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A SURVEY OF MEDICAL DIAGNOSTIC REASONING ALGORITHMS AND THEIR APPLICATIONS IN MEDICAL EXPERT SYSTEMS

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ABSTRACT

Clinical diagnosis is gradually shifting into the homes of patients. This swing is owned to humanizing efforts geared towards the creation of more approximate medical diagnostic reasoning algorithm (MDRA). Researchers have crafted different models to make autonomous approach, clinicians have built their study and experienced on how to tackling diagnostic tasks. Some of these models are based on statically, mathematical, fuzzy and rule based. Despite their different approaches, they are all oriented towards a MDRA with higher precision. This paper chronicles a list of medical diagnostic algorithms, and then x-rays their key features. Furthermore, a careful study is carried out to identify their various weaknesses as well highlights their benefits over the others. Meanwhile, a comparative study of the MDRAs is presented in this paper. This comparison is metricized around the reasoning mechanism in the algorithm, the accuracy or approximation of diagnosis and the type of ailment they are best used to diagnose. This will help enlighten and chart the course for those who might intent to build a more approximate and efficient MDRA from a hybrid of existing ones. This paper concludes with a discussion into the future research, which are yet to be made in MDRA development.

Keywords*: Pattern Recognition, Genetic Algorithm, Fuzzy logic, medical Diagnosis,*

INTRODUCTION

The World Health Organization's definition of health is not merely the absence of disease but the attainment of a state of physical, mental, emotional and social wellbeing (Omotosho *et al*, 2005).While eHealth is simply the use of information Communication Technology (ICT) in delivery healthcare services. The gap that exist in the use of technology in healthcare delivering between the developed and developing nations is being gradually closed by technological transfer and globalization of the entire world. This has translated into the development and deployment of varying eHealth applications. Most of these applications have been used in tackling problems of patient record keeping and registration, hospital equipment inventory keeping, financial and billing systems, and pharmacy systems. More so, medical professionals have also employed the use of technology in advancing information sharing across borders (Rwashana and Williams, 2008), thereby having a great impact on the healthcare delivery.

However, there remains a more rewarding aspect of technology which when exploited in automating healthcare delivery, the service delivery will help mitigate the patient-doctor ratio problem; especially in developing nations. This aspect of computing is the field of artificial intelligence or expert systems. Some of the major features of eHealth expert systems supports increase in accessibility, accuracy (in the absence of proficient medical personnel) and efficiency. Pervasive computing and artificial intelligence put together will result into a stronger framework for deployment of accessible and approximate medical expert systems. Really, artificial intelligent (AI) systems are supposed to support health workers in tasks that rely on data and knowledge manipulation (Coiera, 2003). Systems resulting from this are usually termed clinical decision support systems (CDSS), and are useful in alerts and reminders, therapy critiquing and planning, diagnostic assistance, information retrieval, image recognition and interpretation and prescribing decision support system. Kawamoto *et al* (2005) revealed that CDSS significantly improved clinical practice by 69% of trials. This reechoes the call for more deployment of CDSS in improving healthcare service delivery.

Basically, CDSS help to improved patient safety through reduced medication errors and adverse events and improved medication and test ordering, it also improve the quality of care by increasing clinicians' available time for direct patient care, increased application of clinical pathways and guidelines, facilitating the use of up-to-date clinical evidence, improved clinical documentation and patient satisfaction. CDSS enhances efficiency in health care delivery by reducing costs through faster order processing, reductions in test duplication, decreased adverse events, and changed patterns of drug prescribing favoring cheaper but equally effective generic brands. However, some setbacks of CDSS are readily obvious though this should not hinder a tradeoff of the limitations in favor of the benefits. Hence, some limitation of CDSS includes being perceived as a threat to clinical judgment. CDSS are also considered too inflexible and promotes over-reliance on software. They limits clinicians' freedom to think, and are difficult to evaluate. They are time-consuming to use, possibly lead to longer clinical encounters and create extra work. They are uncertain and untested ethical and legal status. In terms of costing, their maintenance, support and training are required after initial outlay.

In this paper, a survey of medical diagnostic reasoning algorithms is carried out. Each of the selected algorithm is discussed under the following points: their features, strength, weaknesses, and most likely field of medicine they are best-fit for implementation. Meanwhile, some working expert medical systems are also reviewed. The remaining part of this paper is sectionalized into discussing the medical diagnostic expert systems, MDRAs, examples of medical expert systems, prospects in harnessing semantic web idea into MDRAs implementation, and lastly the conclusion.

Medical Diagnostic Experts Systems

Expert systems are computer applications that could be classified as a branch of applied artificial intelligence (Kishan*et al.*, 2012). This category of computer application enables computer to be delegated the task of human decision making. Since the decision making process in humans are coordinated by reasoning pattern or understanding they have garnered over years of experiences, it can be assumed that they have consciously or unconsciously built a coordinated rule system. Hence, when expert systems are being employed in deploying applications that will do almost the same task a human will do, such systems will also need a coordinated rule system. Designing an expert system requires a knowledge engineer and individual who have an understanding of how human experts carry out their decision making process, and then translates the human reasoning pattern into a computer understandable rule system. They tend to solve their problems using heuristics, approximate method or probabilistic theory, and at the end provides explanation of their solutions. Though expert systems have a wide range of application, this paper concentrates on reviewing medical diagnostic oriented expert systems.

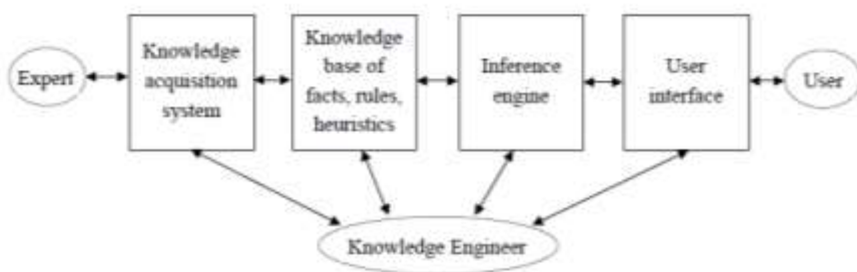

Fig. 1: Architecture of Expert Systems (source: Bullinaria, 2005)

Programming expert systems is quite different from programming conventional systems. One could describe a conventional program by;

Conventional Program =algorithm +data

On the other hand, one would have to describe expert system's program by;

Expert System=inference engine + knowledgebase +data

This equation is efficiently captured in Figure 1. It is advantageous to invest on expert systems given their viable tasks. Expert systems are allows decision making, to solve complex problem. It also allow the experts to concentrate on rarer, more interesting tasks, provides a community memory for sharing and propagating knowledge, permits the standardization of techniques, methods, requirements, and so on. In this section, an outline of some medical expert systems is reviewed. Basically, their features are discussed based on the algorithm upon which they are built and what ailment they are best meant (or intended) to help diagnose.

MEDICAL DIAGNOSTIC REASONING ALGORITHMS

Divers models and approaches have being adopted in diagnostic tasks in the medical field. Considering the uncertainty of data in the field of medicine, some of these models (algorithms) have efficiently resulted in more precise medical diagnoses. These algorithms can be categorized into fuzzy logic, statistical models, data-driven, mathematical models, rule-base, and other approaches. In this section, we shall take a close look at some medical diagnostic algorithms; considering their basic features, strengths and weakness. Furthermore, we shall present a comparative analysis, as shown in Table 1, of the reviewed algorithms.

Scheme-inductive Reasoning (forward thinking)

Scheme inductive reasoning (also known as forward thinking) is based on adding characteristics of the syndrome to narrow the list of potential diagnoses. In scheme inductive reasoning, schemes are drawn to resemble that of road maps. It helps clinicians break down information into chunks, storing them in their memory and then retrieving them subsequently for problem solving task (Anderson, 2006). Scheme inductive reasoning is useful in both problem solving strategy and learning purposes. A great level of expertise is required from the participating physician (or expert system). This is because scheme inductive reasoning relies more on the supporting knowledgebase. It organizes the knowledge into schemes in order to enhance search-and-retrieve task. The accuracy of scheme inductive reasoning is dependent on the mastery of the knowledgebase by either the physician or the expert system. This invariably indicates that given a scanty or unchecked knowledge in the knowledgebase, scheme inductive algorithm may not be efficient; and this is why most times, it is used alongside other medical diagnostic algorithms.

Pattern Recognition

Pattern recognition is employed in machine learning for assigning some outputs to some inputs base on the coordination of a given algorithm (Umoh *et al*, 2012). The output could be values could be a Label while the input be an instance. In deducing a pattern from another credible pattern, an algorithm is used to match some features of the credible pattern against the to-be validated pattern. Some algorithms have being used in pattern matching tasks, and the easiest and cheapest is the nearest algorithm, while back-propagation algorithm is the most computationally demanding. Nearest algorithm when used in pattern matching simply matches the two category of patterns by taking the vector of the unknown pattern and then computes its distance from all proven patterns in the database. The pattern having the nearest distance is chosen as the match for the pattern we seek to recognize. Physicians often instantaneously recognize the patterns of diseases with which their patients present. When pattern recognition is used in medicine, the trigger for the diagnosis is the disease, not the syndrome and not the symptom.

Umoh*et al* (2012) used genetic algorithm to implement a diagnostic system for gonorrhea. The system which enables physicians diagnose the sexually transmitted disease submit patient's symptoms as input into the system. The system which is probabilistic in nature looks out for a similarity in pattern between the input and an already acceptable existing pattern. The system identifies the degree of membership of which the patient's symptoms belongs to a given set of symptoms of gonorrhea. This coordinated algorithm alongside the existing pattern helps physician establish the certainty of a patient having the disease.

Hypothetico-deductive Reasoning

Hypothetico-deductive reasoning involves the self-reflection and informed clinical decision making process of generating and testing hypotheses in association with the patient's presenting symptoms and signs (Kumar *et al*, 2013). It relates to, being, or making use of the method of proposing hypotheses and testing their acceptability or falsity by determining whether their logical consequences are consistent with observed data (accurate but perhaps less than helpful), and is also called Analytical reasoning. Differential diagnoses is used to center on a particular symptom when using the Hypothetico-deductive reasoning. When a combinatorial approach of different algorithms (pattern recognition, scheme-inductive and hypothetico-deductive reasoning algorithms) is embarked upon, hypothetico-deductive reasoning stacks below pattern recognition and scheme-inductive reasoning algorithms.Figure 2 shows a calibration of some of these algorithms along the line of increasing expertise.

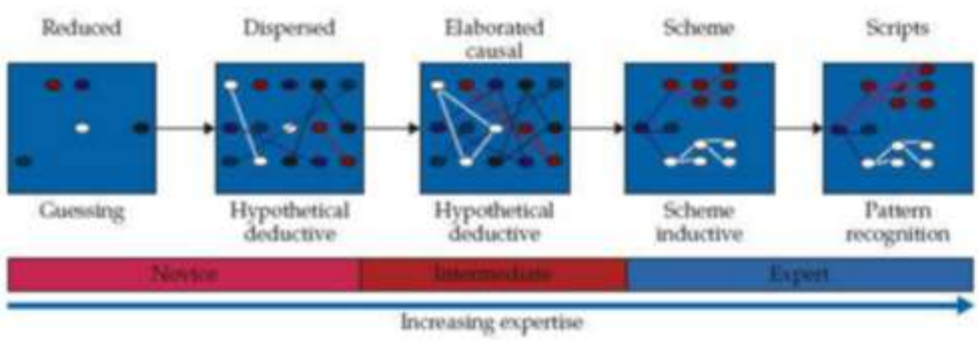

Figure 2: Evolution of knowledge structure from novice to intermediate to expert (Munshi *et al*, 2013)

Backward and Forward Reasoning

Backward and Forward reasoning methods are sometimes used in a coordinated way, both backward and forward reasoning may be used independently. In forward reasoning, the system often work from data to derivation of conclusion based on a given rule, and it is sometimes called data-driven approach. To reason forward, data is matched in working memory against rules in the rule-base. On the contrary, to reason backward, the system moves from conclusion to facts, and sometimes called goal-driven approach. So, backward reasoning match a goal in working memory against conclusions of rules in the rule-base (Lang and Toussaint, 2010). The choice of either using the forward or backward reasoning depends on the nature of problem. Moreover, backward reasoning is desirable when the goal is given in the problem statement while forward reasoning will be desirable when all the facts are provided with the problem statement. However, as earlier stated, combining forward and backward reasoning has being proven by empirical results that the bidirectional probabilistic reasoning can lead to more efficient and accurate planning in comparison to a pure forward reasoning (Lang and Toussaint, 2010).

Although, backward chaining is more focused and attempts to avoid considering unnecessary paths of reasoning. Forward chaining, on the other hand explores all possible search paths. While backward chaining systems are best adopted for diagnostic purposes, they could be inefficient when applied for planning, design, process monitoring, and quite a few other tasks. But forward chaining systems can handle both medical diagnostic tasks and as well those categorized as weak areas of application of backward reasoning. Forward chaining system, includes writing rules to manage sub goals. Whereas, backward chaining systems automatically manage sub goals (Sharma et al, 2012). Forward reasoning is efficient and fast, backward reasoning can be employed to resolve the conflict between two competing hypotheses. A combination of the two reasoning method – backward and forward –with increased experience leads to increased coordination of hypothesis and evidence (Hardin, 2002).But this combination is not without its limitation; for decomposition of the problem into an AND-OR graph.

Lang and Toussaint (2010) combined backward and forward reasoning approaches and presented their result in a paper titled 'Probabilistic Backward and Forward Reasoning in Stochastic Relational Worlds'. The research combined backward with forward reasoning in a bidirectional two-filter approach. Empirical results showed that bidirectional probabilistic reasoning can lead to more efficient and accurate planning (or diagnostic procedure) in comparison to pure forward reasoning. However, they noted that in case of many objects, it will likely lead to increase in state and space complexity in relational domains; this is partially owed to the fact that forward chaining is an all-path-exhaustive method. Forward-backward reasoning when used in improving rule engines, it enables the system so that such engines can efficiently go around solving dialogue-oriented rules. Moreover, intent of the rule, size of the dataset and performance requirements affects the learning curve of the rule engine (Sharma *et al*, 2012).

Parsimonious Covering Theory

Parsimonious Covering Theory (PCT) works on the basis of associating a disorder to a set of manifestations. It uses two finite sets (disorders & manifestations) to define the scope of diagnostic problems (Wainer and Rezender, 1996). Two basic limitations of PCT are that the domain knowledge is atemporal and that one or more disorder or manifestation in the Cover (Parsimonious criterion) adversely affects the explanation.

Models Based on Fuzzy Logic

In fuzzy logic, linguistic variables are used to represent operating parameters in order to apply a more human-like way of thinking (Torshabi *et al*, 2013). One of the main factors affecting fuzzy logic model performance is data clustering for membership function generation.Fuzzy logic is good for classification of values or features, and rules are used in handy. It uses values between 0 and 1 to describe how rule-based agents/systems can be modelled to think as human. It has been used in many areas of medical applications such as in CADIAG, MILORD, DOCTORMOON, TxDENT, MedFrame / CADIAG-IV, FuzzyTempToxopert and MDSS, and is also deployed for use in implementing control systems, household appliances, and decision making systems, the medical and automobile industries(Awosika *et al*,2014).

Ephzibah (2011) designed a model that uses the diabetes dataset and generates the best feature subset using genetic algorithms and fuzzy logic for effective prediction of the disease. The components of the model consists of fuzzification module, rule base with 'if–then' rules and related membership functions, inference engine, and defuzzification module. Zadeh *et al.* (2012) also combined fuzzy-neural logic and genetic algorithmin diagnosing breast cancer.The study focused on the creation of an information bank for thermal imaging. The clustering of the samples in thermal images was undertaken based on fuzzy- neural logic. Difficulties encountered due to the sheer volume of the samples limited the neural–fuzzy module from clustering all of the samples, taking into consideration the full scope of the parameters. To remedy this, a combination module was designed from a genetic algorithm and artificial net in order to decrease the diagnostic parameters.

Models Based on Bayes Theorem

Bayesian networks are oriented acyclic graphs consisting of nodes (circles), which represent random variables; arcs (arrows), which represent probabilistic relationships among these variables (Gadewadikar *et al*, 2010) and this helps in dealing with uncertainties. However, Bayesian medical reasoning depends on utilization of conditional probabilities as a priori probability function and possibilities.

Sampaio *et al* (2008) designed inference algorithms to aid medical diagnosis based on the Bayesian network.They presented the execution time and convergence analyses for exact and approximate algorithms on probabilistic inference.This enables their work to apply the Bayesian reasoning in the supportto the medical diagnosis.Bayesian network have also being explored in diagnosing cancer. Gadewadikar *et al* (2010) developed a decision support system based on Bayesian network in diagnosing breast cancer detection. The decision support system which gives a computer-aided detection in mammography also provides an interface between the project's Bayesian network learning algorithm and the radiologists.

Certainty Factor Model

Certainty factor model is used for managing uncertainty cases in a rule based system (Heckerman, 1990). It was first developed for the MYCIN, expert system used for diagnosing and treating meningitis and infections of blood. Certainty Factor model can be interpreted as measures of change in belief within the theory of probability (Heckerman and Shortliffe, 1992). The model's performance might be sensitive to the domain of application. This is because it was originally made for the domain of MYCIN. Just as indicated in the scheme inductive reasoning model, CF might not also be sufficient in carrying out diagnostic task, most importantly in domainswhere the treatment that will be recommended by the system is sensitive to accurate diagnosis. CFs do not correspond to probabilities. The model implicitly imposes assumptions that are stronger than those of the simple-Bayes model. The assessment of CFs is often more difficult and less reliable than is the assessment of conditional probabilities. CF has the theoretical difficulties of updating beliefs within the CF model. The CF model requires that we encode rules in the direction in which they are used. That is, an inference network must trace a trail of rules from observable evidence to hypotheses.

Konias *et al*, (2002) argued that due to tendency of having missing data in a non-exact or relative sciences like medicine, it could be difficult to find associations among attributes of a data stored in such cases. Hence, they formulated some associational rules which are each assigned a certainty factor. The concept of the certainty factor is to help the system judge the possibility of a rule assigned it produce a good result. The form of these rules is **IF X THEN Y CF** where X and Y itemsets, with $X \cap Y = \emptyset$ and CF a certainty factor. The algorithm which is called Uncertainty Rule Generator (URG-2) consists of two sub-algorithms. The first part of two algorithms finds the existing itemsets and the missing values in the database in an incremental order, while the second sub algorithm mines for the best fitting rule to use. They proved that in a database where finding the association of attributes of data is a concern, specifically in situations of missing data among the overall database, then applying certainty factor to rules helps in achieving such feat.

When certain factors are assigned to multiple rules, they can be used to generate more precise inference which can be used in diagnosing diseases in internal medicine (Munandar *et al*, 2012). In this research, they developed an expert system for diagnosing disease using inference techniques certainty factor with multiple premise rule. Patient determines the symptoms of the disease, this is in order to obtain the final diagnosis according to the patient's level of conviction entered. Depending on the patient’s conviction level, the system has a confidence level of about 90% for diagnostic search results.

Information Processing Approach

Information processing is a model that makes inferences drawn from observation, and the model is patterned after the way human being process their information. The entire process of information process is triggered by a stimuli, this then generate input processes which are stored alongside the implementation of related processes. The output processes produce a response to the stimuli that initiated the model. Clinical decision making are also carried out using information processing approach. This approach first assumes a limitation on the capacity on information. It is a model that both processes and organizes information, and as well build on learning curve of the underlying expert system. The working structure of the information and processing model usually consists of either a scientific or hypothetico-deductive approach (Banning, 2007). A two-way flow of information handling and storage is assumed in the information processing model: sensory and memory. Information are exchanged and processed right from the sensory – point of stimulus and response –and then stored from retrieval in the memory. The memory is categorized into primary (short term) and secondary (long term). Though this approach evolves from the human information processing flow – same as the clinician natural course of diagnoses - however, it has not enjoy sufficient implementation in realizing medical expert systems.

Select and Test

Fernando and Henskens (2013) described the approach for medical diagnostic reasoning based on ST Algorithm model which was earlier introduced by (Ramoni and Stefanelli et al, 1992). In their work, they ascertained the major fact of the algorithms discussed in the previous paragraph is lacking accuracy in their diagnostic approximation result. Hence, they showed that their approach of using ST algorithm in medical diagnostic reasoning yields an approximate reasoning model. The ST Model describes a cyclical process which uses the logical inferences of abduction, deduction, and induction procedures in arriving at its reasoning task. The algorithm involves a bottom-up and recursive process using its four stages of logical inferences (abduction, deduction, and induction). The cyclic flow of these four stages of the ST model. The model adopted a two-layered entity mapping in order to model a simplified knowledgebase representation of diagnosis and symptoms.

The summary of most of the clinical/medical diagnostic algorithms reviewed above, are presented in Table 1.

Table 1: A Comparative analysis of the reviewed medical diagnostic algorithms

Medical Reasoning Algorithms	Reasoning Technique/Approach	Field/Area of Application in medcine	Strength	Weaknesses	Features
Scheme-inductive Reasoning	Rule based and uses inference engine	expert systems, business and production rule systems	It discourages the rote memory and helps in the development of scientific attitude.	Insuffiencet rules impairs the diagnosis process	Production rules
Pattern Recognition	Classification technique	Well used in clinical reasoning when there are difficult cases and	most common form of non-analytical processes, and allows clinicians to formulate diagnostic	Diagnostic accuracy does not depend as much on	Uses features for making a link between a given

		when case is more pattern recognition or direct automatic retrieval.	hypotheses very fast	strategy but on mastery of content.	clinical situation and patterns stored in the long-term memory
Hypothetico-deductive Reasoning	Analytical reasoning	Used by physicians when the intuitive system is unable to generate early relevant solutions to complex or rare problems.	It helps in strengthening or ruling out the initial hypotheses	The reasoning strategy ignores under determinatio n	Observation and testing features
Backward and Forward Reasoning	Rule based and uses inference engine	Rule based medical reasoning systems	Exploits the benefits of both forward and backward reasoning.	There must be provision for conflict resolution strategy	It has rules sets for moving in both direction of goals-facts and facts-goals.
Parsimonious Covering Theory	Uses something similar to association rule	Applicable in medical conditions present clear manifestations	Exploits the basis of associating a disorder to a set of manifestations.	The domain knowledge is atemporal and that one or more disorder or manifestation in the Cover (Parsimonious criterion) adversely affects the explanation	Association rules
Models Based on Fuzzy Logic	Fuzzy sets and rule sets	Applicable in medical cases with uncertainties	Appropriately handles cases with vague input or incomplete medical data. The Algorithm can be defined with little data and memory	Fuzzy logic reasoning is classified as an approximate form of reasoning.	Rules, fuzzier, defuzzier, and inference engine.
Models Based on Bayes Theorem	Inference making	Applicable in medical cases with uncertainties	It facilitates representing and taking fuller account of the uncertainties related to models and parameter values. It also has the ability to incorporate prior information. Good at inference/prediction/decisio n making	It has an important bearing on the final outcome of the analysis and for which there is considerable uncertainty. It often comes with a high computational cost.	
Certainty Factor Model	rule-based	Best used to manage uncertainty in clinical cases/diagnosis	Created to avoid the unreasonable assumptions in the idiot-Bayes model. Successful in application and stable against changes.	The model imposes the same sort of modularity on uncertain rules that we ascribe to	Rule set, inference network.

				logical rules. In certain circumstances , the CF model implicitly imposes assumptions of conditional independence that are stronger than those of the idiot-Bayes model. Increased search.	
Information Processing Approach	Clinical decision making are also carried out using information processing approach	The approach evolves from the human information processing flow – same as the clinician natural course of diagnoses.	Large amounts of information is processed into a meaningful value; It has not enjoy sufficient implementation in realizing medical expert systems	Characterizes the environment as the culprit for providing the input of data that is transformed through individuals' senses	The working structure of the information and processing model usually consists of either a scientific or hypothetico-deductive approach. Stimuli for triggering input and and output processes
Case-based reasoning (CBR)	Reasons base on similarity of cases	Applicable when there are loads of effective/similar medical cases	Since much of human expert competence is experience based and it makes sense to adopt a reuse-based methodology for developing knowledge based systems, its means CBR might more accurate. CBR are used to develop knowledge based systems because it involves less knowledge engineering.	Memory intensive technique; it allows the development of knowledge based systems in weak theory domains; If CBR can work without formalizing a domain theory then there is a question about the quality of solutions produced by case-based systems.	Large memory for storing reusable cases, uses case comparison algorithms like distance measurement .
Select and Test	Rule-based with inference engine	Applicable in clinical domain where clinical guideline/protoco l is available and	Exploit the use of multiple (three) inference making models	An approximate reasoning algorithm	Uses the abduction, deduction, and induction

		clear.			reasoning pattern.

Application of Medical Reasoning Algorithms to Medical Diagnosis

In this section, an outline of some applications of medically diagnostic expert systems is discussed. Some of these systems includes MYCIN, INTERNIST-I, CADUCEUS, DENDRAL, CADIAG-2, MEDICO, PUFF and ESTDD. MYCIN is an early expert system for the diagnosis and treat meningitis and bacteremia, and was developed from the Certainty Factor Algorithm.

INTERNIST-I is an experimental computer-based diagnostic consultant for general internal medicine (Miller *et al,* 1982), and it has the capacity to diagnose multiple and complex diagnoses. Due to its generality in diagnostic task, it differs from other medical expert systems in its knowledgebase size (precisely describes about 570 diseases in internal medicine) and wide-scope of information its stores. However, Miller *et al* pointed out that an evaluation of the workings of INTERNIST-I proves that it is not reliable for clinical applications. It is opined that a narrowing of medical expert system to a particular ailment will help guarantee its reliability and precision. The omission of differential diagnoses and its inability to reasoning anatomically edges it out. Another similar medical expert system to INTERNIST-I is Quick Medical Reference (QMR). QMR also diagnoses ailments relating to internal medicine, and relies on the INTERNIST-I knowledgebase as a means of sourcing its information. It can viewed as "an electronic textbook of medicine" serving as an information tool aiding users to review and manipulating the diagnostic information from the knowledgebase (Miller *et al,* 1986).

Computer Assisted DIAGnosis (CADIAG-1 and CADIAG-2) are expert system for diagnosing disease relating to internal medicine. CADIAG-1 is built purely on symbolic logic while CADIAG-2 was designed to work on the fuzzy set theory and fuzzy logic (Kolarz and Adlassnig, 1986). Its rule set in the form of IF-THEN rules capable to represent uncertain relationships between distinct medical entities (Klinov and Parsia, 2011). Like other expert systems, it consists of two basic components: inference engine and knowledgebase. These two components characterizes it in solving uncertain information. However, the large size of the rules of CADIAG-2 makes it difficult to validate its consistency, hence Klinov *et al* (2010) a probabilistic approach was added to it to correct this error. Also, CADIAG-2 rule sets are conflicting and uncertain in their nature. This implies that the satisfiability of a rule is gauge to a certain degree an information confirms the other.CADIAG-2 supports medical personnel in making findings on symptoms, signs, interpreting laboratory test results, and clinical findings. CADUCEUS is an expert system similar to MYCIN. Its inference engine shares same features with that of MYCIN, and was actually meant to be an improvement on MYCIN (Oluwafemi, *et al, 2014*).INTERNIST-I knowledgebase was use as the data source of CADUCEUS - also known as INTERNIST-II. It surpasses INTERNIST-I in speed of arriving at solution while it eliminates a large part of the search path right away. One major limitation of CADUCEUS is that it lacks temporal reasoning.

DENDRAL is a large scale group of programs (which may be executed as subtasks) that is both rule-base and as well having a heuristic program make up. It was the first rule-base expert system to be applied to solve real world problems. DENDRAL's knowledge driven – strongly functional base on its knowledge base –capacity adds up to enhancement. Originally, DENDRAL generates only ring-free structure, and is also known as DENDRitic Algorithm. It was a procedure for exhaustively and non-redundantly listing all the topologically distinct arrangements of any given set of atoms, consistent with the rules of chemical valence (*Lindsay et al*, 1993).Though an interdisciplinary expert system, it mostly used by chemist in their research goals than the original designer. A unique feature of DENDRAL is how well defined it problems are declared, resulting in a feasible way of reaching success. Azar and Hassanien (2013), designed an Expert System for Thyroid Disease Diagnosis (ESTDD). The ESTDD was patterned after a Linguistic Hedges Neural- Fuzzy Classifier with Selected Features (LHNFCSF).

PUFF is originally created on a research machine at Stanford, named SUMEX, and was later redesigned to run in a production state for use in the hospital. Its purpose is to interpret the pulmonary function test for patient with lung cancer. PUFF is reputed to be the medical expert system to be deployed for clinical practice. Backward reasoning (goal driven) approach is the underlying reasoning framework adopted in PUFF, and this reasoning framework reasons over 400 production rules. Moreover, the rule interpreter used in PUFF is that of MYCIN, this includes the explanation and knowledge acquisition strategy of NYCIN. This is why PUFF is rumored to be developed using EMYCIN.MEDICO,

EVALUATION AND PROSPECTS OF MDRAS

In this section, we present an evaluation and discussion in comparison of literature on researches which have applied some of these medical diagnosing algorithms. We have chosen to compare the category of algorithms reviewed in this paper with those of machine learning and machine reasoning. Our comparison in this section is listed in Table 2

.

Table 2: Performance some medical diagnostic algorithms

Authors/Year	Algorithms used	Category of Machine Intelligence	Accuracy
Aloraini (2012)	Bayesian Network, Naïve Bayes, Decision trees J4.8 , ADTree, and Multi-layer Neural Network	Machine learning (ML)	95.6%
Sene (2018)	Evidence theory and data mining	Data mining & Semantic clarification through ontology	N/A
Tapi Nzali (2018)	Linguistic and statistical approaches	Data mining	N/A
Tapi Nzali (2017)	Classic text mining technique, latent Dirichlet allocation (LDA)	Data mining	N/A
Agarap (2018)	GRU-SVM, R, MLP, NN, SR, and SVM	Machine learning (ML)	>90.0%
R. Seising (2006)	Fuzzy logic	Machine reasoning	Not stated
Rakus-Andersson and L. C. Jain (2009)	Approximate reasoning algorithm and Fuzzy sets	Computational intelligence	Not stated
Alharbi and Tchier (2016)	Fuzzy-Genetic Algorithm Method	Machine reasoning (MR)	97.33 %
WBCS	Medical experts	Human intelligence	100 %
Fernando et. al. (2013)	Select & Test (ST) algorithm	Approximate Reasoning (Abduction, deduction and induction inference)	N/A
ST-ONCODIAG	Select & Test (ST) algorithm	Ontology learning & Semantic machine reasoning (MR)	88.72%

Those of Aloraini (2012) and Agarap (2018) which are machine learning (ML) based techniques have accuracy of 95.6%, 90.0%, and 97.36% respectively. Furthermore, the works of Alharbi and Tchier (2016) is a fuzzy-genetic based algorithms attained accuracy of 97.33%. However, fuzzy-genetic algorithms are limited by difficulty of genetic algorithm to guarantee optimality and solution weakens with increased size of the problem. Similarly, it has being revealed that ML algorithms may suffer the problem of acquisition of relevant knowledge or data which usually have impact on the performance of ML. This is contrary to MR which adapts to more flexible adaptation even in big data investigations. Finally, the works of Fernando et. al (2013) and Oyelade et al (2017) which were focused on logical inference making (using abduction, deduction, and induction) process, may be categorized under machine reasoning.

A major issue that characterizes technological advances in a particular field is the prospects it holds for future improvement. Most of these features include scalability, backward compatibility, and developmental strategies on its underlying languages, frameworks and components. In this section, the projection of MDRA is basically narrowed to the Semantic web idea. Exploiting the following in implementing MDRAs for medical expert systems will further improve the diagnostic approximation of the expert system.

a. Modeling the knowledge base of the expert system in an ontological approach. Ontology languages with their corresponding constructs, peculiar to a given domain have being developed. One approach to this is to continue to promote ontology language particular to each field of medicine where the MDRA is proposed for deployment. Another approach is to create a well-defined ontology knowledge base, exploiting the OWL/OWL2 constructs that are capable of supporting inference making.
b. Rule based systems are characterized by production rules. The semantic web provides rule languages such as SWRL and Rule ML for encoding rules while porting the rule system to a semantic web application. Designing and implementing a coordinated rule system with such rule languages, and as well assigning a certainty factor value to each rule in the rule system, will complement the knowledge base in realizing the expertise in the system.
c. Reasoners such as Pellet and Fact++, and rule engines like JESS can be combined to help integrate the coordinated rule system into the semantic web application.
d. Calibrating the result of a medical expert system so as to enable the user know the severity of the diagnosed ailment is a necessity in result presentation. Some mathematical models can be imported into the semantic web application for achieving this task.

CONCLUSION

In this paper, a retrospective research was done, detailing the basic features of some major medical diagnostic reasoning algorithms, and their best-fit in terms of implementation. This MDRAs discussed in this paper were also highlighted to be the underlying working structure of medical expert systems, necessitating the need to explore a few number out of the medical expert systems developed so far. Finally, we made some notable considerations to guide the thoughts of future researchers in formulating or hybridizing or even improving existing medical reasoning algorithms

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