An Overview of Clinical Decision Support System (CDSS) as a Computational Tool and Its Applications in Public Health

Praveen Kumar Gupta, Abijith Trichur Ramachandran, Anusha Mysore Keerthi, Preshita Sanjay Dave, Swathi Giridhar, Shweta Sudam Kallapur, and Achisha Saikia

1 Introduction

The world today has become synonymous with the presence of large amount of data due to the perpetual rise in the human population. Drastic changes in the environment have led to multiple epidemics, drug and antibiotic resistance, superbugs, etc. Demographically, distinct health concerns are steadily mounting as well. In order to tackle these difficulties, novel technologies that can aid the human brain in efficient diagnosis are the need of the hour. One such technology is the clinical decision support system, commonly abbreviated as CDSS. A specialized algorithm is built into the system that helps in the generation of patient-specific suggestions. The roots of CDSS can be traced back to the very beginning of medical informatics. The earliest known record of the origins of CDSS can be found in a 1959 paper based on the logic behind a physician's reasoning. The paper described a probabilistic model for medical diagnosis, based on the set theory and Bayesian inferences. The primitive systems were mainly based on broad user inputs, and therapy suggestions were based on them [1]. The paradigms of CDSS have constantly changed over the past few decades with newer research coming into the picture. Clinical decision support systems commonly work in tandem with an electronic health record (EHR). The EHR is a database that contains a patients' medical records. The EHR can be queried with a keyword to search and retrieve the

P. K. Gupta (✉) · A. M. Keerthi · P. S. Dave · S. Giridhar · S. S. Kallapur · A. Saikia
Department of Biotechnology, R.V. College of Engineering, Bangalore, India
e-mail: praveenkgupta@rvce.edu.in

A. T. Ramachandran
Department of Computer Science, R.V. College of Engineering, Bangalore, India

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patient-specific data. The CDSS algorithm is then applied to these data to obtain recommendations on the course of treatment.

The intricate structure of the clinical decision support system ensures its effective implementation. Data mining in conjugation with relevant clinical research may be employed to examine patient medical records in a CDSS. The methodologies used in the implementation of CDSS are detailed below:

Fuzzy logic rule-based approach: Fuzzy logic mimics the human decisions as per the inputs given to the system. Since all the medical data need not lie in state of extremes such as absolute truth and absolute false, fuzzy logic allows the ability to compute data in the form of relative property and thus enhances the understanding, severity and decision logics in a much more specific manner, similar to the workings of a human brain.

The Bayesian networks: Any diagnosis, prognosis, treatment options, etc. are uncertain in nature. These problems can be tackled effectively using probabilistic methods such as Bayesian network. This type of CDSS is considered to be the most effective method for managing uncertainty.

Rule and evidence-based systems: Rule-based systems are fully based on human crafted rules or curated rules, which can also serve as the basis for decision-making and help in the mapping of the neural network.

Evidence-based systems are based on the computation of results based on the previously existing evidential data, and this helps in the estimations of use of drugs and treatments on a person, which is completely relative to the past results on decisions.

Genetic algorithms: They are roughly based on survival of the fittest, and the solutions to a processed outcome are further tested on various medical parameters to find the best suitable procedure for a given problem.

Artificial neural network: It is a modelling technique used in building relationships by extracting and analysing the pre-historic data, to understand the relationship between the input and the outcome of the processed data. Since no analysis and relationship can be extracted for the processed outcome, usage of such a method is highly unaccountable. Ergo, with further research, this could prove to be a viable method.

Hybrid systems: It is the interconnection of systems between the components responsible for physical inputs and properties with the systems responsible for analysis and computation for capturing live medical data, such as pulse rate and blood pressure, which is captured in analogue systems, and these act as the inputs for decision-making with the incorporation of fuzzy logic or artificial neural network to provide a solution or a suggestion for further processes to be required.

Three methods are primarily used to distinguish clinical decision support system for enhancing clinical practice functioning as a single variable analyses, direct experimental information, and multiple logistic regression analyses. Clinical outcomes of CDSS include morbidity studies, mortality studies, screening for cardiovascular disease (CVD) risk factors, antimicrobial treatment decisions, mental health, substance abuse treatment, and various other outcomes. Medication and prescription dosage levels can be cross-checked and verified in order entry systems, giving clinicians access to the right information at the right time and reducing errors which may occur due to the illegibility of medical prescriptions. CDSS combined with EHR has the capability to reduce rehospitalizations when used to aid pharmacogenetic testing for patients older than 50 years who often take multiple medications and experience adverse drug events (ADEs). It is not only beneficial to patient care, but it also results in potential health resource utilization savings. It has also paved the way for policymakers to improve the quality of health care and reduce costs. A meta-analysis of 148 randomized control trials to evaluate for clinical outcome improvement and cost reduction with clinical decision support revealed with strong evidence that CDSS usage can improve process outcomes like increased cautionary services with an odds ratio of 1.42 and increased ordering of apt medical treatment with an odds ratio of 1.57.

EHR can be defined as "an electronic version of a patient's medical history, which is maintained by the provider over time, and may include all the key administrative and clinical data relevant to that person's care under a particular provider, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations and laboratory data." [2]. Clinical decision support systems are often consolidated with EHRs to smoothen workflow and acquire the benefits of existing data sets. The incorporation of the EHR system, which uses real-time data to ensure high-quality patient care, with CDSS has the potential to revolutionize the health-care industry.

CDSS can be used by clinician's pre-diagnosis, diagnosis or post diagnosis in the form of a diagnosis decision support system (DDSS), which proposes appropriate diagnosis based on patient data, or a case-based reasoning (CBR) system, which utilizes previous case data to determine appropriate treatment options. CDSS can be knowledge based, where a pre-compiled, updatable knowledge base is combined with the patient's medical history to provide appropriate results, or it can be non-knowledge based where machine learning is employed to find patterns in clinical data and make suitable recommendations.

CDSS market share distribution globally with respect to three continents shows that North America accounts for 72% of the market share, with US holding 92% of shares, followed by Europe – 15% of global share, leading countries being France, Germany, and the United Kingdom. Asia accounts for 8% of shares, leading countries being Japan and China. The rest of the world accounts for only 5% of the total global share. There is, thus, an immense potential for the application of this system in underdeveloped and developing countries, where there is a higher prevalence of nutritional diseases and epidemics and decreased resources to tackle these issues. CDSS can be utilized to improve the standard of health care in such countries, having a major impact in terms of access to standard health care and effective treatment options. According to new market intelligence estimates, the value of the CDSS market in India is at USD 43.8 million. The sector is expected to grow to USD 206.1 million by 2025, by which time the total health-care IT market of India will reach a USD 2530.3 million valuation (BIS Research, Global Big Data in Healthcare Market-Analysis and Forecast, 2017–2025).

Skilful usage of the clinical decision support system can enhance the quality of health care, improve physician performance and amplify clinical performance for drug dosage. For example, it has proved to be a blessing in the field of palliative care where a clinical decision support tool called palliative care outcome scale (POS) has been proven to be a multidimensional measure to assess patient symptoms and conditions over long periods of time. The clinical decision support system has many forms, enabling it to accept multiple parameters, thereby making it a highly adaptable system. However, this system is not without flaws. CDSS is still at its infancy stage and has to be explored and developed further to extract the maximum use out of it. Most of the CDSS tools being released in the market are unidimensional. Multidimensional forms of CDSS are patient specific and provide rapid decision-making. They are based on real-time patient data such as medical history, physical examinations and laboratory data. Clinical prediction rules and evidence-based algorithms are able to accurately predict the patient's diagnosis, prognosis and the probability of the likely response to treatment. But the implementation of these tools is highly complex, making the rate of adoption of these tools very low. The drawbacks that exist due to various factors of the clinical decision support have been extensively delineated in this chapter.

CDSS, thus, serves as an efficient system to monitor and improve global health-care scenario, and if implemented effectively, clinical decision systems represent the future of health care.

2 Significance of CDSS

A CDSS aids and enhances clinical practice by effectively boosting the standard, nature and safety of the world health-care system. A CDSS software assists fundamental care providers and clinicians by presenting well-timed data to viably diagnose a patient by efficaciously pointing out to the actual health problem, reducing misdiagnosis, medication errors and elevating the quality of the care patients receive.

A handheld clinical decision guide system implemented into computers acts as an active knowledge system, which makes use of patient precise information to produce case-specific advice. This system keeps a record of the medical history of the patient and recommends a patient-specific treatment.

CDSS has reliable mechanisms and tools which can provide reminders, recommendations and databases to store the data related to a particular patient for protection and preventive care. They can also supply constant alerts on probable dangerous drug interactions. The usage of CDSS can decrease expenses and increase efficiency and alert medical practitioners on ineffective testing. This practice enhances patient protection by avoiding potentially unsafe and high-priced complications, reducing patient inconvenience.

Furthermore, CDSS allows for more accurate medication information and dosing calculations that can be adapted into the clinical setting without much difficulty and significantly changing the pre-existing work structure enabling accurate evaluation of patient-specific statistics promptly resulting in an appreciably improved clinical practice.

Advantages of using CDSS over manual systems are several. For example, it is built into the medical process from the starting till its completion in a proper workflow rather than its integration in a discrete screen. The fact that CDSS is digital as an alternative to paper-based makes it more time saving and convenient to the practitioner. In addition to that, it offers real-time data, and hence, the information is offered at the current time and location as opposed to checking the patient earlier but providing the result later. Conclusively, a clinical decision support system presents recommendations for care rather than just assessments to be filled.

3 Benefits of CDSS

Patient Safety
The safety of the patients is improved by high involvement of system-initiated advice that provides safety information to the patient, for example, alerting the care providers to the seriousness of drug interactions, contraindications (a situation where drugs or any medical procedure could be harmful to a patient) with different drugs and awareness against prescribing medications for infants and elderly. Additionally, it also involves sending out messages to patients like time duration of therapy and forms of drugs.

Medical Errors
CDSS can be an integral tool in decreasing medical errors. This is done by helping out the practitioners in averting negative drug reactions and lowering unsuitable drug dosing to a patient. CDSS minimizes error rates by monitoring human errors by the medical practitioner's behaviour by offering numerous approaches to decision support, which includes caution, reminders, evaluation and guidelines for improving health care.

Basic or unsophisticated clinical decision support provides information and recommendations on drug doses, time interval and frequencies. Sophisticated clinical decision support performs functions such as drug allergic reaction checks, drug laboratory value checks, and drug–drug interaction checks. Two of the most noticeable functions are it provides reminders about drug guidelines such as advising the person about the necessary information while taking up the drug to avoid adverse effects and sequence orders, for example, causing the person to order glucose checks after he or she has ordered insulin [3].

Diagnostic and Workflow Process
CDSSs show great potential in minimizing clinical diagnostic errors and enhance the quality of medical care. Computerized CDSS assists practitioners to confirm

that they meet the necessities of long-term care. These computerized systems are programmed to examine a person's trait and condition and provide suggestions regarding the upcoming diagnosis.

It is imperative to plan and implement a beneficial CDSS so that it improves and enhances a physician's workflow. CDSS results in an ideal and reliable system that produces an acceptable and smooth system performance. Additionally, implementing CDSS depends on important factors such as finance, clinician ethics, leadership and management [4].

4 Structure and Applications of CDSS

4.1 Fuzzy Logic-Based CDSS

Fuzzy logic is derived from artificial intelligence and is used to represent the mathematical modelling of linguistic terms (variables) and human comprehension of knowledge. This enables the computers to solve problems and tackle problems similar to medical professionals.

Inaccurate data which can be vague and contain many uncertainties can be dealt by fuzzy logic which is typically difficult to be comprehended and understood by humans, which results in a high probability of error in the medical procedure if not observant.

The decision support system created using fuzzy logic is relatively successful in processing linguistic data compared to conventional sequential systems. Since the problems found around us majorly comprise uncertainties and vagueness, it proves to be extremely difficult to represent such problems into a mathematical model, which can then be used to build sequential algorithms to solve such problems [5].

Fuzzy logic helps in providing a deterministic conclusion based on multiple information, that is, the input of the experts and the biomedical sensors in order to arrive at a distinct solution.

In simple words, the structure of the fuzzy logic is nothing but IF C_1 AND C_2 THEN S, where C_1 and C_2 represent the condition cases for the event S or operation S to occur. These are used to express terms of linguistic data members (variables). Since the complexity of the system and architecture increases for mathematical formulas, therefore linguistic terms are preferred.

The number of rules and logic required for a complex computation generally depends on the number of inputs, outputs, and also on the goal of a computation based on the designers control response [6].

The usage of this type of approach proved to be useful in various medical operations/procedures such as injecting customized or tailored amount of anaesthetics required for patients, and this would result in a minimized dosage of the standard amount injected in patients. It also has the potential of decreasing the workload of

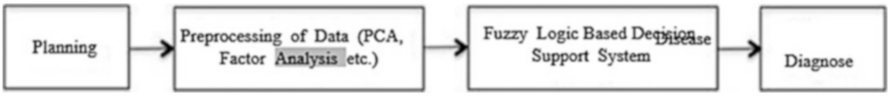


Fig. 1 Clinical decision support system with fuzzy logic [5]

the anaesthetics injected and thereby achieve the preferred depth of the anaesthesia used. It could provide clinical support to the medical professionals in maintaining a consistent and adequate number of anaesthetics to be used during a surgery, thereby giving time and room for the professionals to carry out high prioritized tasks instead of diverting attention on other tasks required to be performed simultaneously (Fig. 1).

Fuzzy logic is used due to its inaccurate reasoning; therefore, all logic dictates truths that are half done or relatively accurate in terms of the standards and structures defined for the fuzzy logic.

It dictates the human capabilities like human reasoning and judging uncertainty.

Since fuzzy logic is based on inaccurate reasoning, we refer human reasoning to be interpolative reasoning as the process neither lies in complete truth nor complete false but lies somewhere in between. This approach requires fuzzy logic to compute partial truth unlike in the conventional cases systems only processes complete Boolean output, that is, 1 s and 0 s.

4.1.1 Proposed Systems

Following the above ideology, a fuzzy-based clinical decision support system can be built on the illustrated design below. The proposed system consists of components such as rule-based system, inference engine, fuzzifier and defuzzifier. Different biomedical sensors feed their output to the inputs connected to the fuzzifier. The fuzzifier is responsible for the conversion of the outputs of the different sensors into quantifiable information that can be read and understood by the inference engine. The inference engine then activates and applies the rules on the data obtained. The observed and expert knowledge is saved in the rule-based system. The rule base system consists of all the fuzzy logic quantification, which gives the idea or the method to obtain good control of the current event. Linguistic fuzzy terms are nothing but the medical professional's knowledge on the occurrence of an event. The inference machine is responsible for correlating the data obtained from the fuzzifier and the rule base system in order for interpreting the description of the input based on the rule. The defuzzifier then converts the output of the inference engine into an appropriate human comprehendible language [6] (Fig. 2).

4.1.2 Applications in Clinical Studies

Pulmonology

Chronic obstructive pulmonary disease (COPD) is a disease caused due to exposure of mustard gas. It has many negative effects, such as cancer and pneumonia, and causes early as well as late complications. The chemical-injured victims majorly suffer from chronic respiratory complications. In order to provide extensive care and remedies for the patients, the fuzzy systems were used. One of the most common methods is the Mamdani fuzzy inference model, which controls a combined steam engine with a set of linguistic rules gathered from the patient's past experiences [7].

The measurement of lung disability is based on the Spiro metric measure, which is represented in percentage. The COPD is calculated with the aid (Fig. 3).

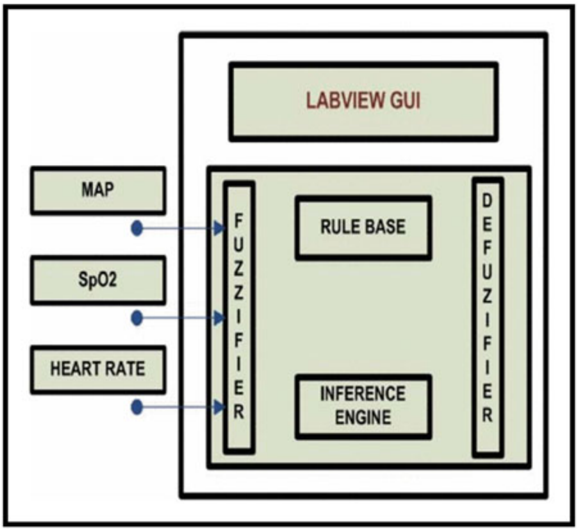


Fig. 2 Block diagram of the proposed system [6]

Severity (percentage)	Spirometry	Classification
0	FVC>80/FEV1>80 65<FVC<80	Passive lung disease
5-20	65<FEV1<80 50<FVC<65	Mild
25-45	50<FEV1<65 40<FVC<50	Moderate
50-70	40<FEV1<50	Severe

Fig. 3 Classification of pulmonary disease based on Spirometry [7]

NO		Variable	Rules	Linguistic Label	Fuzzy interval
1	inputs	FEV_1	FEV_1>80	VH	75–85–95–100
			65<FEV_1<80	H	60–70–80–85
			50<FEV_1<65	L	45–55–60–70
			40<FEV_1<50	VL	0–10–45–55
2		FVC	FVC>80	VH	75–85–95–100
			65<FVC<80	H	60–70–80–85
			50<FVC<65	L	45–55–60–70
			40<FVC<50	VL	0–10–45–55
3		FEV_1/FVC	FEV_1/FVC>80	VH	75–85–95–100
			65<FEV_1/FVC<80	H	60–70–80–85
			50<FEV_1/FVC<65	L	45–55–60–70
			40<FEV_1/FVC<50	VL	0–10–45–55
4	output	Severity	At risk	At risk	0–1–2–3
			Mild	Mild	2–3–4–5
			Moderate	Moderate	4–5–7–8
			Severe	Severe	7–8–10–11

Fig. 4 Overview of membership functions [7]

After the inputs are processed by the fuzzifier, these variables are used for determining the extremity in the decision-making table. The classifications of severity are as follows:

(i) Forced vital capacity (FVC)
(ii) Forced expiratory volume (FEV)
(iii) FEV_1 /FVC ratio

Figure 4 gives the membership functions of the input and output fuzzy variables.

On the analysis of the membership functions, it was inferenced using the Mamdani fuzzy inference system (Figs. 5 and 6).

Cardiology

Fuzzy logic can be extensively used in the risk prediction of heart patients. The process consists mainly of two phases:

(i) Generation of the weighted fuzzy rules by an automated approach.

In order to obtain the weighted fuzzy rules, it requires attribute selection of attributes, attribute weighting mechanism and data mining.

(ii) Developing a fuzzy rule-based decision support system.

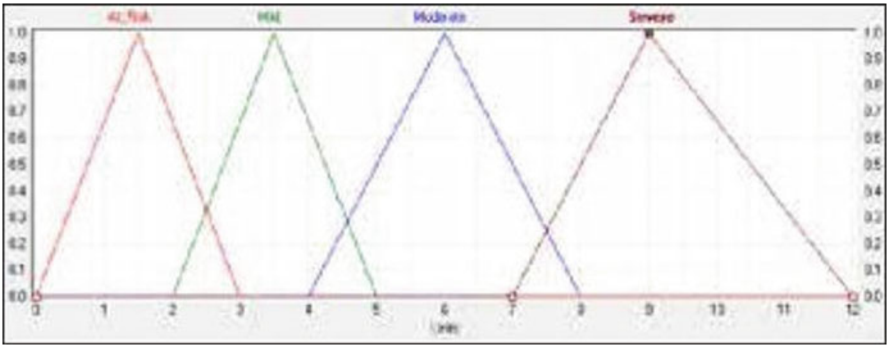


Fig. 5 Output of the membership functions for severity variable [7]

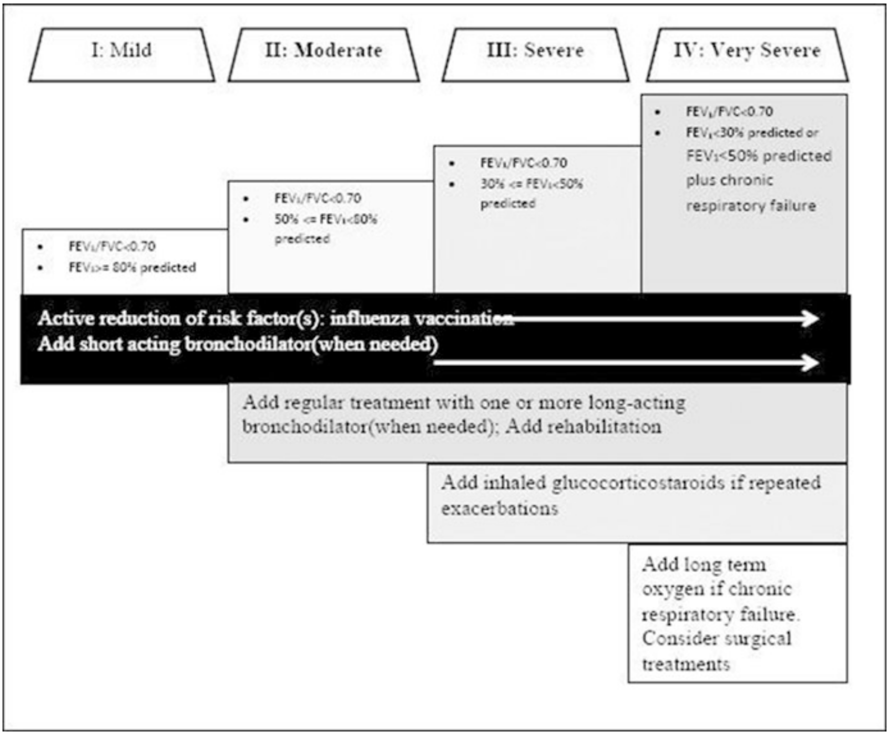


Fig. 6 Therapeutic recommendations [7]

The disease dataset of the heart may contain some noisy information and missing values; hence, there is a need for data pre-processing in order to remove the noise and missing values. The input database is divided into two subsets using class label, which are required for the mining of frequent attributes. On using the deviation range which are computed using the frequent attributes, the construction

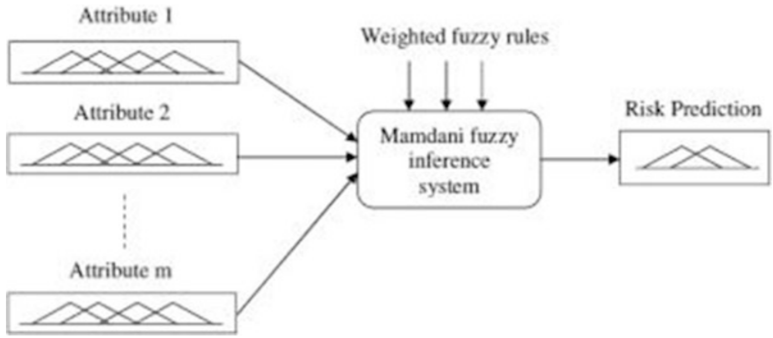


Fig. 7 Fuzzy inference system designed based on weighted fuzzy rules [8]

of the decision rules is made and these are scanned in the learning database to the corresponding frequency. The weighted fuzzy rules are obtained from the frequency, and on using the Mamdani fuzzy inference system, risk prediction fuzzy is developed, which proposes or produces the statistical data of the risk (Fig. 7).

4.2 The Bayesian Network

The conventional approaches to model casual or relationship between different diagnostics, which are not just a simple logical sequence of a rule, are implemented by a first-order logic. This is impractical due to the presence of incomplete knowledge and exhaustive rules that cannot be applied to solve the problems. The incomplete knowledge can be either theoretical due to the lack of advancement in science or practical due to the lack of data.

Bayesian networks can be used to model these types of casual relationships using degree of belief which are used to enable the system to compute reasonable under uncertainty. On using Bayesian networks, complex decisions can be represented using a directed acyclic graph.

The represented graph may contain all the relevant information required whose random variables may be connected by any abstract or casual dependencies responsible for decision-making [9].

Each variable represented in the graph contains a conditional probability table which indicates the probabilistic cause or influence of the variable. From the graph obtained, we can determine the patient's characteristics and other factors which can be termed as evidence. These evidences are computed by different inference algorithms which are then sent throughout the network on the consideration of the probabilistic occurrence for all the existing unobserved variables present within the same network. The unobserved variables can be any undiagnosed patient's condition, treatment performed or therapy alternatives. If required, we can further analyse it using different algorithms to identify any findings which are extremely influential or any variables that have not been observed yet having a high diagnostic value. Due to the fact that clinical distribution support systems require considerable amount of readjustments, they generally fail to be clinically integrated and thus are a source and termination for university projects. There is always a good probability of generating exaggerated results by a Bayesian network system, which could render the system unreliable if not given enough resources and modelling required [10].

For the efficient functioning of a clinical decision support system, expert and detailed modelling is required, which is costly, and for complex designs, the level of detail lies between the information which is extremely simple but useless to medical professionals and extremely detailed information which is typically hard to model and computed. However, the case may be the Bayesian networks describe a decision based on the joint probability distribution over a specific number of possible events. Depending on the number of variables having a possible direct influence, the number of required parameters used for indicating a single variable and its associated network can increase exponentially.

Due to the above reasons, the models need to be modelled with an extremely high grade of detail, which would allow derived graphs to be simplified to the most associable variables required. This type of processing and modelling is required as there exists restrictions in data for learning probabilities.

Bayesian networks are powerful tools that can be used to aid the clinical decision due to its probabilistic inference (Fig. 8):

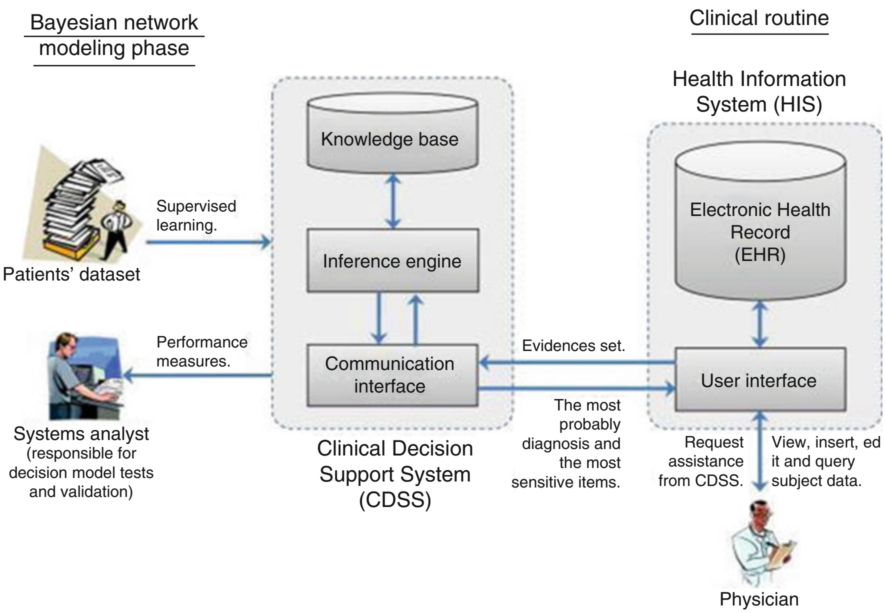


Fig. 8 Clinical decision support system components [11]

1. It can be easily understood by a clinician or a medical professional due to the inherent graphical nature of the networks output.
2. They can formally incorporate prior knowledge while learning the structure and parameters of the network.
3. Since the joint probability has a compact representation, they help in parameter estimation.
4. They allow observational inference and causal interventions.
5. They are more versatile when compared with classifiers that are build based on specific outcome variables and hence can be used to query any given node in the network.
6. They perform well in making predictions with incomplete data, since the predictor variables are used to estimate not only the query variable but also one another provided that the degree of modelling and associations are of high grade [12].

4.2.1 Applications in Clinical Studies

Diagnosis of Dementia, Alzheimer's Disease, and Mild Cognitive Impairment
Dementia generally involves symptoms affecting the memory and thinking abilities. It causes memory loss in patients, and Alzheimer's disease is nothing but the extreme progression of dementia. The memory loss could be due to variety of factors such as damage or loss of nerve cells and their associated connection.

On modelling a Bayesian network using a combination of data-oriented modelling and professional knowledge, it showed better results in the diagnosis of dementia, Alzheimer's disease and other mild cognitive impairments when compared to other known classifiers.

It also states the contribution of factors to the corresponding diagnosis, thus providing additional useful information to the clinical professionals [11].

Lung Cancer Care
Lung cancer is caused due to cigarette smoking. It is a malignant lung disease and often has no symptoms until the severity is complicated and advanced. General treatment for lung cancer is chemotherapy, surgery, radiation and targeted drug therapy. Therefore, it is very difficult to predict the survivability of a patient and hence causes extensive uncertainty.

The lung cancer experts can be aided by providing them with treatment selection suggestions and patient-specific survival estimates which can be done through Bayesian networks since they are effective in reasoning with the uncertainty domain [12].

Predicting Post-Stroke Outcomes
A stroke is a medical condition which results in poor amount of blood flow to the brain, hence causing death of brain cells. It is one of the most common causes of death and is also the leading cause of long-term disability.

Using Bayesian network, the mortality of different patients having stroke could be predicted with consequently a smaller number of risk variables in obtaining the risk rate, thus enabling medical professionals to provide better care and alternatives for the patients [13].

4.3 Belief Rule-Based Architecture System

Generally, an architecture of a system is nothing but how different components consisting of inputs, processes, and outputs are organized. The style of an architecture is the layout or pattern of system organization.

The proposed belief rule-based architectural system consists of the following layers:

- Interface layer:
  - This layer deals with the interaction between the user and the system. The interface layer is responsible for the data to be fed in by the user and proposed or suggested output to be displayed. In the below proposed system, the interface facilitates acquiring the leaf nodes that is the antecedent properties of the belief rule-based data. These data consist of clinical data, medical data, signs, symptoms, etc. By taking the account of belief of the domain expert, the data are distributed over the referenced values that are associated with the antecedent properties.
- Application processing layer:
  - The application processor deals in the interaction with the training module and the inference engine. The belief rule-based inference system consists of various number of components, for example, transformation of the inputs, rule activation weight calculation, updating of rule and the aggregation of the rules.
  - The evidential reasoning algorithm deals with the aggregation process of the inference engine.
  - The inference engine of this model works by first reading the input from the interface layer. The input data are then transformed into readable or referential values of the belief rule-based model antecedent properties. Then, all the activation weights of the belief rule-based model are calculated, which is then updated to the belief degree of the consequence. In rules and on using the evidential reasoning algorithm, all rules are aggregated.
  - The subsequent layer is solely responsible in building the training module by finding an optimal parameter and also by reducing the variation in the system results and the sampled data.
- Data management layer (Figs. 9 and 10):
  - The data management layer is based on the belief rule-based, clinical facts and other medical data. In order to develop the belief relief-based knowledge base, any of the following procedures can be used to implement.

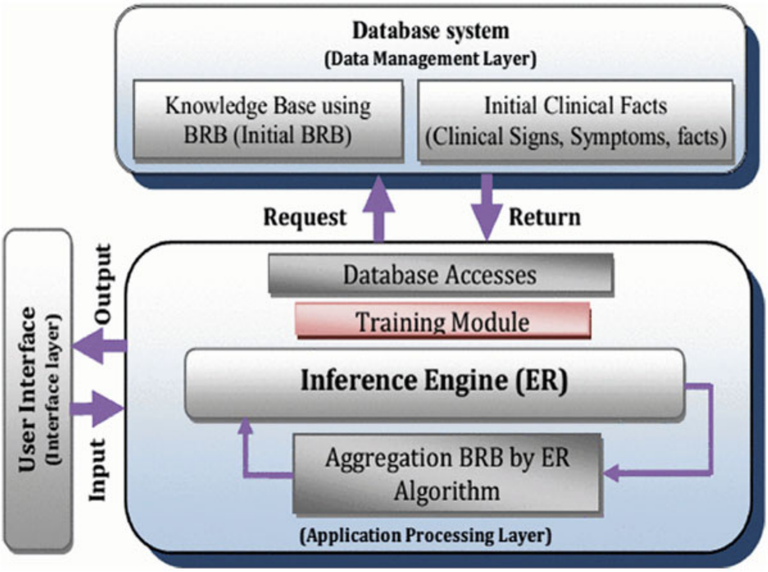


Fig. 9 Design level BRB CDSS architecture

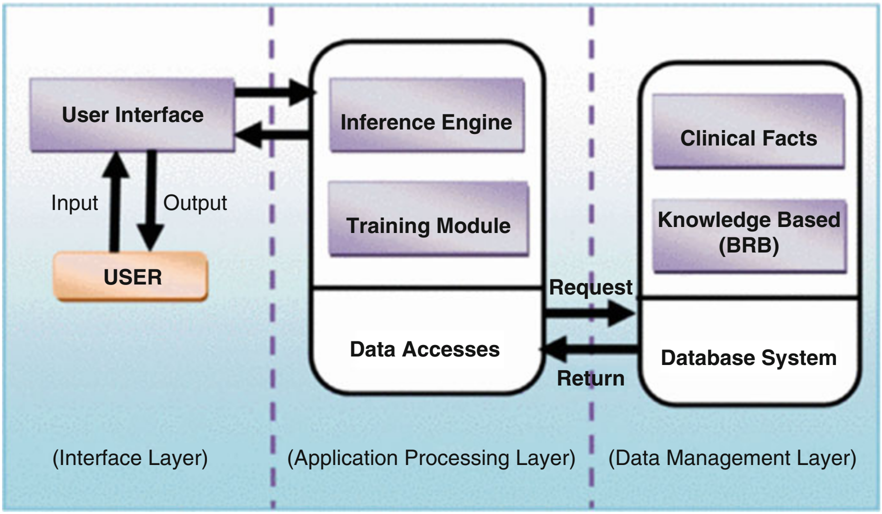


Fig. 10 Implementation level BRB CDSS

- Using the expert knowledge, the belief rules can be extracted from it.
- On the examination of previous or historical data, patterns can be generated and extracted for the belief rules.
- On the extraction of previously developed belief rules.
- Usage of arbitrary rules without any prior knowledge or data.

4.3.1 Logic-Based Systems in Clinical Studies

Assessing the Suspicion of Heart Failure
Any structural or functional cardiac disorder that causes inability of the heart to function normally can be termed as heart failure. This results in very short breath and, in many cases, can cause death. It occurs due to coronary artery diseases and usually affects the elderly in majority of the cases.

On using signs, symptoms and risk factors of patients, a belief rule-based clinical decision support can be constructed, which uses RIMER that allows handling of variety of uncertainties thus making it a robust and efficient tool. Usage of this system has not only caused reduction of costs in many lab investigations and assessments but also facilitate patients in taking the necessary precautionary steps. It has found to be more reliable and informative compared to the traditional cardiologists' suggestions [14].

4.4 Evidence-Based System

Evidence-based clinical decision systems are nothing but the CDSS that solve or tackle medical situations based on evidence-based data or practice. It uses a systematic approach to ensure consistent and best care of all patients provided by the health-care delivery system. An important tool for implementing the evidence-based practice is by clinical practice guidelines, which are based on the detailed expert consensus and latest research on the specific domain which primarily focuses on improving the diagnostic accuracy, enhancing treatments and reduction in the variations on the medical decisions involved.

In the case of physician guideline adherence, the following factors play a vital role for the evidence-based system:

- Awareness
- Familiarity
- Agreement
- Self-efficacy
- Outcome expectancy

Different field of medicine has its own set of factors or combined set of factors from adjacent domains.

On this concrete foundation, it has shown that there is a reduction in practice variability and substantially, providing a more satisfiable outcome for the patients. The clinicians recommend the CPG to be low, which is around 3–5 despite the benefits involved. Policymakers are encouraged by the use of IT to translate research findings into practice.

Therefore, when clinical decision support systems are applied to the evidence-based logic, they are referred as evidence adaptive. The goal of this system is to bridge the gap between practice and evidence and has shown great potential in achieving this [15].

Evidence-based system in nursing has proven to be a crucial aid for the best possible care, as they provide evidence-based recommendations to the nurses during the procedure or an event.

Clinical practice guidelines can be implemented, which has proved to be effective (Fig. 11):

- Remainder system
- Academic detailing
- Combined interventions
- Interventions that deliver accurate and patient-specific advice on real time and space

4.4.1 Applications in Clinical Studies

Nursing
Nurses have viewed the clinical decision support system to be of critical use as it improved interdisciplinary communications and helped their decision-making and self-confidence on treating the patients during any emergency crisis. The system has also enabled them to access information on best practice, which therefore enables them to provide a consistent care [16].

4.5 Artificial Neural Networks

Overview of artificial neural networks
Artificial neural network (ANN) is a popular type of non-knowledge-based CDSS. Non-knowledge-based CDSS uses machine learning rather than user-based knowledge. Neural networks learn by example, they cannot be programmed to perform a particular task. Neural networks are inspired from neurons that are present in our bodies. An ANN works the same way the biological one does. ANNs simulate human thinking by evaluating and eventually learning from existing examples/occurrences. ANNs consist of artificial neurons which are known as perceptrons.

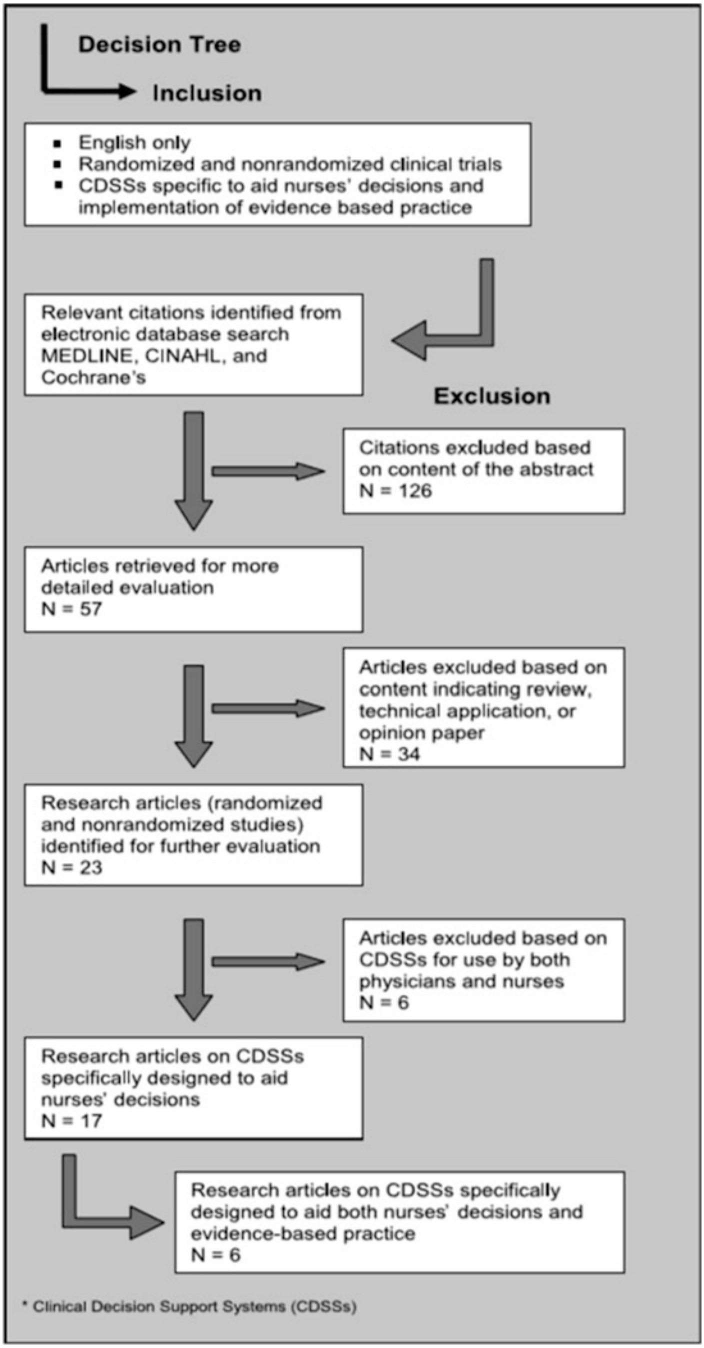


Fig. 11 Inclusion and exclusion criteria for literature search on evidence adaptive CDSSs in nursing

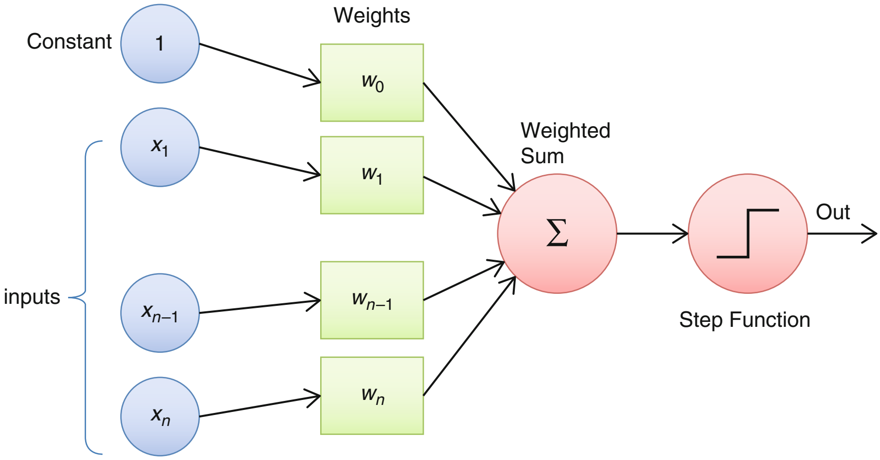


Fig. 12 Diagram depicting a perceptron

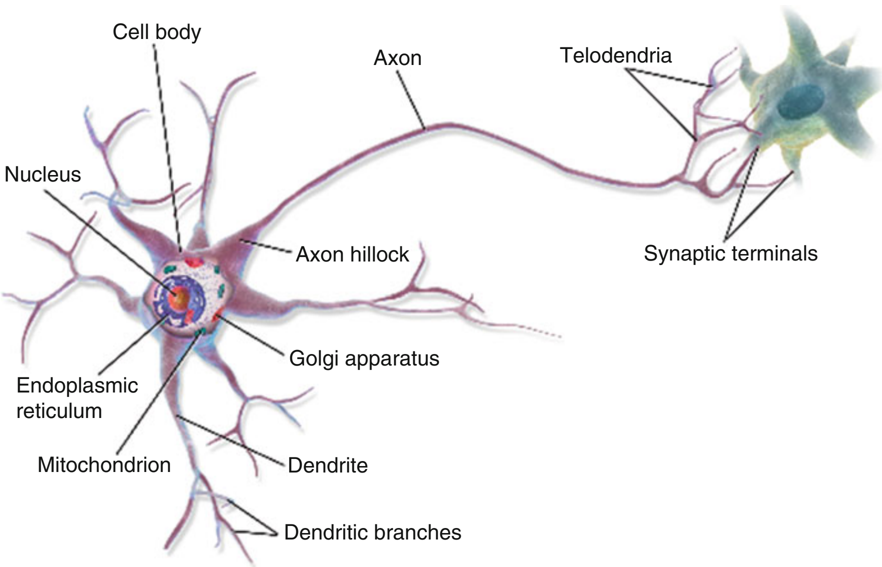


Fig. 13 A biological neuron

Figures 12 and 13 explain the working of ANN. Multiple inputs $x_1, x_2 \ldots x_{n.}$ are fed to the network. Each input has its own corresponding weights, that is, w_1 for x_1, w_2 for x_2 and so on. Next, the weighted sum of these elements is calculated and then passed through a step function which is a type of activation function. The step function provides a threshold value above which the neuron will fire. Finally, the perceptron contains outputs. There are two modes in a perceptron: training mode

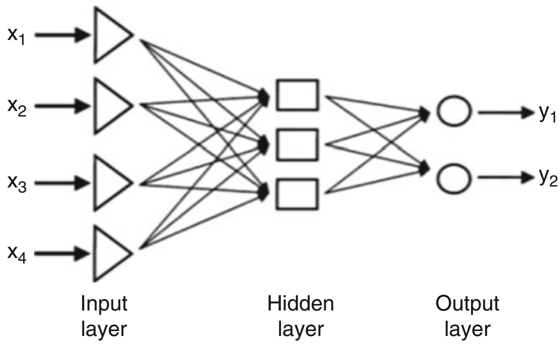


Fig. 14 Model of a neural network

and using mode. In the training mode, the neuron is trained to fire or not fire for distinct input patterns; this essentially means that the neuron is being trained to fire for certain sets of inputs and not fire for other sets of inputs. In the using mode, when a known input or input on which the neuron has been trained on is fed to the perceptron, the associated output is obtained. The using mode always occurs after the training mode. Various activation functions are used in a perceptron, they include step function, sigmoid function, hyperbolic-tangent function (TANH), RELU (Rectified Linear Unit) and sign function. A sigmoid function gives a smooth gradient and prevents jumps in output values. A step function cannot give multi-value outputs. TANH function is thought to be a zero-centred function; this means that it is sufficiently easier to model strongly negative, neutral and strongly positive values. The RELU function is computationally extremely efficient. Weights play an important role in the working of ANN; the perceptron can prioritize certain factors over others by the use of weights. Multilayer perceptron is otherwise known as the artificial neural network. A neural network can be thought as a combination of perceptrons which are connected in different ways and operating on different activation functions. There are three main layers in an artificial neural network: input layer, output layer and hidden layer. The number of hidden layers depends on the application; it can be different for different applications. The most common method by which the network can be trained is known as backpropagation. In this method, once the weighted sum of inputs is passed through the activation function, propagation is done backward and the weights are updated to reduce errors and, hence a more desirable output is obtained [17] (Fig. 14).

4.5.1 ANN in CDSSs

In CDSSs, ANN can be used to study the patient data, and these data are then mapped to symptoms, and hence, a possible diagnosis can be obtained. In order to achieve this functionality of neural network, the network must first undergo the training mode. In the training mode, the network is fed with a vast amount of clinical data, which include symptoms, signs, diagnosis, prognosis, medication, etc. The network then analyses these inputs and gives a possible outcome. The outcome is then correlated with actual clinical results, and by using the backpropagation method, the weights are adjusted to match with the actual clinical outcome. ANN can proceed even with incomplete data; the network makes educated guesses about the possible outcome, and by comparing with the actual clinical results, necessary modifications can be made. ANN is particularly advantageous as it eliminates the need for manual prescriptions and handwritten records. With proper training, the neural network can provide with accurate diagnosis and can help in the early detection of certain fatal diseases such as cancer. The main disadvantage of artificial neural network is that it is not cost effective, as a lot of money and time are required for the training of a neural network. The ANN recognizes patterns using the patient's data, and this ability of the neural network enables the ANN to be focused on a specific disease such as myocardial infarction, commonly known as heart attack [18]. The first application of ANNs in medical diagnostics came about in the late 1980s in the work by Szolovits et al. [17]; since then a number of different studies have come about in this field. ANNs have been used in the diagnosis of a variety of conditions such as colorectal cancer [19], pancreatic disease [20], early diabetes [21] and colon cancer [22]. ANN has also been widely used in the field of cardiology [23] and paediatrics [24]. Artificial neural networks have recently been used in the search for biomarkers [25]. Cancer and diabetes are the most common diseases found in the world population today. A study by the World Health Organization (WHO) reveals that around 30 million people of various ages and breeds suffer from various forms of diabetes 1. Due to its high prevalence, the clinical data obtained from the patients suffering from these diseases are vast. This large amount of clinical data provides an input to the neural network, and hence the properties of neural networks can be exploited to help in the early detection of such devastating diseases.

4.5.2 Applications in Clinical Studies

Cardiovascular Diseases

Cardiovascular diseases are a major health concern for majority of the world population. Cardiovascular disease is a disease class that involves the heart and blood vessels· A study by the American Heart Association shows that an estimated 17.3 million people lose their lives as a result of this disease per year, particularly due to heart attack, stroke, pulmonary heart disease, coronary heart disease, etc. These numbers are highly disturbing, and hence the need for an effective diagnostic tool that can detect the early onset of this disease became a requirement. A large amount of people suffering from such diseases generated a large amount of clinical data ranging from signs, symptoms, prognosis, diagnosis, medical imaging, etc. These data paved way for artificial neural networks to be used as diagnostic tools. For ANN to be used, data preparation is the foremost important step. Data which are obtained from the patient are categorized into various attributes, such as sex, age, weight, blood sugar and cholesterol level. Appropriate weights are assigned to each of these attributes. The neural network is trained with these various attributes for effective heart disease prediction. The disadvantage is that ANN cannot accurately predict the type of heart disease, and hence it cannot be relied on for further diagnosis and medication.

Diabetes

Diabetes is another common disease found in the world population. It is a heterogeneous group of multifactorial, polygenic syndromes characterized by elevated fasting blood glucose, or absolute absence of insulin. Diabetes is the major cause of adult blindness, renal failure, nerve damage, heart attack and a plethora of other conditions. Here again, the first step is data preparation. The data are collected from patients and are divided into attributes such as age, sex, fasting blood sugar and random blood sugar. Each attribute is assigned a particular weight. The data were collected periodically and were assessed for blood sugar levels. The set of input along with the respective weights is fed to the multi-layer perceptron, and the network is trained to predict the blood sugar level. This way patients need not make continuous visits to the hospital for blood tests, checking diastolic and systolic blood pressure, urine test, etc. To obtain more accurate results, the weights are modified such that it matches with the clinical result. Hence, using ANN can help in the early detection of diabetes, and it also provides a more accurate results, which paves way for better medical treatment and improved clinical management [21].

Cancer

A survey by the World Health Organization (WHO) revealed that nearly 16% of the world population die due to cancer and about 70% of these deaths occur in low- or middle-income countries. Worldwide only 14% of the people receive proper care. Cancer is a disease which has a better chance of being cured if detected early. Hence, highly accurate diagnostic and early detection systems are becoming a necessity. Artificial neural networks are trained so that they can identify the presence of cancer and the type of cancer if present. ANN is fed with inputs which include age, sex, cholesterol level and lifestyle attributes such as cigarette smoking and alcohol consumption. With appropriate training the network will be able to detect cancer and possibly predict which type it is. With more advances in technology, neural networks can now determine the type of brain tumour with the help of MRI images. Hence, ANN qualifies as an excellent diagnostic tool for the early detection of cancer and can enhance the quality of medical treatment [22].

Figure 15 provides an overview of the working of artificial neural networks in medical diagnosis. In the first step, a large amount of clinical data are fed to the system. The next step is a crucial step wherein certain features or attributes are selected; these attributes play in an important role as they determine what type of outcome will be obtained. The ANN is then trained and then verified. In the verification process, all the data that are redundant and that are capable of producing a negative result referred to as outliners are eliminated. The presence of outliners in the input can affect the training process and hence give rise to poorer results. Once all the outliners are removed, the database is said to be verified. This ends the

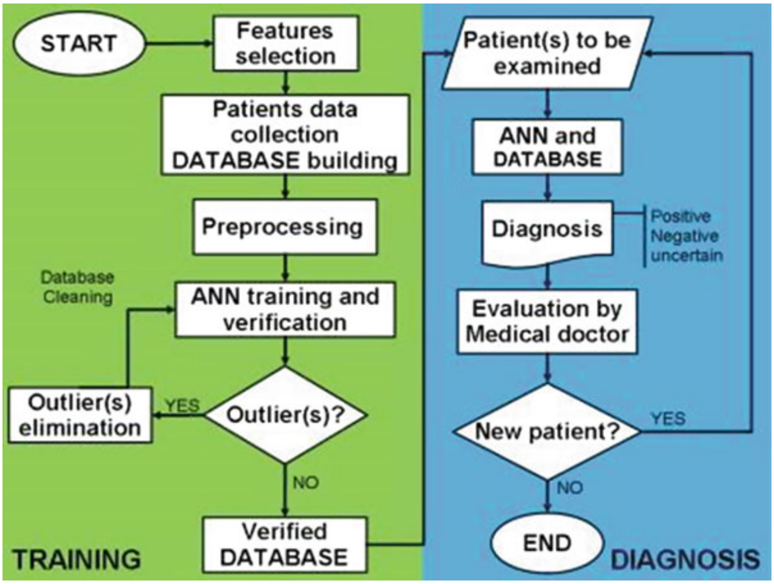


Fig. 15 Artificial neural networks in medical diagnosis [26]

training process. In the next step, the network is used for the diagnosis of the patient. In this step, the patients are examined and the required clinical data are obtained. These data are then fed as input the two multi-layer perceptron; the ANN takes all the inputs it has been trained for and correlates them with the desired result. The output is the diagnosis which can be positive, negative or uncertain. The diagnosis is then compared with the actual clinical diagnosis by a medical doctor and the course of medical treatment is decided. The neural network then prepares for new input from a new patient. This cycle continues. If more accurate data are fed to the ANN during training, a more accurate diagnosis can be obtained in the using mode [26].

4.6 Hybrid Systems

The efficiency and accurateness of solving any diagnosis in a rule-based reasoning is insufficient to pinpoint the different influences and causes. Hence, in order to enhance and optimize this simple structure, we combine the case-based reasoning and rule-based reasoning techniques to develop an effective model in the medical domain for controlling and handling knowledge-based structure, which can produce better results than the working of individual units separately.

The architecture of the proposed clinical decision support system is shown in Fig. 16. The system consists of the user interface, knowledge/case base, reasoning

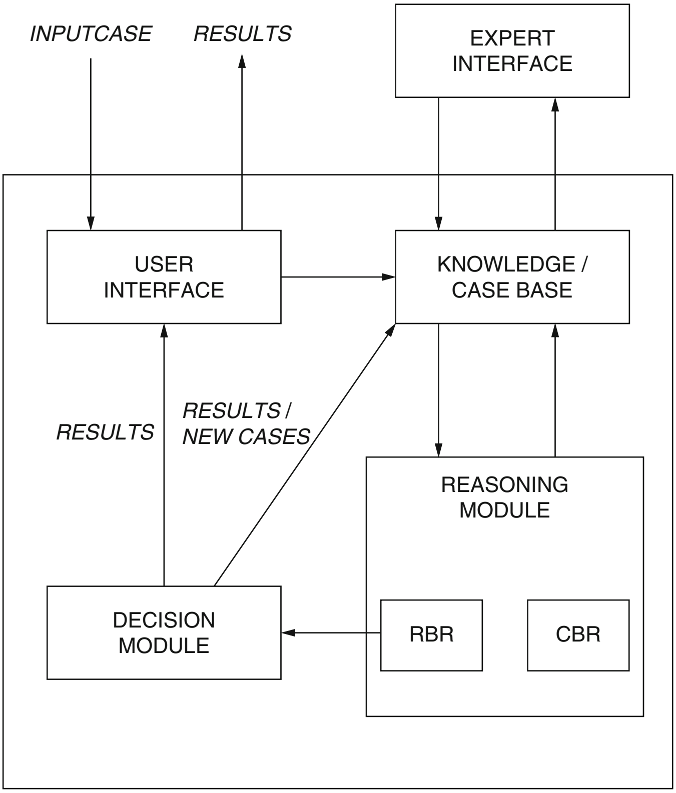


Fig. 16 CDSS architecture [27]

module, decision module and the expert interface. The user interface is responsible for the input of different cases or symptoms, which is then transmitted to the reasoning module via knowledge/case base. Knowledge/case base module is responsible to check whether the given input is distinct and unique from all the cases present in its database, and if unique, it adds it to its database. From the above architecture, it is confirmed that the numerous inference methods include rule-based reasoning, fuzzy logic, artificial neural networks and Bayesian networks among other mechanisms. Since rule-based reasoning comprises of a specific set of knowledge base using “if-then” logic, clinical-based reasoning enhances with the four R’s technique as shown below [27] (Fig. 17).

The four R’s include:

1. Retrieve: Involving retrieving different cases from the memory.
2. Revise: Forming associativity and mapping the present cases with any previous cases.
3. Reuse: Verify if the solution obtained is a distinct and new solution.
4. Remember: Only new distinct solutions are stored thereby reducing redundancy.

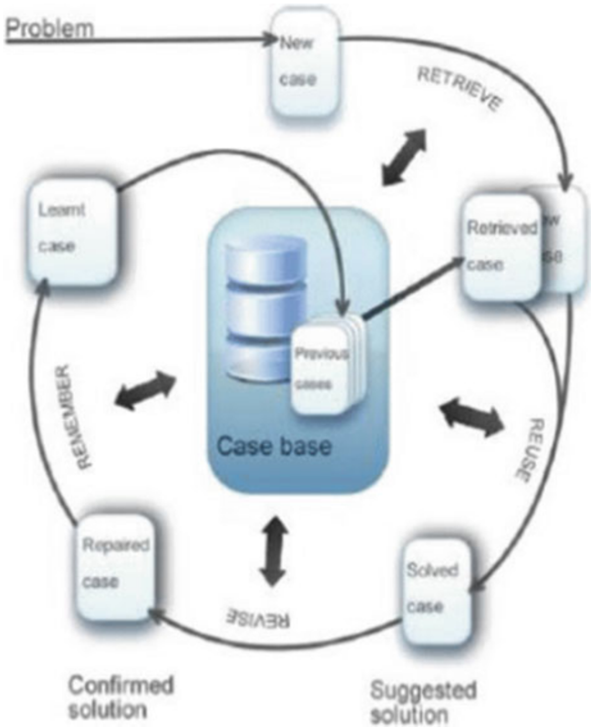


Fig. 17 The four R's in clinical-based reasoning [27]

During the search operation, the system builds relationships between similar cases once retrieved. There exists a threshold which defines a specific case to old or new deepening on its associated value assigned after the operation. Due to major differences, the revised solution is generated by the adaptation process. This hybrid system can be used in the diagnoses of variety of diseases like lung diseases, diabetes and heart diseases. For an effective reasoning approach, the different methodologies can be combined. Case-based reasoning is mainly used due to its simplified empirical clinical cases. This also has certain drawbacks that include the measurement of cases and retrieval process but can be substantially improved with the help of rule-based reasoning. In these cases, the rule-based reasoning only deals with firing the basic rules and the major decision-making system is handled by the case-based reasoning. Hence, the rule-based reasoning is extremely effective in dealing with explicit knowledge and clinical-based reasoning works effectively in implicit knowledge base [27].

4.7 *Genetic Algorithm*

Genetic algorithms fall under the category of non-knowledge-based CDSS. Genetic algorithms are highly sophisticated algorithms based on natural selection and genetics. They are randomized optimization algorithms. Genetic algorithm was one of the first bio-inspired computational methods. Genetic algorithms are based on Charles Darwin's theory of natural selection. Just as organisms in the environment constantly adapt and adjust to changing conditions, genetic algorithms also adapt to optimize results. As with Darwin's theory of "survival of the fittest," genetic algorithms generally begin by attempting to solve a problem through the use of randomly generated solutions. Genetic algorithms continuously modify the population, and with progressive step, the algorithm chooses random parents to produce an offspring. As the generations further, the population evolves and provides an optimal solution.

4.7.1 Structure of Genetic Algorithm

Figures 18 and 19 describe the structural aspects of a genetic algorithm. The first step in a genetic algorithm is to randomly generate a population which has the ability to give rise to a solution. The population is represented by chromosomes. The chromosomes are character strings and are essentially encoded solutions to a particular problem. In the next step, the fitness of each chromosome is evaluated. Depending on what solution is required, a specific fitness criterion is set. The fitness criterion is a fitness function also known as evaluation function. This function estimates the closeness of a given solution to the optimal solution. Once fitness is assigned, selection error must be evaluated. If there is high selection error, then the fitness is low. Hence, it is a necessity to reduce the selection error to obtain optimal solutions. The attributes with greater fitness level are more likely to be selected in the population. Different methods can be used for fitness assignment, but the most commonly used method is the rank method. The next step is the application of genetic operators. Here, the attributes that satisfy the fitness function are selected. The genetic operator known as the selection operator will make this selection. The selected attributes are parents which give rise to the next generation. The most commonly used selection method is the roulette wheel method. In this method, the

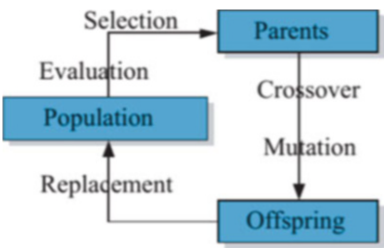


Fig. 18 Structure of a genetic algorithm

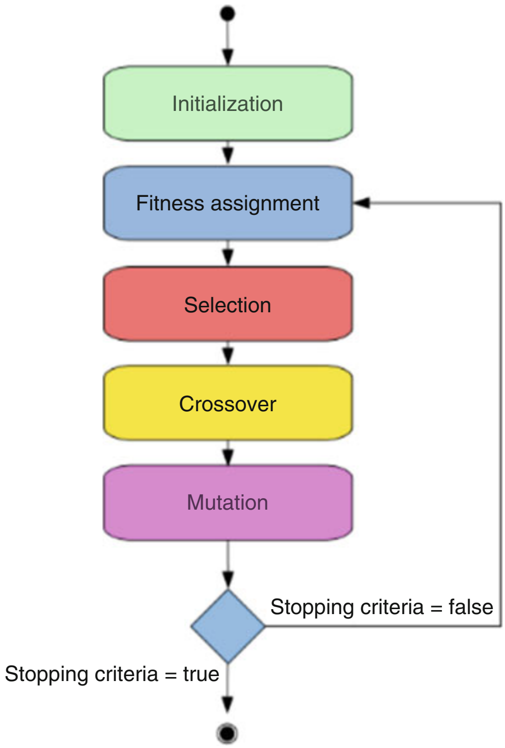


Fig. 19 The evolutionary cycle

selected attributes are placed on a roulette wheel and are enclosed in areas that are proportional to their fitness. The next operator in action is the cross-over operator. This operator is involved in the recombination of the selected attributes to generate the new population or the next generation. The operators select two individuals at random and recombine them to generate four offspring; this process continues till the new population size matches the old one. Hence, at the end of the crossover, the population size remains constant. The first-generation offspring generated are very similar to their parents, and this results in loss of diversity. To solve this problem, the mutation operator comes into the picture. The mutation operator mutates some of the offspring at random by changing their values. This leads to a more diverse population. Each iteration in the cycle produces a new set of chromosomes. Figure 19 depicts the evolutionary cycle. Typically, genetic algorithms run from 50 to 1000 generations. At the end of any typical genetic algorithm run, there is at least one chromosome that is highly fit. The main advantage of using genetic algorithm is that it is faster and more efficient compared to other traditional methods. It provides us with a set of good solutions and not just a single solution. Genetic algorithms have the ability to manage a data set which is encompassed with many features. The main disadvantage of using genetic algorithm is that it is very expensive in computational terms and a lot of time has to be invested in making the prediction model [28].

4.7.2 Applications in Clinical Studies

Genetic algorithms have been widely used in clinical studies.

Oncology
With an aim to provide non-invasive diagnosis for cervical cancer, genetic algorithms have been used. A number of studies revealed that genetic algorithms were successfully able to differentiate between a normal and dysplastic cervix [29].

Paediatrics
A cheap and non-invasive technique to monitor and assess foetal heart rate and uterine contraction is achieved through cardiotocography. In his study, Ocak [30] applied the principles of genetic algorithms to select the most optimal readings from cardiotocography. This enabled him to further optimize the support vector machine (SVM) classifier. The now-optimized system could classify foetal health conditions with 99% accuracy [30].

Autism is another common neuro-related condition that occurs in children. Latkowski and Osowski in their study used genetic algorithms to identify the genes that most frequently occurred in association with this disease.

The most common type of blood cancer or leukaemia occurring in children is acute lymphoblastic leukaemia (ALL). Various subtypes of ALL are known to occur frequently. In a study by Lin et al., genetic algorithms were used to select the genes that were required for the accurate classification of ALL [31].

Cardiology
Myocardial infarction is a leading cardiovascular condition. It is commonly referred to as heart attack. Formation of plaque is one of the major reasons for the incidence of this condition. If medical professionals could determine the properties of the plaque, a better medical diagnosis and treatment can be mapped out. Khalil et al. in his study used genetic algorithms to determine one of the properties, elasticity.

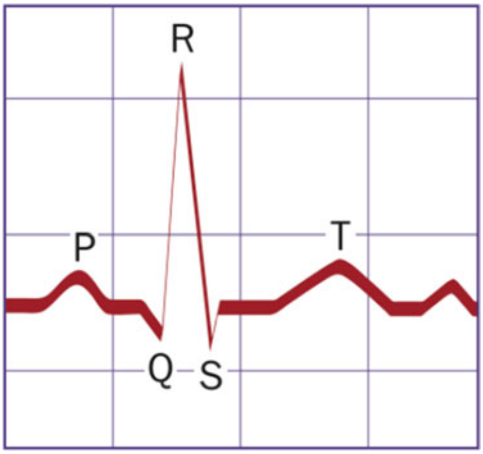
Major adverse cardiac event (MACE) can be predicted using genetic algorithms. Zhou et al. used genetic algorithms to predict the risk of MACE.

Q wave, R wave and S wave of the electrocardiogram combine to give what is known as the QRS complex (Fig. 20).

A complete analysis and understanding of the QRS complex are essential for reading and interpreting the ECG. Tu et al. employed genetic algorithms to detect these QRS complexes [32].

Endocrinology
Very low level of blood sugar level causes a condition known as hypoglycaemia. Hypoglycaemia is an indicator of a health problem. The symptoms of hypoglycaemia include anxiety, fever, shakiness and nausea among others. Hypoglycaemia can induce changes in electroencephalograms (EEGs). Nguyen et al. used genetic algorithms along with ANN to predict hypoglycaemia based on EEG signals [33].

Fig. 20 QRS complex [32]



5 CDSS in Clinical Practice

5.1 Virtual Psychiatrist

In countries like India, mental health-care services are in their infancy stages due to a huge mental gap. India being a low- and middle-income (LAMI) country is deficient in resources and workforce pertaining to mental health care. The usual way to bridge this mental gap is to train physicians to identify different types of mental disorders and provide the respective care required. However, there are many roadblocks to solve these issues such as difficulty in training personnel and inadequate funding [34].

With the aim of solving these issues, a project to deliver psychiatric services to three remote sites with the help of digital information communication technology was initiated at the Department of Psychiatry at the Postgraduate Institute of Medical Education and Research (PGIMER), Chandigarh, India [35].

Hence, a model for digital mental health care was developed, and its potential for service delivery in LAMI countries was determined. The model was powered by an online fully automated clinical decision support system (CDSS). It has modules for diagnosis, treatment, management and follow-up, and it is usable by non-specialists with brief training and nominal supervision by psychiatrists [36].

Sites in Himachal Pradesh (HP), Uttarakhand (UK) and Jammu and Kashmir (JK), Chandigarh being the nodal site, were chosen for the assessment. The three sites have very large stretches of geographically difficult and inaccessible terrains, with a very low number of psychiatrists.

The project consists of two components:

1. Development and standardization of the diagnostic and management application (or CDSS)
2. Deployment of the digital application service and testing in real time.

A brief overview of the development of the CDSS application software has been provided below. These modules were based on conditional logic and clinical knowledge to generate specific diagnosis and quickly sort out patient data and generate patient-specific recommendations [37].

A set of mental illnesses were taken into consideration based on the *International Statistical Classification of Disease-10* and *Diagnostic and Statistical Manual of Mental Disorders-IV* criteria. Separate CDSS applications were created for common psychiatric disorders such as dementia, depression, alcohol dependence and obsessive-compulsive disorder. The modules developed contained an essential core section and also an additional history section. The additional history section entails many sub-modules including family history, stress factors, environmental factors, physical illnesses and many other factors affecting mental health. The CDSS application format could be read in English or Hindi, depending on the patient's lingual ability [38].

The diagnostic module had two types of questioning sub-modules, which are the "Rater's rules" and the "Decision Rules." Rater's rules stated how an interviewer should rate an item as present or absent, based on the objective of the question. This allowed to create a routine clinical environment. The screening module acts as the first checkpoint to be passed, and then based on the responses in the first round, specific questions are asked based on an inbuilt hierarchy. Altogether, there are three levels of hierarchy for a certain mental illness, and a certain checkpoint has to be crossed in order to reach the next level. Decision rules are based on the diagnostic thresholds set by the official classifications [39] (Fig. 21).

Finally, a summary profile of the diagnosis of the patient is generated. These profiles generated can be used by a general physician or a psychologist to provide a

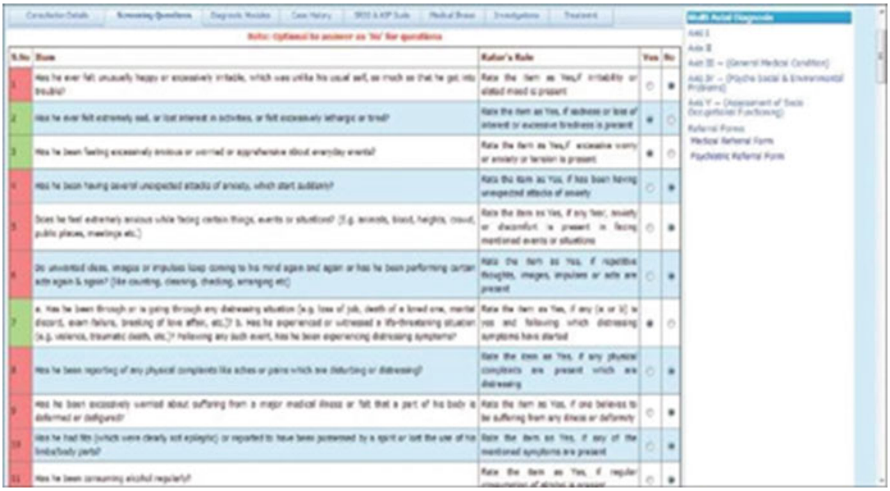


Fig. 21 Screenshot of the screening module of the clinical decision support system [36]

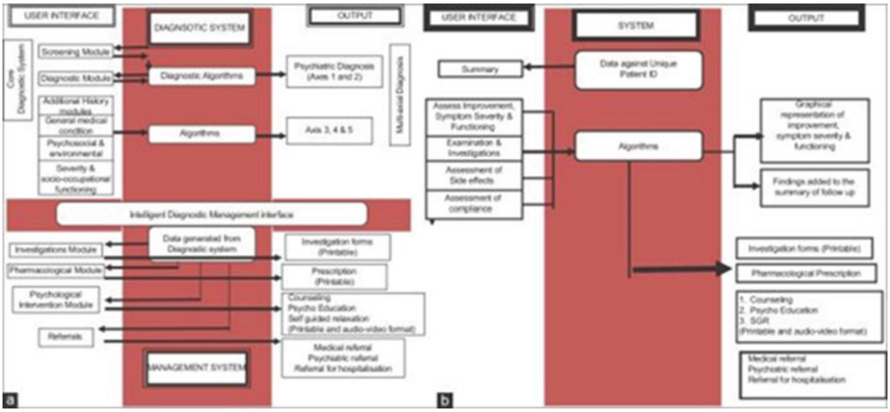


Fig. 22 (a) First consultation. (b) Flow of the system of the follow-up consultation [36]

better interpretation to the patient of what they are going through. Figure 22 shows the workflow of the CDSS and the way different decisions are made.

Finally, a follow-up module contains instructions on assessing improvement. It might also make changes to the treatment if required and records side effects or new symptoms if produced, and it also refers the patient for specialist care when required.

A majority of the patients found the CDSS application user friendly and were satisfied with the language used and the style in which the interview was conducted. The physicians and psychiatrists at the remote sites were satisfied with the choice of drugs and prescribed drug dosages. The counselling and relaxation training modules were useful and easy to understand by the patients or their caregivers. Hence, most of the patients were satisfied with the comprehensive assessment the CDSS application was able to provide [36].

5.2 Coronary Computed Tomography-Based Clinical Decision Support System

A coronary computed tomography-based CDSS has been designed to provide coronary decision support. This system uses a machine-learnt predictor to predict clinical decision for patients based on various input sources. This support may be provided to the physician prior to reviewing coronary CT data, thus helping with the decision to send patients to the catheterization laboratory. This is beneficial as a significant number of patients undergoing the procedure are reported to have no ischemia causing lesions [40].

The coronary CT data representing the patient's heart are obtained from the CT system. In addition to this, non-invasive patient data like patient history, demographics, blood pressure measurements, blood test data, molecular measurement information and results from other medical devices are obtained through tests and computerized clinical record databases. An anatomical evaluation of patient coronary arteries comprising of plaque size and volume, stenosis grading, lesion grading, calcium score and a physiological evaluation of patient coronary arteries comprising of IFR, WSS, FFR, etc. are performed using quantitative and other tools. From this, data values which serve as input to the machine-learnt predictor are extracted. The machine-learnt predictor, comprising of a cascade or parallel set of machine-learnt classifiers, uses trained machine-learning algorithms to generate a clinical decision for patient treatment based on the input data values. The output is transmitted in the form of a decision tree of the clinical decision predicted, other possible clinical decisions and recommended treatment options. This aids in the generation of clinical decisions regarding sending the patient for invasive stenting, invasive measurement, non-invasive tests, medicine prescription and discharge. This CDSS system can help physicians in charting a treatment path personalized for different individuals [40].

6 Drawbacks of CDSS

Drawbacks of CDSS mainly result from improper data storage and retrieval resulting in inaccurate datasets. The resistance to its adoption in clinical settings due to possible machine errors and the impersonal nature of CDSS is another major drawback.

Dependence on Centralized Data Repositories
Knowledge base is a critical architectural component of CDSS, which is dependent on a centralized repository of clinical data. This calls for the need of standardized representation of data. Repositories can be used to manage the storage and retrieval of these data. Lack of a well-managed and accurate knowledge base can impact the quality of clinical counsel offered by the CDSS. Good-quality repositories are required by data mining algorithms to be able to extract the relevant information necessary for clinical decision-making.

Large volumes of clinical datasets are obtained from content available on EHR, EMR and PHR. Corrupt databases can result from lack of standardized data capture methods. Corrupt databases provide an inaccurate representation of the patient population. It is, therefore, essential that data repositories and data capture methods are accurate to enable mining algorithms to extract patient-specific care recommendations [41].

Efficient Knowledge Management
The efficient assimilation of knowledge requires certain rules and guidelines. Knowledge management emphasizes on the articulation, capture and distribution of explicit and tacit knowledge in different formats. This is required to assimilate

existing knowledge to derive new knowledge. Creation of new knowledge is routinely observed in the medical field in the creation of new databases to define new disease and treatment methods. However, if the existing data on which the knowledge is based is of substandard quality, the outcome can be devastating in a clinical setting. Therefore, appropriate knowledge management is necessary to ensure patient-specific treatment recommendations. Information obtained from the CDSS must be analysed by health-care providers before decisions are made [41].

Improper Interpretation of Clinical Data

Data available in the CDSS are prone to misinterpretation and misrepresentation. This can arise from machine-related errors and can result in misdiagnosis. Further, automation biases generate errors that might not correlate with the practical knowledge of physicians. It is also noted that real data obtained from patient interviews and medical records are not appropriately organized and can alter the performance considerably [41].

Possible Source of Inconvenience to Clinicians

In actual clinical settings, it cannot be practically feasible for a clinician to consult a CDSS frequently during routine examinations; CDSS can sometimes increase the workload of physicians, and routine consultation with a system can alienate them from direct contact with their patients. Health-care providers with experiential knowledge are less likely to consider clinical decisions presented by a CDSS. Experienced physicians choose to rely on personal knowledge to devise a strategy for treatment rather than relying on existing clinical data. These attitudes can impede the acceptance and usage of CDSS in clinical practices. CDSS should therefore be customizable to suit the needs of the clinician [41].

7 Ethical and Legal Issues

Some of the ethical and legal issues related to CDSS have been summarized below.

Care Standard

The use of a CDSS might increase the risk of error. There are instances where despite accurate preliminary diagnosis made with the help of data collected from a patient, the treatment can turn out to be inaccurate, challenging the initial diagnosis. In such cases, a trained medical practitioner must use his expertise in deducing the appropriate treatment, something a system might not be capable of. Some patients might not be very comfortable with their diagnosis being determined by an informatics tool. Use of such tools will also result in the lack of personal interaction of the physician with the patient, which might result in inefficient data collection. All these challenges to the practical implementation of CDSS raise certain ethical questions and make clinicians reluctant to use the system to its full potential [18].

Appropriate Use

Appropriate use of a CDSS is important for ensuring good patient care. If a CDSS designed with an educational intent is depended upon for clinical decision support or if a system designed for modest decision support is used in a way that diagnosis by clinical experience is abandoned, the results can be disastrous. Therefore, the users of CDSS must have the appropriate qualifications and training to efficiently use the system [18].

Liability

The main legal issue associated with CDSS is the liability for misuse of the system to make or assist in medical decisions. In case a patient is injured due to defective diagnosis by the system, the clinician must be liable for negligence [18].

8 Conclusion and Future Scope

Clinical Decision Support Systems have provided a wealth of information to scientists and physicians to make patient-specific medical decisions using advanced computational approaches. CDSS helps in improving patient care by assisting a clinician from initial consultation to diagnosis and treatment. The future applications of this technology are numerous with its adoption in fields like pharmacology, pharmacogenomics, predictive medicine, antimicrobial treatment and pathology. This system has been used for providing antimicrobial treatment. This is achieved by interpreting patient data on the history of antibiotic medication administered, microbiology data and drug allergy information. CDSS has been shown to select the appropriate antimicrobial treatment regimens more frequently than physicians. The use of computational data assessment tools like CDSS in medicine has provided an opportunity for its utilization in antimicrobial and antibiotic resistance research [42]. It has been used in drug allergy checking and drug dosage. Future applications will be to optimize dosage selection using low-cost genomic analysis which would enable the prediction of drug metabolism based on the genetic makeup of patients. Although this might require a large data set, once established, a CDSS tailored to this purpose will permit patient-specific evidence-based treatment options [43]. It has also been used in the analysis of pathology reports. Advances in EHR databases and histopathological techniques have allowed for acquisition of large amount of patient data. Such CDSSs have been used to pool cancer data and provide prognostic tools. They have also been used to predict probabilities of inheritance of specific mutations in cancers by analysing patient data and family history. This illustrates the immense potential of medical informatics to guide preventive medicine. If improved, these systems can be valuable tools in the treatment of conditions like cancer which requires multidimensional approaches [43].

The significance of CDSS is especially evident in underdeveloped and developing countries which report higher incidences of nutritional disorders and outbreaks. A well-managed CDSS can equip such countries to handle such emergencies by providing real-time patient history. This can have a major impact in terms of improvement of general health of the population. The combination of medicine and informatics has resulted in numerous important advancements in medical treatment. The adoption and implementation of CDSS can assist clinicians and benefit patients by decreasing cost and increasing the standard of health care. CDSS thus serves as an effective system to monitor and improve health care globally and has the potential to revolutionize the future of health care.

Conflict of Interest The authors have no conflict of interest. There was also no problem related to funding. All authors have contributed equally with their valuable comments which made the manuscript to this form.

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