International Journal of Engineering Research and General Science Volume 3, Issue 4, July-August, 2015
ISSN 2091-2730

A WEB BASED DECISION SUPPORT SYSTEM DRIVEN FOR THE NEUROLOGICAL DISORDERS

Shiny Mathew[1], Shilu Mathew[2], M.Haroon Hamed[3]and Ishtiaq Qadri[3*]

[1]Department of multimedia technology, Karunya University, Coimbatore, India

[2]Center of Excellence in Genomic Medicine, King Abdul Aziz University, Jeddah, Saudi Arabia

[3]Department of biological sciences, King Abdul Aziz University, Jeddah, Saudi Arabia

[4]King Fahad Medical Research Center, King Abdul Aziz University, Jeddah, Saudi Arabia

Tel.:+966549574512; fax: +966549574512, E-mail: ishtiaq80262@yahoo.com

ABSTRACT- "Neurology Diagnosis System" is a web-based expert system for diagnosis of neurologic disorders or the disorders of our nervous system. It is built by using Web based decision support system (WBDSS) by encoding rules of the neurology domain and by developing a framework to learn from the cases of the patients. This knowledge encoding is essentially the implementation of two artificial reasoning techniques called case-based reasoning and rule-based reasoning and is ultimately used to assist the diagnosis of neurological disorders based on the principles and practices of medical diagnosis. Concerning the methodology, the basic principle is to encode the knowledge of the neurology domain in the form of rules and representative cases and use this knowledge to solve new cases of patients. To perform the reasoning, input to be provided is the clinical examination data along with medical history. The result of performing rule-base reasoning is a list of probable diseases and the output of case-based reasoning is a list of cases similar to the one being diagnosed. The proposed system will assist medical personnel especially in rural areas where there are shortage of doctors in providing quality health care services. The proposed system can be useful for new practitioners for neurological diagnostics.

INTRODUCTION

Neurology is the division of medicine that covenants by the nervous system and its disorders. The field of artificial intelligence (AI) attempts to understand these capacities better known as intelligent entities. AI being a broad topic combines computer science, physiology and philosophy. Computer programs provide assistance to store, retrieve and organize relevant medical information which is required by practitioners to handle intricate cases and to recommend suitable prognosis, diagnosis and curative decisions. One of the large scale applications of the field of AI is the development of expert systems. An expert system contains knowledge of human experts of particular realm.

Among the various types of expert systems, this project reports the development of a hybrid expert system which is an assimilation of two reasoning techniques i.e. case-based reasoning and rule-based reasoning techniques. Rule-based system is used when problem area is narrow and the domain has well-understood theory [1]. To overcome these limitations, case-based reasoning technique is also integrated. This unravels new dilemmas based on the elucidation of akin past problems rather than merely using rules. Expert System (ES) is a smart integrative computer-based decision means that utilizes information and rules to decipher tricky real life problems based on the knowledge attained from one or more human expert(s) in a picky domain. ESs has user gracious edges that formulate them extremely interactive in nature and endow with precise and suitable solutions to thorny real life problems. To tackle the scantiness of the usual methods of diagnosis, ES were suggested. ES emerged during early 1970s, has become one of the most important innovations of AI [2, 3].

Clinical Decision Support System (CDSS) create a noteworthy contribution to medical knowledge management technologies, through sustaining the clinical progression and the use of knowledge, from diagnosis to enduring care. The demand of CDSS and its recognition in clinical practice is escalating. Various studies have exposed that CDSS can progress physicians' performance and precision, but that the eminence may rely on the technical advancement used to model medical information [4].

Reasoning mechanisms had been designed by researchers to proficiently operate the knowledge stored in the knowledge based system. Reasoning mechanisms can be classified into two categories: deductive and inductive reasoning approach [5]. They are already executed to facilitate the diagnosis process related to, heart problems, blood infections and kidney disorders. This project concerns the implementation of a system for the neurology domain. Neurology deals with disorders of the nervous system with all types of ailment including the peripheral, central, and autonomic nervous systems, their covering blood vessels, and muscle. This research proposes a WBDSS built by encoding rules of neurology domain and by developing a framework to learn from the patient`s record. A hybrid system is developed by integrating of both techniques to facilitate the prognosis of neurological disorders [6].

The system was extended to provide a decision support platform for medical researchers, practitioners, and health care contributors. In rural areas, particularly, practitioners will be benefited more by this system where severe shortage of healthcare is faced [2, 7].

OBJECTIVE

- To build a WBDSS (Web based decision support system) by encoding rules of the neurology domain and by developing a framework to learn from the cases of the patients.
- To build a hybrid system by the integration of both techniques, will help for the prognosis of neurological disorders.
- The anticipated system will support medical workforce chiefly in rural areas where severe shortage of healthcare is faced [4].

- This system can be valuable for fresh practitioners for neurological diagnostics.

- V. Kurbalijaand M. Ivanovic, (2012) proposed another area of artificial intelligence known as CBR (Case-Based Reasoning). In this system, new problems are worked out by acclimatizing the solutions done successfully in previous problems [6].

- To apply CBR, the field of medicine is best suited because medical experts have knowledge of both textbook and experience, which contains all cases. Major objective of anticipated system is to facilitate medical expert in taking stiff pronouncements. Another very important benefit of this system is to bridge the gap between beginner physicians and experienced experts. Additionally, by creating a rule based system for the diagnosis of MS disease will help to simulate the textbook knowledge of physicians. Afterwards, both case-based and rule-based system will entirely simulate the decision making process of physician [8].

- Mobyen U.A and Jerker Westin, (2012) introduced FIS (fuzzy inference system) which make available the support in dose modification of duodopa infusion in Parkinson`s patients, by utilizing the data from motor state considerations. The DSS has a web based graphical edge that gives vigilant alerts demonstrating non optimal dosage and states, by recommending (typical advice with typical dose) resulting statistical summary. One data set was based on tuning and designing of FIS while other was used to appraise performance compared with actual provided dose [9].
- The users of this system will be physicians and nurses (clinical staff) at neurology clinics. Typically the system will be used shortly before or at patient-visits. Pattern of user necessities was ended by interrogating a little skilled users and leasing them to assess user interface prototypes [10, 11].

COMPARISION TABLE

Table 1: Comparison Of Merits And Demerits Of Existing Techniques

S.No	TITLE	METHODOLGY	MERITS	DEMERITS
1	An Approach of a Decision Support and Home Monitoring System for Patients with Neurological Disorders using Internet of Things Concepts	The Decision Support and Home Monitoring System gives assistance to the physicians in diagnosis, home monitoring, medical treatment, medical prescriptions, rehabilitation mainly for Parkinson's disease.	Geographically independent environment	Only supports spreadsheet
2	INKBLOT: A neurological diagnostic decision support system integrating causal and anatomical knowledge	Uses anatomical localization in much the same way as human neurologists., INKBLOT-l generates a set of hypothetical localizations relative to a coordinate system of nested cubes and then uses these localizations as input data.	Complexity is reduced	-Time-taking -Less user satisfaction
3	Elicitation of neurological knowledge with argument-based machine learning	An efficient technique called argument-based machine learning (ABML) is created by using Expert's knowledge in practice.	Conceptual simplicity and easy utilization. .	Lack of informative data
4	Rule-Based Expert System for the Diagnosis of Memory Loss Diseases	CBR is used as method of reasoning paradigm to solve memory loss diagnosis problems.	Faster processing	Complexity in deriving the variables
5	Dynamic Case Based Reasoning in Fault Diagnosis and Prognosis	A neuro-fuzzy-Case Base Reasoning (CBR) driven decision support system basically used for depression disorder diagnosis.	Accuracy, sensitivity and Specificity	Improper result prediction
6	Intelligent Decision Support System for Depression Diagnosis Based on Neuro-fuzzy-CBR Hybrid	The methodology involves Case-based reasoning to facilitate experience reuse of retrieving previous similar temperature profiles.	System is flexible and easy to be maintained.	Incomplete implementation
7	A Case-Based Decision Support System For Individual Stress Diagnosis Using Fuzzy Similarity Matching	Involves in the mapping of Adaptive neuro-fuzzy inference system consisting of fuzzy rules outcome and local similarities of each category of symptoms for global similarity measurement.	A free to use assistance , stand-alone diagnosis.	Daily updation is required
8	Integration of Rule Based Expert Systems and Case Based Reasoning in an Acute Bacterial Meningitis Clinical Decision Support System	Allows reutilizing change experiences, combined with a classic rule-based inference engine for Higher level of RBC.	Convenient to use, user interface easily aligned	Attributes has to be recorded outside the XML
9	Multiple Sclerosis Diagnoses Case-Base Reasoning Approach	The Domain application uses simple CBR methodology.	Easy and time saving, Useful and user friendly.	More detailing is required.
10	A Fuzzy rule-based decision support system for Duodopa treatment in Parkinson	A web enabled GUI that gives alerts indicating non optimal dosage and states, recommendations provided and statistical summary measures.	KB is needed to be updated regularly.	KB is needed to be updated regularly.
11	Attitude of Iranian physicians and nurses toward a clinical decision support system for pulmonary embolism and deep vein thrombosis	Weight and the impact of each one of these factors were determined and extracted. .	Reduce the morbidity and mortality.	Requires more accurate qualitative inter-views.
12	A pilot study of distributed knowledge management and clinical decision support in	The Clinical Decision Support Consortium is used to make the study.	Feasible and reasonable support for clinical decision-making.	Issues regarding semantic interoperability,

	the cloud.			and usability
13	Decision support from local data: Creating adaptive order menus from past clinician behavior.	Makes use of Bayesian Network (BN) methodology.	It produces human-readable treatment-diagnosis networks human expert to reduce workload .	Poor performance
14	Application of probabilistic and fuzzy cognitive approaches in semantic web framework for medical decision support.	Graphical influence graphs are used such as BBNS and FCMS	-Accuracy -High performance	Missing data and incomplete knowledge
15	Developing a disability determination model using a decision support system in Taiwan: A pilot study	The Scale of Body Functions and Structures Disability Evaluation System	-Severity -category of the disability determined.	Concerns of accuracy and correctness.
16	An intelligent mobile based decision support system for retinal Disease diagnosis.	A low cost Smartphone based intelligent integrated system.	-Efficient algorithm -Very easy to be operated -Efficient low cost mobile solution	Complex and very expensive.
17	Expert system for determining the level of stress before pediatric dental treatment	To undergo this study, we used the following methods: -Psychometric methods -Statistical methods	Expert system greatly eases clinical work by helping the dentist to take the best medical decision at the Beginning of the young patient’s treatment	Complex system.
18	An approach for solving multi-level diagnosis in high sensitivity medical diagnosis systems through the application of semantic technologies	Presents a semantic based technology.	-Flexibility -higher truthfulness if these rules are coded correctly.	Lower sensitivity. More information the accuracy
19	A sustainable and affordable support system for rural healthcare delivery	DSS for medical staff to decide on the each course of diagnosis.	Efficient system for caregivers to monitor.	Patients take less regard in visiting hospital due to the monitoring system.
20	Safety and usability evaluation of a web-based insulin self-titration system for patients with type 2 diabetes mellitus.	Think-aloud sessions with four patients and three DNs are used for evaluations.	No prior experience is needed to use this system.	Incorrect diagnosis, if not used accurately
21	Ovarian cancer diagnosis using a hybrid intelligent system with simple yet convincing rules.	Neural fuzzy inference system is used	Provides Correct diagnoses when benchmarked against other computational intelligence based models.	More time is required.
22	Ontology driven decision support for the diagnosis of mild cognitive impairment	Specialized MRI knowledge is encoded into ontology.	knowledge-based decision support for the identification of MCI to enable automation of decision-support	The sensitivity enough to be used to diagnose MCI alone.

23	A data mining system for providing analytical information on brain tumors to public health decision makers.	Data mining, data warehousing and ontology methodologies are used.	Data mining system that allows public health decision makers to access analytical data.	Algorithms are not given open access.
24	Artificial intelligence framework for simulating clinical decision-making: A Markov decision process approach	Markov decision processes and dynamic decision networks are integrated.	The cost is lesser based on the unit change.	Complex treatment .
25	A decision methodology for managing operational efficiency and information disclosure risk in healthcare processes.	DSS for operational functioning and management.	Helps in problematic security issues pertinent to the organization	Security conflicts
26	Informing the design of clinical decision support services for evaluation of children with minor blunt head trauma in the emergency department: A socio technical analysis.	Clinical decision support services (CDSS) are integrated into electronic health records (EHRs).	CDSS interventions developed for use with an EHR must minimize clinical workflow disruption in the ED.	Results may not be generalizable to health systems and settings
27	'Rapid Learning health care in oncology' – An approach towards decision support systems enabling customized radiotherapy.	Methodology involves semantic interoperability to enable distributed learning and data sharing.	Improves the predictability of outcome.	Reports low levels of involvement
28	Pilot study to validate a computer-based clinical decision support system for dyslipidemia treatment (HTE-DLP)	Provides specific reminders for lipid treatment and diagnosis.	Use of a CDSS in resulted in a significant reduction in LDLC levels of certain patients.	The limited number of short follow-up period.
29	Bridging challenges of clinical decision support systems with a semantic approach. A case study on breast cancer	clinical workflow integration method is used which is followed by a federated approach	Provides reutilization of decision support systems along	Not possible classical validation, Lengthy data gathering process.
30	A web-based system for clinical decision support and knowledge maintenance for deterioration monitoring of hemato oncological patients	We introduce a clinical decision support system (CDSS) based on rules and a set covering method.	-High accuracy	Only few patients can be diagnosed over a period of time.
31	Decision support system for Warfarin therapy management using Bayesian networks	decision support system (DSS) using Bayesian Networks.	Provides assistance for making dose-adjustment and follow-up interval decisions.	The probability elicitation process is lows.
32	An experimental comparison of fuzzy logic and analytic hierarchy process for medical decision support systems.	The case comparative study of the fuzzy and AHP methods	Enhanced understanding of decision variables is induced.	Inappropriate to assign crisp value .
33	Feasibility of Using Algorithm-Based Clinical Decision Support for Symptom Assessment and Management	SAM-L created for symptom management.	Promotes evidence based care systems.	System into the electronic medical record was not possible

	in Lung Cancer			
34	A bi-level belief rule based decision support system for diagnosis of lymph node metastasis in gastric cancer	Belief Rule Base (BRB) is used to model clinical domain knowledge and reasoning is implemented by Evidential Reasoning (ER).	BBRB is more suitable in evaluating LNM than BRB.	Has the best performance compared to other methods.
35	Smart Anesthesia Manager(SAM)—A Real-time Decision Support System for Anesthesia Care during Surgery.	Smart Anesthesia Manager (SAM) that works in conjunction with an AIMS to provide clinical and billing decision support.	Improves quality of care, patient safety reduce consumption of anesthetic agents.	SAM will not work with different AIMS system without modification
36	A hybrid decision support system based on rough set and extreme learning machine for diagnosis of hepatitis disease.	A new hybrid medical decision support system based on rough set (RS) and extreme learning machine.	Used for diagnosing the disease in clinical practices.	Some missing indicators.
37	Clinical Decision Support System (CDSS) for the Classification of Atypical Cells in Pleural Effusions	The objective of this research is to develop a prototype Clinical Decision Support System (CDSS) to aid pathologists in correctly discriminating between reactive mesothelial cells and malignant epithelial cells	The purpose of this initial research effort is to develop a prototype CDSS to aid pathologists in correctly discriminating reactive benign mesothelial from malignant epithelial cells.	More data accompanied by patient outcomes and other experimental information will be critical to validating and developing the CDSS.
38	Diagnosis Support System based on clinical guidelines: comparison between Case-Based Fuzzy Cognitive Maps and Bayesian Networks	A new approach to case based fuzzy cognitive diagnosis & evaluation is done by BBN(Bayesian belief networks)	Provides better results approximate reasoning and incomplete information	It makes use of clinical practice guidelines (CPG).
39	Privacy preserving clinical decision support system using Gaussian kernel based classification	A novel privacy presenting protocol for CDSS where the patients data always remain in an encrypted from during diagnosis process.	Accuracy Patients data will not be revealed to the remote server	Used only for distributed scenario not in client server model
40	Research on clinical decision support system development for atrophic gastritis screening	Makes use of base classifier algorithms C4.5,CART	Quality enhancement Simplicity	Did not bring significant increase in classifier efficiency

SYSTEM ARCHITECTURE AND RESEARCH METHODOLOGY

The architecture of the proposed Web-Based Decision Support System (WBDSS) for the diagnosis is presented in (Fig. 1).

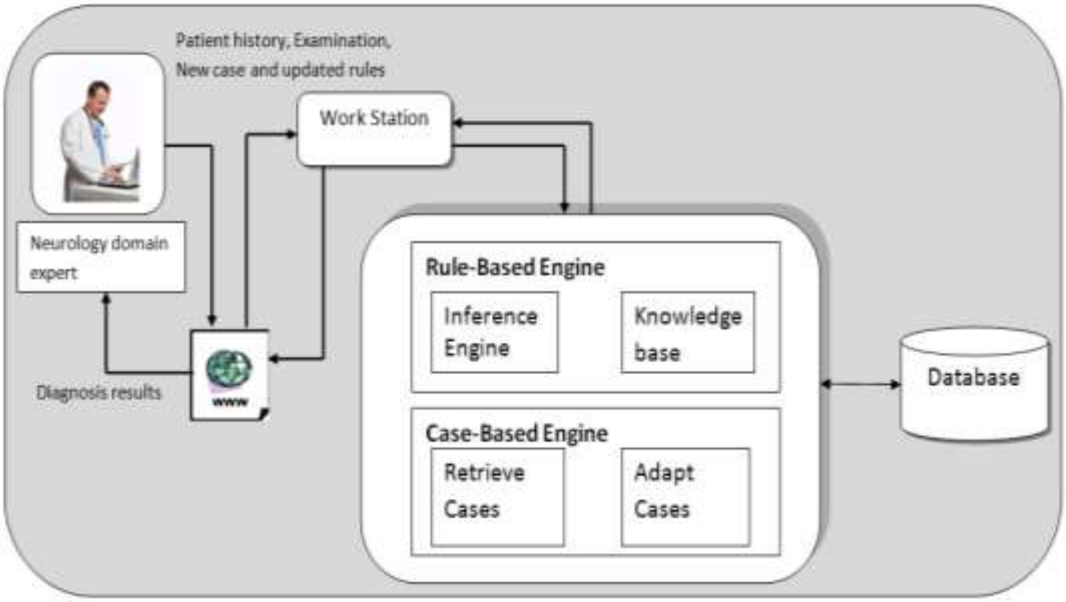

Fig 1 Basic System Architecture

The system comprises to two major components: Case-based reasoning component and the Rule-based reasoning component. These two components operate separately to give the expert system solution. Hybrid expert systems which involve rule-based systems handle problems with well-defined knowledge bases, which limit the flexibility of such systems. To overcome this inherent weakness of rule-based systems, case-based reasoning is adopted to improve the performance of the expert system by incorporating previous cases in the generation of new cases.

PERFORMANCE METRICS AND RESULT ANALYSIS

PERFORMANCE METRICS

The performance of the system is evaluated by using three different methodologies to determine the difference in the retrieval of their similarity measure using nearest neighbor [1, 12].

SIMILARITY FUNCTIONS

MANHATTAN DISTANCE

This similarity function is also known as Absolute distance or Manhattan distance. It is computed by taking the weighted sum of the absolute value of the difference in independent variables between the current case and a past case (from the case library) [13, 14]. The weight associated with each independent variable is provided by the user or the analyst. This distance function is primarily used for numeric attributes, and is given by:

$$d_{ij} = \sum_{k-1}^{m} w_k \left|x_{ik} - c_{jk}\right|$$

Where *m* is the number of independent variables, and w_k is the weight of the *kth* independent variable. In our study, w_k =1for the City Block distance and the Euclidean distance similarity measures.

EUCLIDEAN DISTANCE

This similarity function views the independent variables as dimensions within an *m* dimensional space, with m being the number of independent variables. A current case is represented as a point within this space [15, 16]. The distance is calculated by taking the weighted distance between the current case and a past case within this space. This distance function is also commonly used when the data set contains quantitative attributes, and is given by:

$$d_{ij} = \sqrt{\sum_{k-1}^{m} \left(w_k\left(x_{ik} - c_{jk}\right)\right)^2}$$

MAHALANOBIS DISTANCE

This distance measure is an alternative to the Euclidean distance. It is used when the independent variables are highly correlated [3, 9].

$$d_{ij} = \left(x_i - c_j\right)' S^{-1}(x_i - c_j)$$

and the independent variables do not need to be standardized.1 it is given, S is the variance-covariance matrix of the independent variables over the entire case library, and S−1 is its inverse.

MEAN ERROR RATE

It is identified by the error induced during calculation of similarity measure

$$ME = (100\text{-}SFM) \times 100$$

Lower the ME higher is the accuracy of the methodology used in the system.

We take into consideration of 4 cases available in the database to study the similarity matching functions for the retrieved new case and mean error is identified for the cases.

MAXIMUM SIMILARITY FUNCTION

A new patient case is taken whose variables have the most matches with the already existing past case and the similarity function is determined in Table 2 [17].

Table 2: Calculation of Maximum Similarity Function

S.NO.	Euclidean Distance		Manhattan Distance		Mahalanobis distance	
	Case ID	SFM	Case ID	SFM	Case ID	SFM
1	3	98.23	3	92.22	3	95.32
2	2	87.31	2	86.67	2	83.32
3	1	70.52	1	65.48	1	68.88
4	4	50.01	4	30.21	4	66.71

MEDIAN SIMILARITY FUNCTION

A new patient case is taken whose variables have the median matches with the already existing past case and the similarity function is determined in Table 3.

Table 3: Calculation of Median Similarity Function

S.NO.	Euclidean Distance		Manhattan Distance		Mahalanobis distance	
	Case ID	SFM	Case ID	SFM	Case ID	SFM
1	2	52.23	2	51.21	2	48.32
2	3	42.33	3	40.44	3	40.22
3	1	40.12	1	39.10	1	38.10
4	4	20.00	4	19.52	4	24.34

A new case which has 50 percent of match is taken and matched with the available cases in the database and the similarity function is determined.

MINIMUM SIMILARITY FUNCTION

A new patient case is taken whose variables have the least matches with the already existing past case and the similarity function is determined in Table 4.

Table 4: Calculation of Minimum Similarity Function

S.NO.	Euclidean Distance		Manhattan Distance		Mahalanobis distance	
	Case ID	SFM	Case ID	SFM	Case ID	SFM
1	1	10.11	1	13.56	1	20.03
2	3	5.23	3	11.34	3	15.88
3	4	3.22	4	8.00	4	10.28
4	2	1.01	2	4.56	2	8.02

The Minimum similarity function can be determined by taking the new case which has almost no match with existing cases in the database and the similarity function is calculated.

MEAN ERROR RATE

The mean value of all the cases identified in Max. SFM, Median SFM and Min. SFM is taken and the Mean Error Rate is calculated in Table 6.

Table 6: Calculation of Mean Error Rate

	Euclidean Distance	Manhattan Distance	Mahalanobis distance
Max. SFM		31.355	21.44
Median SFM	11.33	12.432	12.25
Min. SFM	4.89	9.365	13.552
ME	13.23	17.717	15.747

ACCURACY

The accuracy of the system is calculated by (100-ME) x100.Thus Accuracy and Mean Error Rate are inversely proportional. Lower the MER higher is the accuracy of the given Similarity Function is shown in Table 7.

International Journal of Engineering Research and General Science Volume 3, Issue 4, July-August, 2015
ISSN 2091-2730

Table 7: Calculation of Accuracy

	Euclidean Distance	Manhattan Distance	Mahalanobis distance
ME	13.23	17.717	15.747
Accuracy(100-ME)*100	87%	82%	84%

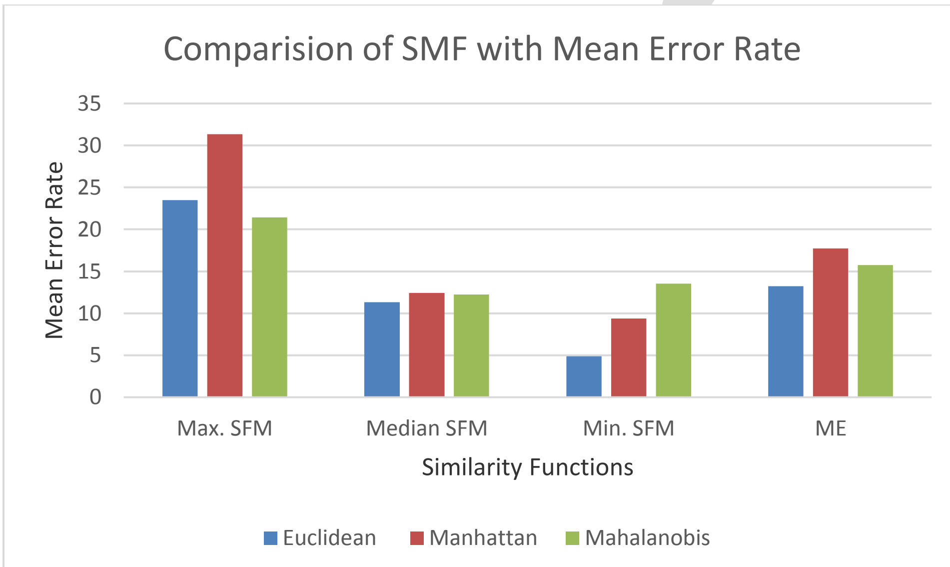

Fig 2 Shows the Comparison of SMF with Mean Error Rate

Fig 3 indicates that the Euclidean distance provides good results for Higher SFM compared to the other Similarity Functions. It also provides less value for Minimum SFM which indicates less is the Error Rate.

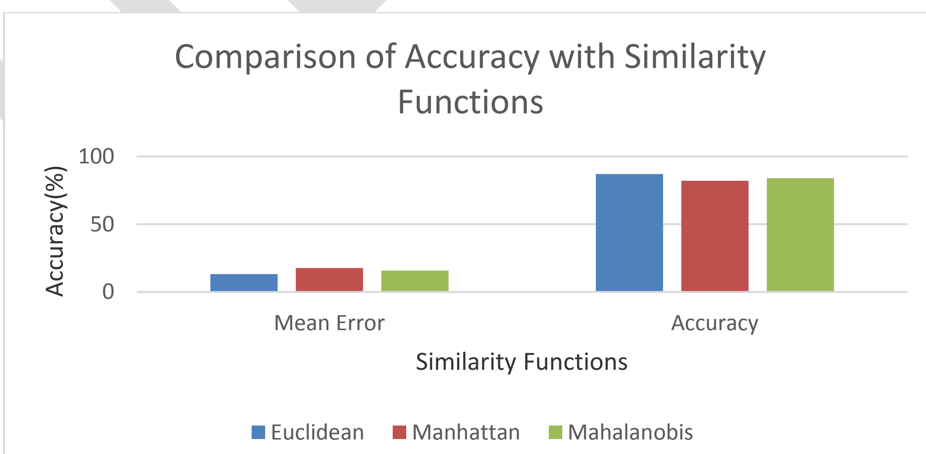

Fig 3 Shows the Comparison of SFM with Accuracy

EXPERIMENTAL RESULTS AND ANALYSIS

The proposed system was tested by 50 neurologic patients whose status was input into the system to get probable diseases and these cases where trained for testing data. 40 cases were properly solved by the system. Of all the cases, 3 cases could produce accurate results because of the cases being complex (involved not only neurology but other domains as well)

Using a Consultant Pathologist's interpretation as a "gold standard" (reference test), the system's parameters were calculated.

A.True positive (TP):

The diagnostic system yields positive test result for the sample and thus the sample actually has the disease.

B False positive (FP):

The diagnostic system yields positive test result for the sample but the sample does not actually have the disease.

C True negative (TN):

The diagnostic system yields negative test result for the sample and the sample does not actually have the disease.

D False negative (FN):

The diagnostic system yields negative test result for the sample but the sample actually has the disease.

There by the following parameters are calculated,

$$Sensitivity = [TP/(TP+FN)] \times 100\% \quad (1)$$

$$Specificity = [TN/TN+FP] \times 100\% \quad (2)$$

Using equations (1), (2), respectively are the Sensitivity, Specificity of the system :

Sensitivity = 93%;

Specificity = 86.6%;

The output of the Nearest Neighbor Algorithm was tested against the results obtained from WEKA, a data mining tool. A set of 50 different cases was prepared. These cases were represented in the format required by WEKA and Simple K- Means algorithm was applied with K as 17. Then cluster analysis was performed after adding one more case as a new case. The result of cluster analysis was noticed to identify 2 cases that were nearest to the new case. Same cases were inserted into the case base of the system as learnt cases. Then the same new case was provided as the input. The similar cases displayed by the system, were found to be exactly same as those shown by WEKA (Table 7 & 8).

Table 7: variation between nearest neighbor and Simple K means algorithm

Attributes	Nearest Neighbor Search	Simple K means algorithm
Classified instances	91.667	89.71
Unclassified instances	8.333	10.29
TP Rate	0.99	0.951
FP Rate	0.25	0.51
Precision	0.889	0.833
Recall	1	0.81
F-measure	0.941	0.956

Table 8.Variation between Euclidean distance and Manhattan distance

Attributes	Euclidean Distance	Manhattan distance
Correlation Coefficient	98.45	83.58
Mean Absolute Error	16.81	8.46
Root Mean Square Error	25.58	9.30
Relative absolute Error	13.55	68.23
Root Relative squared error	17.70	64.39

CONCLUSION

This paper discussed the development of a knowledge-based hybrid expert system for diagnosis of neurologic disorders. The constructed system exploited computer as an intelligent and deductive instrument. Thus, the system attempts to improve the effectiveness of diagnosis (in relation to accuracy, timeliness and quality). Therefore, the diagnoses made by the system are at least as good as those made by a human expert.

From the development and analysis of Clinical Support System, it is evident that CBR technique of Artificial Intelligence (AI) is appropriate methodology for all medical domains and tasks for the following reasons: cognitive adequateness, explicit experience and subjective knowledge, automatic acquisition of subjective knowledge, and system integration. CBR technique presents an essential technology of building intelligent Clinical Support System for medical diagnoses that can aid significantly in improving. The proposed method gives a Sensitivity = 93% which is better than the existing methods. Future research should involve more intensive testing using a larger neurologic patient disease database to get more accurate results.

FUTURE ENHANCEMENTS

The present version of the expert system was developed with knowledge engineering performed by engineers as system analysts and a few neurology experts. The process of encoding knowledge is incomplete unless extensive number of domain experts involve in the knowledge engineering process. An expert system depends totally upon the knowledge base that it holds so to improve the quality and quantity on knowledge, cooperative participation of multiple neurologists will make the system a real expert.

CONFLICT OF INTEREST:

All authors disclose no conflict of interest.

FINANCIAL DISCLOSURE:

Financial support for this work was provided by KACST grant # 162-34 to Prof. Ishtiaq Qadri

REFERENCES:

1. Szolovits P, Patil, R. S., & Schwartz, W. B. (1988). Artificial intelligence in medical, diagnosis. Journal of Internal Medicine, 80–87.
2. Durkin JJEsdadNJP-H.
3. Maitri Patel APaea, (2013)Maitri Patel,Atul Patel,Paresh Virparia, "Rule Based Expert System for Viral Infection Diagnosis", International Journal of Advanced Research in Computer Science and Software Engineering,Volume 3, Issue 5, May 2013.
4. Robert T.H. Chi MYKAIAor-bac-brfdsA, Texas : s.n., 1991, ACM, p. 258.
5. Bourlas P, Giakoumakis, E., & Papakonstantinou, G. (1999). A knowledge acquisition and management system for ECG diagnosis. In Machine learning and applications: Machine learning in medical applications (pp. 27–29). Chania,Greece.
6. Dennis L. Kasper EB, Stephen Hauser, Anthony S. Fauci, Dan Longo, J. Larry Jameson, J. Larry Jameson.(2008). Harrison's Principles of Internal Medicine. s.l. : McGraw-Hill Professional
7. Shortliffe EHCptscdmJotAMA, 258(1), 103–119.
8. R. L. Simpson Acmoc-bripsaiitdodm, Ph.D. dissertation, School of Information and Computer Science,Georgia Institute of Technology, Atlanta, GA, 1985.
9. Mahabala HN, Chandrasekhara, M. K., Baskar, S., Ramesh, S., & Somasundaram, M. S. (1992). ICHT: An intelligent referral system for primary child health care. In Proceedings SEARCC'92: XI conference of the South East Asia regional computer confederation. Kuala Lumpur.
10. K. J. Hammond C-BP, Academic Press, San Diego, CA, 1989.

11. K. Sycara Uc-brfpaar, in Proceedings of the Case-Based Reasoning Workshop, DARPA, Clearwater Beach, FL, Morgan Kaufmann,San Francisco,pp. 425–434, 1988.
12. T. R. Hinrihs PSiO, Lawrence Erlbaum Associates, Hillsdale,NJ, 1992.
13. Wan HWI, & Fadzilah, S. (2006). Artificial intelligence in medical application: An exploration. School of Information Technology, Universiti Utara Malaysia, 06010 Sintok, Kedah, Malaysia.
14. Zelic I, Lavrac, N., Najdenov, P., & Rener-Primec, Z. (1999). Impact of machine.
15. Ruseckaite RCisfaovpdIMlaaMliapC, Greece.
16. Shankar K. Pal SKSFoSCBR.
17. R. Bareiss E-BKAAUAtC, Classification, and Learning, Academic Press, San Diego, CA, 1989.