask Learning for Medical Risk Evaluation. Advances in Neural Information Processing Systems 8, The MIT Press, Cambridge, pp. 959-965.

[52] Pranckeviciene, E. (1999). Finding Similarities Between An Activity of the Different EEG’ s by means of a Single layer Perceptron. Machine Learning and Applications: Machine Learning in Medical Applications. Chania, Greece, pp. 49-52.

[53] Partridge, D., Abidi, S. S. R., and Goh, A. (1996). Neural Network Applications in Medicine. Proceedings of National Conference on Research and Development in Computer Science and Its Applications (REDECS’96), UniversitiPertanian Malaysia: Kuala Lumpur, pp. 20 - 23.

[54] Shortliffe, E. H., Fagan, L. M. and Yu, V. L. (2000). The Infectious Diseases Physician and the Internet. In Mandell, G.L., Bennett, J.E. and Dolin, R. (Eds.), Mandell, Douglas, and Bennett' s Principles and Practice of Infectious Diseases, Churchill Livingstone, Inc., Pennsylvania, pp. 3258-3263.

[55] Detmer, W. M. andShortliffe, E. H. (1997). Using the Internet to Improve Knowledge Diffusion in Medicine. Communications of the Associations of Computing Machinery, Vol. 40, No. 8, pp. 101 - 108.