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Applied computer technologies in clinical decision support systems for pain management: A systematic review

Nuno Pombo[a,*], Pedro Araújo[a] and Joaquim Viana[b]
[a]*Instituto de Telecomunicações, and Department of Informatics, University of Beira Interior, Covilhã, Portugal*
[b]*Faculty of Health Sciences, University of Beira Interior, Covilhã, Portugal*

Abstract. Millions of people around the world suffer from pain, acute or chronic and this raises the importance of its screening, assessment and treatment. Pain, is highly subjective and the use of clinical decision support systems (CDSSs) can play an important part in improving the accuracy of pain assessment, and lead to better clinical practices. This review examines CDSSs, in relation to computer technologies and was conducted with the following electronic databases: CiteSeer^x, IEEE Xplore, ISI Web of Knowledge, Mendeley, Microsoft Academic Search, PubMed, Science Accelerator, Science.gov, ScienceDirect, SpringerLink, and The Cochrane Library. The studies referenced were compiled with several criteria in mind. Firstly, that they constituted a decision support system. Secondly, that study data included pain values or results based on the detection of pain. Thirdly, that they were published in English, between 1992 and 2011, and finally that they focused on patients with acute or chronic pain. In total, thirty-nine studies highlighted the following topics: rule based algorithms, artificial neural networks, rough and fuzzy sets, statistical learning algorithms, terminologies, questionnaires and scores. The median accuracy ranged from 53% to 87.5%. The lack of integration with mobile devices, the limited use of web-based interfaces and the scarcity of systems that allow for data to be inserted by patients were all limitations that were detected.

Keywords: Clinical decision support system, pain measurement, medical informatics, machine learning

1. Introduction

Clinical decision support systems (CDSSs) are designed to assist healthcare professionals in decision-making tasks. These systems are widely used in countless healthcare processes such as triage, early detection of diseases, identification of changes in health symptoms, extraction of patient data from medical records, in-patient support, evaluation of treatment and monitoring. A general model of CDSS encompasses the following components: input, output, knowledge base and inference engine. The input (user interface) ensures that the clinical information is entered into the CDSS, whereas the output presents the decisions and/or suggestions provided by the system. The knowledge base contains the medical information which comprises for example rules and probabilistic associations while the inference engine includes formulas for combining the rules and associations [1]. These two components are critical in the design of a CDSS and its combination is chiefly important to ensure the generation of medical advices based on patient data [2]. In addition, CDSSs face additional challenges when applied to patients with symptoms of pain.

According to the International Association for the Study of Pain [3, 4], pain is an unpleasant sensory

*Corresponding author. Nuno Pombo, Instituto de Telecomunicações, and Department of Informatics, University of Beira Interior, Covilhã, Portugal. E-mail: ngpombo@ubi.pt.

and emotional experience related to past or potential tissue damage or it may be described in terms of such damage. Furthermore, pain is the fifth vital sign for indicating basic bodily functions, health and quality of life [5, 6], together with the four other vital signs: blood pressure, body temperature, pulse rate and respiratory rate. The symptom of pain can be distinguished according to its duration. When occurring with a relatively short duration it is known as acute pain. However, when pain persists over a long period of time it is regarded as chronic pain [7]. In both situations, pain is a highly subjective experience for each individual, and this makes it harder to produce an assessment that leads to the right treatments [8]. We are not measuring an objective physical parameter but an emotional status that happens inside the mind of each individual and we can say more appropriately that we "estimate" or "translate" pain rather than measuring it.

Nevertheless, apart from the philosophical considerations, the occurrence of pain diminishes the quality of life and working abilities of people [9]. Moreover, in accordance with findings from the US Committee on Advancing Pain Research [10], chronic pain alone, affects at least 116 million American adults (circa 37% of the total population), exceeding the total affected by heart disease, cancer, and diabetes combined. This results in costs for the country of up to $635 billion dollars each year in medical treatment and lost productivity.

Therefore the CDSSs should be developed to ensure that, despite the subjectivity of pain, these clinical tools can be used to improve patients' health and well-being through the intelligent application of resources. This study aims to describe CDSSs applied to pain management focusing firstly on computer technologies, and secondly on medical conditions, clinical settings, main decisions, and system accessibility. In addition, this study presents the sample size and the percentage of decisions produced by each system that are in line with medical decisions also known as accuracy.

2. Methods

2.1. Research questions

The primary questions of this review were (RQ1) which computer technologies have been used in CDSSs applied to pain? (RQ2) What is the overall accuracy of these technologies?

2.2. Inclusion criteria

Studies measuring and assessing pain using CDSSs were included in this review if they met the following criteria. (1) Constituted a decision support system, (2) related to acute or chronic pain complaints, (3) included data about pain values or (4) the system produced results based on the detection of pain occurrences, (5) used computerised systems, (6) were published between 1992 and 31st December 2011, and (7) were written in English. There were no age or disease restrictions: participants could be adults or children, chronic pain patients, healthy individuals with pain complaints, or individuals experiencing an episode of acute pain.

2.3. Search strategy

The team searched for studies, meeting the inclusion criteria in the following electronic databases: CiteSeer^{x}, IEEE Xplore, ISI Web of Knowledge, Mendeley, Microsoft Academic Search, PubMed, Science Accelerator, Science.gov, ScienceDirect, SpringerLink, and The Cochrane Library. One study, [11] was published online (November 2011), while the team was researching the electronic databases and therefore qualified for this review. The study was subsequently published in February 2012.

Every study was independently evaluated by two reviewers (NP and PA) and its suitability determined with the agreement of both parties. A third reviewer was considered to adjudicate on differences of opinion but was not required because a consensus was reached. The studies were also examined to identify and isolate clusters reporting the same data, so as to avoid the risk of bias [12]. When different studies reported the same CDSS, they were considered independently since they comprised the different marked symptoms and approaches (e.g. the studies [13] and [14], relative to the CDSS of [15–20]).

Also, the references of the studies were analysed for any additional CDSSs studies applied to pain. The abstracts and/or full text papers of these studies were subsequently evaluated by both reviewers, following the same criteria they applied to the database searches.

2.4. Extraction of study characteristics

The data extracted from the studies, were tabulated (see Table 1) and comprised the following characteristics: year of publication, clinical information (i.e. condition, setting, task, decision, and improvement in

Table 1
Selected studies

Study	Year	Clinical							System	
		Condition	Setting			Task	Decision	IPP	Users	Ubiquity
Fathi-Torbaghan [21]	1994	Abdominal pain	A	PC	SC	Diagnosis	Prediction of the presence of abdominal pain	Yes	Physicians	
Blazadonakis [22]	1996	Abdominal pain	A	EC	SC	Diagnosis	Triage of patients in emergency: discharge, follow-up or operate	No	Physicians	
Ohmann [23]	1996	Abdominal pain	A	EC	MC	Diagnosis	Prediction of the presence of abdominal pain	No	Physicians	
Eich [24]	1997	Abdominal pain	A	EC	MC	Diagnosis	Prediction of the presence of abdominal pain	-	Physicians	
Ellenius [25, 26]	1997	Chest pain	A	EC	MC	Diagnosis	Myocardial infartion prediction	Yes	Physicians	
Kennedy [27]	1997	Chest pain	A	EC	MC	Diagnosis	Myocardial infartion prediction	Yes	Physicians	
Pesonen [28]	1998	Abdominal pain	A	EC	MC	Diagnosis	Acute appendicitis prediction	No	Physicians	
Vaughn [29]	1998	Low back pain	C	PC	SC	Diagnosis	Classify into classes: Simple Low Back Pain, Root Pain or Abnormal Illness Behaviour	Yes	Physicians	
Aase [30]	1999	Chest pain	A	EC	SC	Diagnosis	Acute ischemic heart disease prediction	Yes	Physicians	
Wang [31]	2001	Chest pain	A	EC	MC	Diagnosis	Myocardial infartion prediction	Yes	Physicians	
Baxt [32]	2002	Chest pain	A	EC	SC	Diagnosis	Myocardial infartion prediction	Yes	Physicians	
Kuziemsky [33]	2003	Palliative care	C	SI	MC	Treatment	Pain management	-	Physicians, Nurses	
Wilkie [34, 35]	2003	Cancer pain	C	SI/SO	MC	Treatment	Score and interpretation of McGill Questionnaire	Yes	Physicians, Patients	Mobile devices
Farion-Michalowski [15–20]	2004	Abdominal pain	A	EC	SC	Screening	Triage of patients in emergency: discharge, observation or consult	Yes	Physicians, Nurses	Web-based interface [20], and mobile devices [19]
Blaszczynski [14]	2005	Abdominal pain	A	EC	SC	Screening	Triage of patients in emergency: discharge, observation or consult	Yes	Physicians, Nurses	
Farion-Michalowski [13]	2005	Scrotal pain	A	EC	SC	Screening	Triage of patients in emergency: discharge, observation or consult	Yes	Physicians, Nurses	
Lin Lin [36]	2006	Low back pain	C	SO	MC	Diagnosis	Classify patients with low back pain	Yes	Physicians	Web-based interface
Sadeghi [37]	2006	Abdominal pain	A	EC	SC	Screening	Triage of patients in emergency : admit, refer or discharge	Yes	Nurses	
Westfall [38]	2006	Chest pain	A	EC	MC	Diagnosis	Acute ischemic heart disease prediction	No	Physicians, Nurses	
Chang [39]	2007	Palliative care	C	SI/SO	SC	Treatment	Pain management	-	Physicians, Nurses, Patients	Integration with EMR/PHR
Lai [40]	2007	Knee pain	C	PC	SC	Diagnosis	Patellofemoral pain syndrome prediction	Yes	Physicians	

Table 1
(*Continued*)

Study	Year	Clinical							System	
		Condition		Setting		Task	Decision	IPP	Users	Ubiquity
van Gerven [41, 42]	2007	Abdominal pain	A	PC	SC	Risk assessment	Carcinoid heart disease prediction	Yes	Physicians	
Binaghi [43]	2008	Myofascial pain	A	PC	MC	Diagnosis	Temporomandibular disorders prediction	Yes	Physicians, Patients	Web-based interface
Elvidge [44]	2008	Palliative care	C	SI	SC	Treatment	Pain management	-	Physicians	Web-based interface
Hsin-Min Lu [45]	2008	Abdominal pain	A	EC	SC	Screening	Classify patients into syndromic categories	Yes	Physicians, Nurses	
Watt [46]	2008	Knee pain	C	SO	MC	Diagnosis	Prediction of the presence of knee pain	Yes	Physicians	
Abas [47]	2011	Postoperative pain	A	SI	-	Treatment	Pain management	-	Physicians, Nurses	Integration with HIS
Farooq [48]	2011	Chest pain	A	PC/SO	SC	Risk assessment	Chest pain risk assessment	-	Physicians, Patients	Web-based interface
Jinglin [49]	2011	Low back pain	C	SO	SC	Diagnosis	Prediction of the presence of low back pain	Yes	Physicians	
Kong [11]	2011	Chest pain	A	EC	SC	Risk assessment	Chest pain risk assessment	Yes	Physicians	Web-based interface
Simonic [50]	2011	Rheumatoid arthritis pain	C	PC	SC	Treatment	Pain management	Yes	Physicians	

A: Acute pain; C: Chronic pain; EC: Emergency Care; PC: Primary Care; SI: Secondary/Tertiary In-patient Care; SO: Secondary/Tertiary Out-patient Care; SC: Single Center; MC: Multi-Center; IPP: Improvement in Practitioner Performance; -: None Reported.

practitioner diagnosis) and system information (users and ubiquity). The studies were separated into machine learning (ML) and content processing (CP). The ML (see Table 2) comprised rule based algorithms (RBA), artificial neural networks (ANN), rough and fuzzy sets (RFS), and statistical learning algorithms (SLA). The ML characteristics included study identification, year of publication (the earliest year, where studies reported from the same dataset), healthcare condition, number of learning/training/testing records, and accuracy (percentage of system decisions that are in line with medical decisions). The CP encompassed terminologies, questionnaires, and scores (see Table 3). The CP characteristics included study identification, year of publication, healthcare condition, number of records and type of content used. Each study and its content can be referenced across a wide and diverse range of ML and CP topics.

3. Results

As illustrated in Fig. 1, our review identified 1,245 citations, of which 75 were duplicates. The remaining 1,170 citations were evaluated, in terms of title, abstract, and keywords, resulting in the exclusion of 1,081 citations because they clearly did not meet the inclusion criteria. Full text evaluation of the remaining 89 papers resulted in the exclusion of 57 papers that did not match the defined criteria. In addition, the reference tracking allowed for the inclusion of seven additional papers. In summary then, our review examined 39 papers, representing 31 unique studies, because where studies reported the same data, they were clustered to avoid risk of bias.

As shown in Table 1, the most representative symptoms were abdominal pain, reported in ten studies (32%), chest pain, included in eight studies (26%), followed by low back pain and palliative care with three studies each (10%). These symptoms represented 78% overall. Meanwhile, the remaining symptoms comprised knee pain, with two studies, cancer pain, myofascial pain, post-operative pain, rheumatoid arthritis pain, and scrotal pain, all contained in one single study. Moreover, nine of the thirty-one studies (29%) included in this review were published before or during 2000, and of the remaining 22 studies, only seven were published by the end of 2005 (23%). Finally, 15 studies (48%) were published between the beginning of 2006 and the end of 2011.

Sixteen studies (52%) related to emergency care (EC), and six studies (19%) highlighted primary care (PC). Secondary/tertiary care which includes in-patient care and out-patient care were both reported in three studies (19%). The subject of in-patient and out-patient care was proposed by two studies whereas PC and out-patient care was suggested by just one study. The clinical tasks were divided among diagnosis (17 studies, 55%), treatment (six studies, 19%), screening (five studies, 16%) and risk assessment (three studies, 10%).

In addition, 25 studies presented results in terms of practitioner performance, of which 84% reported improvements in this area. Only four studies (13%) presented systems with patient interaction capabilities. The development of web-based CDSSs was reported in six studies (19%), and the usage of mobile devices was proposed in two studies (6%). SLA was the most commonly used technology with 13 of 31 studies (42%), followed by RBA with seven studies (23%) and ANN with six studies (19%).

Finally, RFS and terminologies were both applied in five studies (16%), and questionnaires and scores in two (6 %).

The period from the beginning of 2006 until the end of 2011 showed an absence of studies using ANN. In this period, RBA and terminologies, with three studies each, appeared immediately behind SLA, which remained the most used technology with seven studies.

As shown in Table 2, Bayesian network, logistic regression and fuzzy logic presented the higher accuracy of medical diagnoses (100%). The rough set presented the best performance in terms of screening process (77%), whereas classification and regression tree (CART) revealed the best accuracy of risk assessment algorithms (80%). However, these values should be interpreted with caution due to the fact that they did not result from the comparison among different techniques and algorithms.

3.1. Rule based algorithms

Several RBA were found, namely AQ15 [51], C4.5 [52], CART [53], CN2 [54], ID3 [55], NewId [56], ITRULE [57], PRISM [58], and Inductive Learning by Logic Minimization (ILLM) [59]. The ID3 requires the building of a decision-tree based on rules relating to the choice of attributes. In turn, the C4.5 is based on the ID3, but with extended capabilities, achieved by pruning irrelevant branches of the decision tree. The NewId, also based on ID3, supports structured attributes and ordering [23]. In addition, the PRISM, based on

Table 2
Machine learning: Rule based algorithms, artificial neural networks, rough and fuzzy sets, statistical learning algorithms

Rule based algorithms

Study	Year	Condition	Number of records		Algorithm	Accuracy
			Learn	Test		
Blazadonakis [22]	1996	Abdominal pain	268	67	AQ15	79%
					C4.5	84%
					CN2	86%
					NewId	73%
					ILLM	84%
Ohmann [23]	1996	Abdominal pain	839	415	C4.5	46%
					CN2	47%
					ID3	48%
					ITRULE	43%
					NewId	40%
					PRISM	45%
Eich [24]	1997	Abdominal pain	6815	3418	C4.5	57%
Blaszczynski [14]	2005	Abdominal pain	606	100	C4.5	57%
van Gerven [41, 42]	2007	Abdominal pain	-	-	C4.5	44%
Elvidge [44]	2008	Palliative care	276	-	ID3 (with kNN)	-
Kong [11]	2011	Chest pain	1000	1000	CART	80%
Median			**722.5**	**415**		**57%**

Artificial neural networks

Study	Year	Condition	Number of records		Structure	Accuracy
			Learn	Test		
Ellenius [25, 26]	1997	Chest pain	50	38	MSLP (3 SLPs)	90%
Kennedy [27]	1997	Chest pain	90	200	I/H/O: 53/18/1	92%
Pesonen [28]	1998	Abdominal pain	717	347	I/H/O: 16/6/3	78%
Vaughn [29]	1998	Low back pain	99	99	I/H/O: 92/10/3	67%
Wang [31]	2001	Chest pain	1253	500	I/H/O: 30/15/1	85%
Baxt [32]	2002	Chest pain	1050	926	I/H/O: 40/10/1	93%
Median			**408**	**273.5**		**87.5%**

Rough and fuzzy sets

Study	Year	Condition	Number of Records	Algorithm	Accuracy
Fathi-Torbaghan [21]	1994	Abdominal pain	100	Fuzzy logic	80%
Farion-Michalowski [15–20]	2004	Abdominal pain	328	Rough Set	66%
Blaszczynski [14]	2005	Abdominal pain	100	Rough Set	59%
Farion-Michalowski [13]	2005	Scrotal pain	30	Rough Set	77%
Binaghi [43]	2008	Myofascial pain	50	Fuzzy logic	100%
Median			**100**		**77%**

Statistical learning algorithms

Study	Year	Condition	Number of records		Structure	Accuracy
			Learn	Test		
Blazadonakis [22]	1996	Abdominal pain	268	67	Naive Bayes	89%
Ohmann [23]	1996	Abdominal pain	839	415	Bayes' theorem	45%
Aase [30]	1999	Chest pain	493	290	Bayes' theorem	89%
Wang [31]	2001	Chest pain	1253	500	LR	84%
Baxt [32]	2002	Chest pain	2024	2024	LR	75%
Blaszczynski [14]	2005	Abdominal pain	606	100	Naive Bayes	56%
					IB1	58%
Lin Lin [36]	2006	Low back pain	180	20	Bayes' theorem	73%
Sadeghi [37]	2006	Abdominal pain	90	-	Bayesian network	56%
Lai [40]	2007	Knee pain	27	27	SVM	89%
van Gerven [41, 42]	2007	Abdominal pain	-	-	Naive Bayes	63%
					LR	67%
					Noisy-OR	54%
					Noisy-Threshold	72%
Elvidge [44]	2008	Palliative care	276	-	kNN	-
Watt [46]	2008	Knee pain	4796	200	Bayesian network	100%
					LR	100%
Jinglin [49]	2011	Low back pain	21	21	PSVM	95%
					SVM	90%
Median			**384.5**	**150**		**74%**

-: None reported; I: Nodes of input layer; H: Nodes of hiden layer; O: Nodes of output layer.

Table 3
Content processing: Terminologies, questionnaires, scores

Terminologies				
Study	Year	Condition	Number of Records	Terminology
Eich [24]	1997	Abdominal pain	10233	SNOMED-CT
Kuziemsky [33]	2003	Palliative care	-	UMLS
Hsin-Min Lu [45]	2008	Abdominal pain	2256	UMLS
Abas [47]	2011	Post-operative pain	-	UMLS
Farooq [48]	2011	Chest pain	-	SNOMED-CT
Questionnaires				
Study	Year	Condition	Number of Records	Questionnaire
Wilkie [34, 35]	2003	Cancer pain	213	MPQ
Chang [39]	2007	Palliative care	-	Patient-tailored
Scores				
Study	Year	Condition	Number of Records	Score
Westfall [38]	2006	Chest pain	1861	ACI-TIPI
Simonic [50]	2011	Rheumatoid arthritis pain	175	DAS, and HAQ

-: None reported.

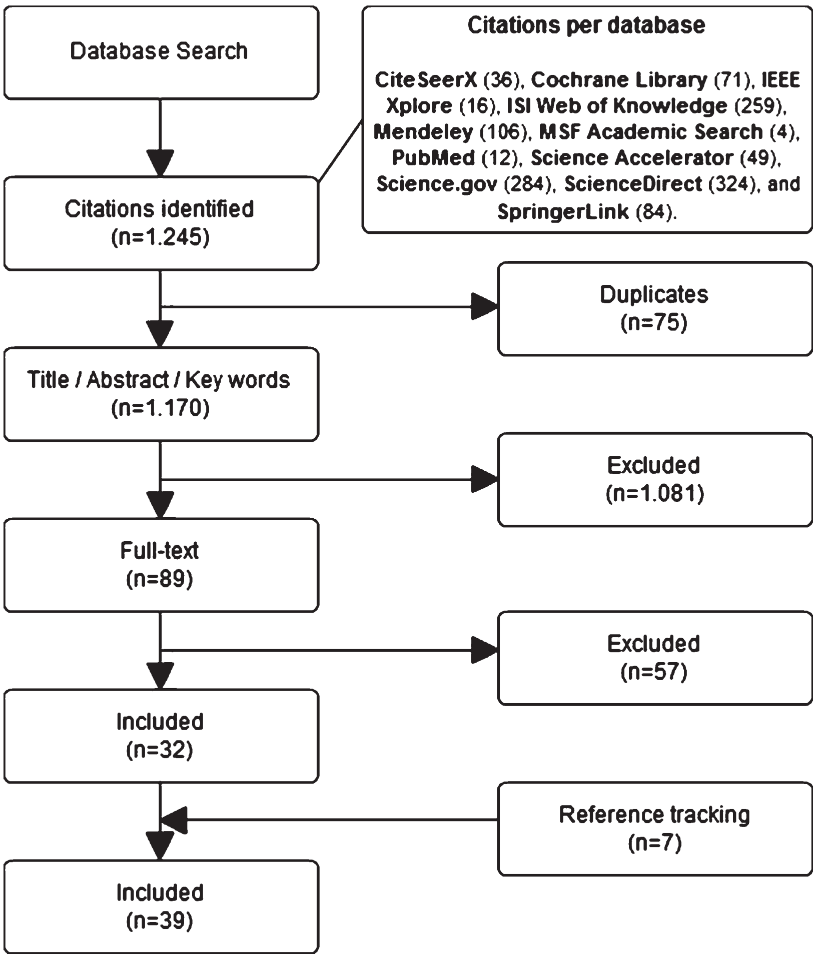

Fig. 1. Flow diagram of identification and inclusion of papers.

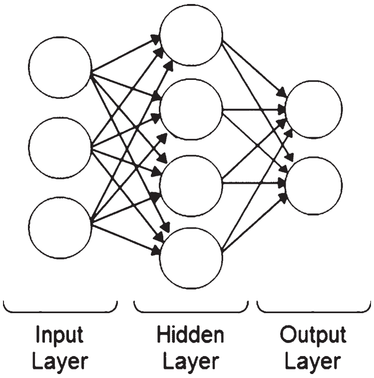

Fig. 2. Illustration of an MLP.

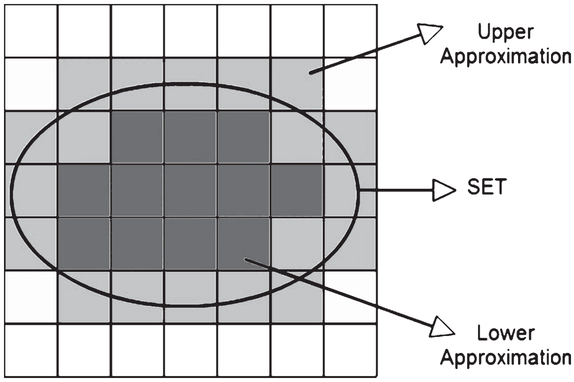

Fig. 3. Illustration of a rough set.

ID3, aims to find just the relevant values of attributes, unlike ID3, which finds one overall attribute, regardless of its relevance and values. The AQ15 aims to remove redundant conditions from the initial rules set [51], while the CN2, based in both ID3 and AQ15, is used to improve the quality of the rules by evaluating and selecting the best ones. The CART is an algorithm that seeks to identify the most significant variables and discards the non-significant ones. Furthermore, the ITRULE searches the space for possible rules and evaluates the information content to establish a ranking [23, 60].

Finally, ILLM is designed to find the minimal logic expression that represents the largest cases of the initial rules set. The clarity and understanding that the classification system gives represents the main advantage of the decision trees [61, 62]. However, some limitations arise such as the overspecialisation [63, 64] or the inefficiency for learning rules from incomplete data [65]. Moreover, the complexity of the clinical problem presents a barrier to reliable estimates of probabilities and decision criteria [23, 66].

3.2. Artificial neural networks

The ANN are composed of interconnected processing elements, called nodes that carry out the classification process. These systems generate an output set where each element represents a particular classification for the input set. This is achieved via the propagation of estimated weights through the nodes of the network. Accordingly, [25, 26] reported a system based on the usage of Single-Layer Perceptrons (SLP) [67] in parallel, also known as multiple-SLP (MSLP). Alternatively, [27–29, 31, 32] described a Multi-Layer Perceptrons approach (MLP) [68]. The SLP is applied

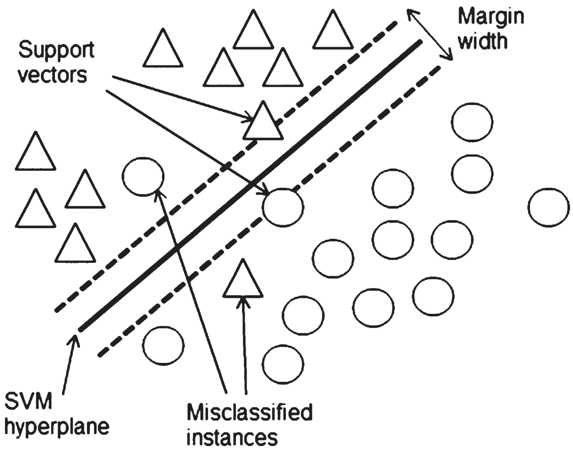

Fig. 4. Illustration of a linear SVM decision function separating class +1 (*circles*) from the class −1 (*triangles*).

to learning from a batch of training, in a repeated way, to find the accurate vector for the entire training set, whereas MLPs aim at the separation of input instances into their appropriate categories. However, despite its robustness to noisy data and its ability to represent complex functions [61, 69], its inability to explain decisions and the lack of transparency of data [27, 61, 64, 70], presents an obstacle for its use in clinical settings. Also, determining the adequate size of the hidden layer is vulnerable to poor approximations (caused by lack of neurons) or overfitting (from excessive nodes) [69, 71, 72].

3.3. Rough and fuzzy sets

The rough set theory [73] proposed by [13–20] comprises a combination of two sets – namely lower and upper approximation. The lower approximation is made up of elements that do belong to the set, whereas the upper approximation is composed of elements that possibly belong to the set. The difference between them results in the boundary region of the rough set. This theory is limited when data tends to be noisy [74] and inefficient computation restricts its suitability for large data sets [74, 75]. The main advantage is that it does not need any preliminary or additional information about data [76]. The fuzzy logic [77] represents a probabilistic logic model that uses reasoning to explain whether an event is about to happen. This model was introduced by [21, 43] with the advantage that it allows for the use of vague linguistic terms in the rules [78, 79]. However it is difficult to estimate the membership functions [80].

3.4. Statistical learning algorithms

The purpose of SLA is to learn structures of interest of a given data set [81]. The learning process occurs through prediction or description of input variable associations. The prediction, pre-supposes the completion of classification and regression tasks, whereas the description searches the data analysis to find some intrinsic structures. In line with this, [23, 30, 36] presented the Bayes' theorem (a.k.a. Bayes' rule) [82] which is a method of inference to precise the subjective degree of belief. This model is time-consuming and requires a thorough knowledge of its parameters [11].

In turn, the naive Bayes [83], applied by [14, 22, 41, 42], is based on Bayes' theorem and assumes that the effect of a predictor in a class is independent relative to the values of other predictors. This model aims at reducing the computational time required by removing irrelevant or correlated parameters [64].

Bayesian network [84], comprises a directed acyclic graph, that includes arrow points (only one direction), no circular paths and nodes that represent a conditional probability value. This model was applied by [37, 46] and is in many ways superior to RBA [37], because it defines probabilistic representations of uncertain knowledge [37, 64]. By contrast, [41, 42] suggested the use of Noisy-OR [85, 86] and a simplification of this model, called Noisy-Threshold [87] that delivers a probabilistic approximation, to minimise the number of required parameters.

Other techniques were described, including k-Nearest Neighbour (kNN) [88], proposed by [44], IB1 [89], presented by [14], and Logistic Regression (LR) [90], used by [31, 32, 41, 42, 46]. The kNN consists of a multi-dimensional space, in which each element is plotted according to its own attribute values. Also, kNN requires large storage, is time-consuming, and is very sensitive to irrelevant parameters [91]. The IB1 is identical to the kNN, with a function that normalises its attributes' ranges, processes instances incrementally and can tolerate missing values [89]. In turn, LR is applied to model data where the target variable is binary and is designed to produce a model that allows for the prediction of assigned values to variables. This model is less susceptible to overfitting [92]. The weaknesses are its unsuitability to deal with non-linear problems and the interactive effects of variables [93].

Finally, as proposed by [40, 49], the Support Vector Machine (SVM) [94] aims to map the training data to a higher dimensional space and separate the different classes of data, by constructing the optimal separating hyper-plane. This model has good generalisation ability and a robustness for high dimensional data [61, 64]. The SVM is more suited to training and performs better compared to ANN [69]. However it is very sensitive to uncertainties [49, 61], and a too high dimensional space can lead to overfitting of the data [69, 95] and so slow the speed of the training [64, 96].

The study reported in [49], uses an extended modelling method from SVM, called Probabilistic Support Vector Machine (PSVM), to handle uncertainties in data samples.

3.5. Terminologies

The Unified Medical Language System (UMLS) [97], reported by [33, 47] (see Table 3), includes large health and biomedical vocabularies and also concepts extracted from several sources. These include; IDC9-CM [98], Logical Observation Identifiers Names and Codes (LOINC) [99], Medical Subject Headings (MeSH) [100], and Systematized Nomenclature of Medicine - Clinical Terms (SNOMED-CT) [101]. The UMLS was also proposed by [45] because it uses the Weighted Semantic Similarity Score (WSSS) [102] to exploit the semantic relationship between the reported symptoms and the UMLS terms. Also, [24, 48] presented a system with a data dictionary based on SNOMED-CT terminology. However, several limitations were found - firstly its complexity due to the high number of terms and relationships [103, 104] and secondly the difficulty in integrating a new terminology [105].

3.6. Questionnaires

As shown in Table 3, a computerised version of McGill Pain Questionnaire (MPQ) [106] was presented by [34, 35] while [39] suggested a CDSSs based on patient-tailored questionnaires, that combined the Computerised Adaptive Testing (CAT) [107] with Item Response Theory (ITR) [108], to obtain the ideal arrangement of questions. The limitations were the time required to complete the questionnaire [24, 34, 35, 50], and the time that elapsed between the editing and the occurrence of pain. This limitation also occurs in scores.

3.7. Scores

The authors [38, 50] (see Table 3) proposed CDSSs based on scores, resulting from the combination of several analysed characteristics. The Acute Cardiac Ischemia Time-Insensitive Predictive Instrument (ACI-TIPI) [109], had no relevant impact on diagnostic screening nor did it contribute to improving the accuracy of chest pain patients as explained by [38]. The Disease Activity Score (DAS) [110] together with Health Assessment Questionnaire (HAQ) [111] was proposed by [50] to optimise the patient treatments. The disadvantage of these systems is the time that is needed to obtain the required information [50].

4. Discussion

This review confirms the findings of previous studies across a range of topics. (1) Difficulty arising from the complexity of the systems, as reported by [112]. It appears to be hard for medical experts to build valid models when too many variables affect the process, leading to the design of low accuracy systems (e.g. due to overspecialisation or overfitting [23]), which may result in inadequate or incorrect diagnosis [36]. So the development and implementation of CDSSs may become more difficult due to their complexity [11]. (2) Opportunity to address therapy changes in a timely manner, as suggested by [113], derived from CDSSs implementation; and (3) difficulty in assessing the economic effects of CDSSs as described by [114]. In fact, the absence of this assessment is confirmed in all studies. (4) In accordance with [115], only two studies provide integration with other systems such as HIS [116], EHR [117] or PHR [118].

New topics are also addressed by this review, namely: (5) content processing is primarily applied to the treatment of patients (5 of 9 studies). The patients can input data in two of these models whereas three allow for use by nurses. The main limitation of these models is (6) the excessive time required to complete the questionnaires and scores. (7) The diagnosis is mostly performed in EC (10 of 16 studies). Four studies note no improvement in practitioner performance, primarily due to the low accuracy rate [23] and poor clinical assessment procedures [22, 28, 38]. (8) All the screening systems are applied in EC (5 studies) and allow for use by nurses. Also, (9) lack of integration of the CDSSs with mobile devices (2 studies, 6%), and (10) reduced web-based interaction with the CDSS (6 studies, 19%). In addition, (11) the involvement of patients with the CDSSs is only verified in four studies (13%). Finally, (12) only ten studies are related to chronic pain (32%).

These topics suggest that the widespread availability and ubiquity of mobile devices and the Internet is not properly exploited by CDSSs. The ability to interact with the system anywhere and at anytime offers invaluable opportunities to physicians, health professionals and patients, which could lead to better and more efficient therapies. For example, these technologies could ensure the monitoring of patients in hospital or in ambulatory care with that data being included in the CDSS and being used to support the long term healthcare of chronic pain patients. Also, the inclusion of patients' data could take advantage of service oriented architecture (SOA) [119] and cloud computing [120] as proposed by [121], to obtain scalable and interoperable systems. The patients themselves could provide reports of their complaints and note the actual moment when pain occurs, also known as ecological momentary assessment (EMA) [122].

The inclusion of these data in the CDSSs could help address the use of unregulated electronic pain diaries, many of which are developed without medical supervision, or integration capabilities, or even evidence of their effectiveness [123]. Moreover, the regularly collected data could result in a more realistic assessment of the patient's health and consequently an accurate diagnosis. Thus, the weaknesses of CDSSs, mentioned by [124, 125], regarding errors in diagnoses and decisions due to the difficulty of tracking patients' symptoms are likely to be minimised.

5. Conclusions

The purpose of this review was to distinguish CDSSs applied to patients suffering from pain, in relation to their computer technologies. Thirty-nine studies were examined and the main findings are summarised as follows:

(RQ1) the computer technologies that have been applied in CDSSs include machine learning and content processing. Machine learning encompasses rule based algorithms (RBA), artificial neural networks (ANN), rough and fuzzy sets (RFS), and statistical learning algorithms (SLA). Content processing comprises terminologies, questionnaires, and scores.

(RQ2) The ANN presented the higher median accuracy (87.5%), and thus outperformed RFS (77%), SLA (74%) and RBA (57%). Moreover, the Bayesian network, logistic regression and fuzzy logic presented the higher accuracy of medical diagnoses. The rough set presented the best performance in terms of screening process, whereas CART revealed the best accuracy of risk assessment.

In addition, the lack of integration with mobile devices, the limited use of web-based interfaces and the scarcity of systems that allow for data to be inserted by patients were all limitations that were detected.

5.1. Limitations

Some limitations of this review should be mentioned. First, the absence, by authors' choice, of studies focused on pain diaries. Second, some studies did not report clearly on data that is used for CDSSs (e.g. absence of number of records concerning learning and test sets, and/or accuracy value). Third, some studies presented skewed data, and this influenced their findings. Finally, only English-language publications were included.

Conflict of interest statement

No conflicts of interest.

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