# CHAPTER 2: THEORETICAL BACKGROUND

## 2.1 Introduction

Inadequate pain assessment, increased medical expenditure, decreased productivity and improper treatment are the global challenging problems which often lead to hindrances and loss of interest in life. Intelligent computing systems (ICS) play a significant role in improving the accuracy of pain assessment and supporting the health care practitioners in the clinical decision-making process. The computational aspects of pain assessment, to acquire knowledge from the clinical data received by patients or experts, are focused in this chapter. The method used an extensive literature search in various reputed journals and electronic databases in order to extract the articles related to ICS considering both chronic and acute pain symptoms of patients, published between 1992 and 2014 in the English language. In total, forty-five studies were analyzed, thirty-two were selected from 1320 citations, and ten were obtained from reference tracking.

The computer technologies identified were grouped together into following four categories in the result section comprising of Artificial Neural Networks, Rule-based algorithms, Statistical learning algorithms and Nonstandard set theory. Methodologies such as questionnaires, scores and terminologies were found for content processing. Literature suggests that the current state of the art focuses on the real-time aspects of pain assessment through facial expressions, demanding the design of intelligent computing system (ICS) to incorporate these issues which provided better accuracy. It would contribute to clinical practice if well-designed computerized methodologies would streamline the process of patient assessment, increasing its accessibility to physicians and improving quality of care.

In summary, we tried to find the answer to these questions:

- What this thesis contributes to the wider global clinical community?
- Intelligent computing system will help patient management and research in real time to overcome the existing barriers in quality of pain assessment.
- Best accuracy rate received of all the computational techniques applied.
- Facilitate patient-physician communications.

Pain is often regarded as the fifth vital sign in regard to healthcare because it is accepted now in healthcare that pain, like various other vital signs, is an objective sensation instead of subjective. Pain is an unpleasant sensory and emotional experience associated with potential or actual tissue damage, or described in terms of such damage. It is a symptom in many medical conditions that interfere with a person's quality of life and regular functioning [Breivik, H. *et al*., 2008]. Pain presence accounts for billions of dollars in annual medical expenditures. Pain is broadly categorized as acute pain and chronic pain. When pain is for a short duration it is called acute whereas which prevails for a longer duration, is said to be chronic [Apkarian, A.V. *et al.*, 2009].

Till date various tools have been developed to assess pain, both acute and chronic pain. Their results vary and are not reliable due to the subjective nature of patients. They do not represent an objective measurement due to the fact that it is an emotional experience that happens inside the mind of each individual. This makes it harder to produce an accurate assessment preventing proper treatment of patient. An attempt has been made by researchers and experts in this field to bring this problem to some sort of objectivity using computational technologies. In connection to this, intelligent computing systems (ICS) have proved to be trustworthy though it too faces additional challenges when applied to patient with symptoms of pain. ICS is interactive expert system computer software, which is basically meant to assist physicians and other health professionals in taking appropriate decisions, such as to determine the diagnosis of patient data. According to the new methodology, ICS makes suggestions of outputs or a set of outputs for the clinician to look through and the clinician officially picks useful information and removes erroneous suggestions. However, regardless of the subjectivity and difficulty in assessment of pain management, the ICS should be developed for pain management to support the clinical process by making use of knowledge, starting from diagnosis and investigation through proper treatment and long-term care. This chapter focuses on examining computer technologies used for ICS for patients that suffer from either chronic or acute pain along with methodologies which infer knowledge from clinical data contributing to clinical decision-making.

### 2.2 Related work

Pain is a global problem and evidence suggests that pain is frequently under-treated. If the information related to health is to be used effectively in patient care, it should be clinically relevant, psychometrically sound and readily available. The findings of previous studies on multidimensional topics have been confirmed in this chapter. First of all the problems arising from the complexity of the systems was reported by [Abad-Grau *et al*., 2008]. The major problem faced by experts in healthcare is to build reliable models considering a large number of variables affecting the process. This tends the design of the system to be less accurate due to the over fitting [Ohmann, C. *et al*., 1996]. Next, to adequately use ICS, quality, availability and standardization of data are essential, which is a challenging task [Midboe, A. *et al*., 2011]. Lastly, the lack of assessment of economic effects that were derived from the use of ICS was observed and is steady with the previous findings [Roshanov, P.S. *et al*., 2011]. Some ICS have the capacity to learn, leading to the discovery of new phenomena and the creation of medical knowledge. These machine learning systems can be used to: develop the knowledge bases used by expert systems, assist in the design of new drugs, and advance research on the development of pathophysiological models from experimental data. Benefits from ICS include improved patient safety, improved quality of care, and improved efficiency in health care delivery.

Generally, machine learning models improve as the training data size increases, and there are advantages in gathering data from multiple sources. However, machine learning is sensitive to heterogeneity in the data, such as different vocabularies and writing styles, and there may be disadvantages in combining data from different sources.

Concept extraction is definitely a complex problem involving various clues present in text. Powerful machine learning algorithms that are used to exploit many overlapping clues (features) is enviable in this task. In the clinical domain, a critical component of text processing systems has been concept extraction and it has been actively studied [Xu, H. *et al*., 2010]. In contrast, application of machine learning for extraction of clinical concept appears to be rather recent [Li, D. *et al*., 2008]. The reason for the deferred application may be due to the phrases extracted from clinical text requires to be normalized to fine-grained concepts, for example those defined in Unified Medical Language System (UMLS) [Bodenreider, O. 2004] and the systematized nomenclature of medicine

(SNOMED CT) [Stearns, M.Q. *et al*., 2001]. Based on dictionaries and hand-coded rules, matured extraction systems have an advantage in comparison to machine learning for name recognition, as the latter approach simultaneously tackles normalization and phrase extraction, and handles rare concepts, while allowing case-by-case error correction. The chapter is emphasized on identifying the various computational technologies used for ICSs for patients who suffer from either chronic or acute pain.

## 2.3 Methods

### Research questions

The major questions of this research are as follows:

- Which computational technologies have been used in ICSs applied to pain?
- What is the accuracy rate of application of these technologies?
- Which technologies are of utmost importance that can improve a physician's decision-making process?

To find the answer to these questions we studied various papers related to the said topic. The step followed by us has been presented below.

### Inclusion criteria

Studies based on intelligent computing systems (ICS) designed to assess and measure pain are included in this chapter if they fulfilled the following criteria: (1) created an intelligent computing system, (2) belonged to chronic or acute pain complaints, (3) included data on pain intensities or (4) based on pain detection used to predict results, (5) used computational aspects, (6) were published between 1992 and the 31st of July, 2014, and (7) were written in English. There was no gender, age or specific type of disease restrictions. Any category of pain, either for children, adults or individuals complaining of pain was considered.

**Strategy**

The following electronic databases were searched in connection with the studies meeting the inclusion criteria: IEEE, Science Direct, ACM Digital Library, Google Scholar, Springer Link, ELIN @ Malardalen, ISI Web of Knowledge, CiteSeerx, Science Accelerator, Science.gov and Microsoft Academic Search. Every study was evaluated independently by the team, and its applicability determined on consent of them. The studies also included forming clusters that reported similar data [Higgins, J.P.T. 2011] to avoid selection bias. In case of different studies reflecting the same intelligent computing system they were considered independently as they represented different symptoms and approaches e.g., the studies [Michalowski, W. *et al*., 2005]. Along with this, references cited by the studies were subsequently analyzed for any ICS studies pertaining to pain. The full chapter was evaluated by the team keeping in mind the above logic.

**Extraction of study characteristics**

The studies were clustered into tables 2.1, 2.2, 2.3 and 2.4 for various machines learning (ML) approaches and table 2.5 represents the content processing (CP). The groups constituted for ML comprised of Artificial Neural Networks (ANNs), Rule Based Algorithms (RBAs), nonstandard set theory (NST), and statistical learning algorithms (SLAs). The Content Processing (CP) group included questionnaires, scores, and terminologies. The characteristic of the ML techniques described includes healthcare condition, study identification, year of publication, number of records (learning/training/testing), and accuracy. The characteristics of CP include clinical condition, study identification, year of publication, number of records and terminology. The content and its study can be referenced towards a diverse range of CP and ML topics. Selected studies focusing on clinical conditions like abdominal pain, chest pain, palliative care, low back pain, scrotal pain and knee pain were considered and analyzed.

The accuracy mentioned is the correctly predicted percentage of records by the model. Accuracy is calculated by ratio of correctly predicted cases in comparison to the total number of cases.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{2.1}$$

where, TP means number of true positive cases, TN stands for number of true negative cases, FN is the number of false negative cases, and FP is the number of false positive cases.

### 2.4 Machine learning techniques

There may be hidden knowledge contained in large medical data sets, correlations and patterns that are not yet known. Machine learning aims at extracting these correlations (= knowledge) and express it as mathematical formulas. These formulas can be used in ICS. These are classified into two categories: supervised and unsupervised learning. Artificial neural network and decision trees belong to the supervised class.

#### 2.4.1 Artificial neural networks

An artificial neural network (ANN) is an interconnected group of nodes, similar to the vast network of neurons inside a brain. Here, an artificial neuron is represented by a circular node and an arrow is used to represent a connection from the output of one neuron to the input of another. Systems, which learn from data such as neural networks, have been used to solve a wide variety of tasks that are difficult to solve using rule-based programming, including speech recognition and computer vision (Table 2.1). Ellenius, J. & Groth, T. (2000) explained a system based on using single layer perceptrons (SLPs). Alternatively, [Kennedy, R.L. *et al.*, 1997] elaborated on multilayer perceptron (MLP) approach. The single layer perceptron is applied to learning though the group of training in a repetitive way so as to find the accurate vector for the entire training set. Accordingly, MLPs focus on separation of input instances into their respective categories. It is robust to noisy data, despite it is rarely used in clinical settings because ANNs are not suitable for making decisions and lacks transparency of data. Other limitations are deciding size of hidden layer caused due to lack of nodes and its over-fitting.

**Table 2.1:** Artificial neural network

| **Condition** | **Study** | **Year** | **Number of records** | | **Structure** | **Accuracy (%)** |
|---|---|---|---|---|---|---|
| | | | **Learn** | **Test** | | |
| Chest pain | Ellenius *et al.* | 1997 | 50 | 38 | MSLP (3SLPs) | 90 |
| Chest pain | Kennedy *et al.* | 1997 | 90 | 200 | I/H/O: 53/18/1 | 92 |
| Abdominal Pain | Pesonen *et al.* | 1998 | 717 | 347 | I/H/O: 16/6/3 | 78 |
| Low Back Pain | Vaughn *et al.* | 1998 | 99 | 99 | I/H/O: 92/10/3 | 67 |
| Chest pain | Wang *et al.* | 2001 | 1253 | 500 | I/H/O: 30/15/1 | 85 |
| Chest pain | Baxt *et al.* | 2002 | 1050 | 926 | I/H/O: 40/10/1 | 93 |
| Median | | | 408 | 273.5 | | 87.5 |

Nodes of: I, input layer; H, hidden layer: O, output layer.

### 2.4.2 Rule based and Evidence based algorithm

While reviewing, several rule based algorithms (RBA) were found, such as: C4.5, AQ15, CN2, NewId, PRISM, ITURTLE and ILLM. A decision tree is created in ID3 based on rules which are related to the choice of attributes. There are several algorithms which are based on ID3, such as NewID, CN2, C4.5, and PRISM. The C4.5 provides some additional capabilities which are being ignored in traversing a decision tree whereas PRISM focus on extracting only the relevant attributes and creates its own combined attribute, unlike ID3. The redundancy is removed by using AQ15 from the initial rule set while NewID supports the attributes that are structured. CN2 incorporates the properties of both AQ15 and ID3, used to select and improve the quality of rules by evaluating it. The space for possible rules is searched by ITURTLE which establishes a ranking based on the information content.

**Table 2.2:** Rule-based algorithms

| **Condition** | **Study** | **Year** | **Number of records**<br>**Learn** | <br>**Test** | **Structure** | **Accuracy (%)** |
|---|---|---|---|---|---|---|
| Abdominal pain | Blazadonakis *et al.* | 1996 | 268 | 67 | C4.5<br>AQ15<br>CN2<br>NewId<br>ILLM | 84<br>79<br>86<br>73<br>84 |
| Abdominal pain | Ohmann *et al.* | 1996 | 839 | 415 | C4.5<br>CN2<br>ID3<br>ITURTLE<br>NewId<br>PRISM | 46<br>47<br>48<br>43<br>40<br>45 |
| Abdominal pain | Eich *et al.* | 1997 | 6815 | 3418 | C4.5 | 57 |
| Abdominal pain | Blaszczynski *et al.* | 2005 | 606 | 100 | C4.5 | 57 |
| Abdominal pain | Van Gerven *et al.* | 2007 | - | - | C4.5 | 44 |
| Palliative care | Elvidge | 2008 | 276 | - | ID3 (with kNN) | - |
| Chest pain | Kong *et al.* | 2011 | 1000 | 1000 | CART | 80 |
| Median | | | 722. | 415 | | 57 |

The CART algorithm seeks to consider the most significant variables discarding the least ones. Lastly, ILLM is used to find the minimal logic expression representing the maximum cases of the initial rules set. The advantageous part of the decision tree is with the clear understanding of their classification system.

Decision tree induction is prone to the problems of fragmentation, repetition, and replication. However, it lacks the learning rules from incomplete data and the other is the overspecialization. Above all, these the complexities of the clinical problem restricts from reliably estimating the decision criteria. For bridging the gap between physicians and the ICS, evidence based approach proved to be a much superior technique. (Table 2.2)

### 2.4.3 Nonstandard set theory (NST)

In computer science, a rough set is a formal approximation of a crisp set in terms of a pair of sets which give the upper and the lower approximation of the original set. In the standard version of rough set theory, the lower- and upper-approximation sets are crisp sets, but in other cases, the approximating sets may be fuzzy sets. This is not useful in the case of noisy data and for larger datasets because of the limited computation. The advantageous part is that it does not require any predefined information about data [Li, H. *et al.*, 2012]. Fuzzy logic is a form of many valued logic; it deals with reasoning that is approximate rather than fixed. It has been extended to handle the concept of partial truth, where the truth value may lie between completely false and completely true [Arabacioglu, B.C. 2010]. Furthermore, in case of linguistic variables, these degrees are generally managed by specific functions. (Table 2.3)

Rough set philosophy is founded on the assumption that with every object of the universe of discourse some information (data, knowledge) is associated. Objects characterized by the same information are indiscernible (similar) in view of the available information about them. The indiscernibility relation generated in this way is the mathematical basis of rough set theory. Any set of all indiscernible (similar) objects is called an elementary set, and forms a basic granule (atom) of knowledge about the universe. Any union of some elementary sets is referred to as a crisp (precise) set – otherwise the set is rough (imprecise, vague). Each rough set has boundary-line cases, i.e., objects which cannot be with certainty classified, by employing the available knowledge, as members of the set or its complement. Obviously rough sets, in contrast to precise sets, cannot be characterized in terms of information about their elements. With any rough set a pair of precise sets, called the lower and the upper approximation of the rough set, is associated. The lower approximation consists of all objects which surely belong to the set and the upper approximation contains all objects which possibly belong to the set. The difference between the upper and the lower approximation constitutes the boundary region of the rough set. Rough set based data analysis starts from a data table called a decision table, columns of which are labeled by attributes, rows – by objects of interest and entries of the table are at tribute values. Attributes of the decision table are divided into two disjoint groups called condition and decision attributes, respectively. Each row of a decision table induces a decision rule, which specifies decision (action, results, outcome, etc.) if some conditions are satisfied. If a decision rule uniquely determines decision in terms of conditions the decision rule is certain otherwise the decision rule is uncertain. Decision rules are closely connected with approximations. Roughly speaking, certain decision rules describe lower approximation of decisions in terms of conditions, whereas uncertain decision rules refer to the boundary region of decisions.

Rough set theory has an overlap with many other theories dealing with imperfect knowledge, e.g., evidence theory, fuzzy sets, Bayesian inference and others. Nevertheless, the theory can be regarded as an independent, complementary, not competing discipline, in its own rights [Zdzislaw, P. 2002].

**Table 2.3:** Nonstandard set theory

| Condition | Study | Year | No. of Records | Structure | Accuracy (%) |
|---|---|---|---|---|---|
| Abdominal pain | Fathi-Torbaghan *et al.* | 1994 | 100 | Fuzzy logic | 80 |
| Abdominal pain | Farion *et al*. | 2004 | 328 | Rough set | 66 |
| Headache | Tsumoto | 2004 | 119 | Rough set | 95 |
| Abdominal pain | Blaszczynski *et al.* | 2005 | 100 | Rough set | 59 |
| Scrotal pain | Michalowski *et al*. | 2005 | 30 | Rough set | 77 |
| Abdominal pain | Wilk *et al.* | 2007 | 574 | Rough set | 72 |
| Myofascial pain | Binaghi *et al.* | 2008 | 50 | Fuzzy logic | 100 |
| Median | | | 100 | | 77 |

### 2.4.4 Statistical learning algorithms

The usability of statistical learning algorithms (SLAs) is to track structures of interest for a given dataset. Unlike frequents procedures, Bayesian classification procedures provide a natural way of taking into account any available information about the relative sizes of the sub-populations associated with the different groups within the overall population [Binder, D.A. 1981].

**Bayesian networks**

A Bayesian network is generally a probabilistic graphical model that specifies a joint probability distribution on a set of random variables. Bayesian networks consist of two essential components: a set of probability distribution tables and. The other is a directed acyclic graph explicitly showing dependencies and independencies between variables. The two specific classes of Bayesian networks that are popular in the context of supervised learning: Tree-Augmented Naive Bayesian networks (TAN) and Naive Bayesian networks (NB). In NB there is a link from the each of the non-target variables to target variable. This means that a non-target variable is believed to be independent of any other non-target variable, given the target variable. As the independence assumptions for NB are often too strong**,** TAN allows taking into account certain extra dependencies between non-target variables by having links between them. It is very important to note that the presumed dependencies or independencies learned by a Bayesian network do not necessarily have to make sense from an empirical, or in this case medical, point of view. A survey of Bayesian Networks applied in health care can be found in the article [Lucas, P.J.F. 2004].

Bayes theorem suggests a method of inference used to present the probability estimate for the hypothesis. Bayesian procedures tend to be computationally expensive and thus, approximations for Bayesian clustering rules were devised. A Bayesian network is probabilistic directed acyclic graphical model that represents a set of random variables and their conditional dependencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. This model has the advantage over RBAs [Sadeghi, S. 2006] as it represents probabilistic representations of uncertain knowledge (Table 2.4). Another algorithm, the k-Nearest Neighbors algorithm (kNN) is a non-parametric method used for classification and regression. In k-NN classification, the output is a class membership. An object is classified by a majority vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k =1, then the object is simply assigned to the class of that single nearest neighbor. A shortcoming of the k-NN algorithm is that it is sensitive to the local structure of the data, requires a large storage space and is time-consuming. Finally, support vector machines (SVMs), are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on.

**Table 2.4:** Statistical learning algorithms

| Condition | Study | Year | Number of records Learn | Test | Algorithm | Accuracy (%) |
|---|---|---|---|---|---|---|
| Abdominal pain | Blazadonakis *et al.* | 1996 | 268 | 67 | Naive Bayes | 89 |
| Abdominal pain | Ohmann *et al.* | 1996 | 839 | 415 | Bayes' theorem | 45 |
| Chest pain | Aase | 1999 | 493 | 290 | Bayes' theorem | 89 |
| Chest pain | Wang *et al.* | 2001 | 1253 | 500 | LR | 84 |
| Chest pain | Baxt *et al.* | 2002 | 2024 | 2024 | LR | 75 |
| Abdominal pain | Blaszczynski *et al.* | 2005 | 606 | 100 | Naive Bayes<br>IB1 | 56<br>58 |
| Low back pain | Lin *et al.* | 2006 | 180 | 20 | Bayes' theorem | 73 |
| Abdominal pain | Sadeghi *et al.* | 2006 | - | 90 | Bayesian network | 56 |
| Knee pain | Lai *et al.* | 2007 | 27 | 27 | SVM | 89 |
| Abdominal pain | Van Gerven *et al.* | 2007 | - | - | Naive Bayes<br>LR<br>Noisy-OR<br>Noisy-threshold | 63<br>67<br>54<br>72 |
| Palliative care | Elvidge | 2008 | 276 | - | kNN | - |
| Knee pain | Watt and Bui | 2008 | 4796 | 200 | Bayesian network<br>LR | 100<br>100 |
| Median | | | 549.5 | 150 | | 72.5 |

This model is robust to high dimensionality data and has good generalization ability. The disadvantage of this model is that it is highly sensitive to uncertainties and also leads to over fitting of data due to high dimensional space (Tan, K.C. 2009).

### 2.4.5 Terminologies

Systematized nomenclature of medicine-clinical terms (SNOMED) CT is a systematically organized computer processable collection of medical terms providing codes, terms, synonyms and definitions used in clinical documentation and reporting. SNOMED CT is considered to be the most comprehensive, multilingual clinical healthcare terminology in the world [Cote, R.A. & Robboy, S. 1980]. The Unified Medical Language System (UMLS) , reported by [Abas, H.I. 2011] is a compendium of many controlled vocabularies in the biomedical sciences representing a large health along with biomedical vocabulary together with concepts extracted from various sources including: IDC9-CM, medical subject headings (MeSH), logical observation identifiers names and codes (LOINC), and systematized nomenclature of medicine – clinical terms (SNOMED-CT). UMLS may also be viewed as a comprehensive thesaurus and ontology of biomedical concepts [Yugyung, L. 2006]. It further provides facilities for natural language processing. The UMLS is also proposed in combination with the weighted semantic similarity score (WSSS) to exploit the semantic relationship between the reported symptoms and the UMLS terms. In addition, presented a system in which a data dictionary is based on the SNOMED-CT terminology. However, limitations traced were: complexity because of a large number of terms and relationships and other was difficulty in incorporating new terminology. The UMLS integrates over 2 million names for some 900000 concepts from more than 60 families of biomedical vocabularies, as well as 12 million relations among these concepts (Figure 2). Vocabularies integrated in the UMLS metathesaurus include the NCBI taxonomy, Gene Ontology, the Medical Subject Headings (MeSH), OMIM and the Digital Anatomist Symbolic Knowledge Base. UMLS concepts are not only inter-related, but may also be linked to external resources such as GenBank. In addition to data, the UMLS includes tools for customizing the Metathesaurus (MetamorphoSys), for generating lexical variants of concept names (lvg) and for extracting UMLS concepts from text (MetaMap).

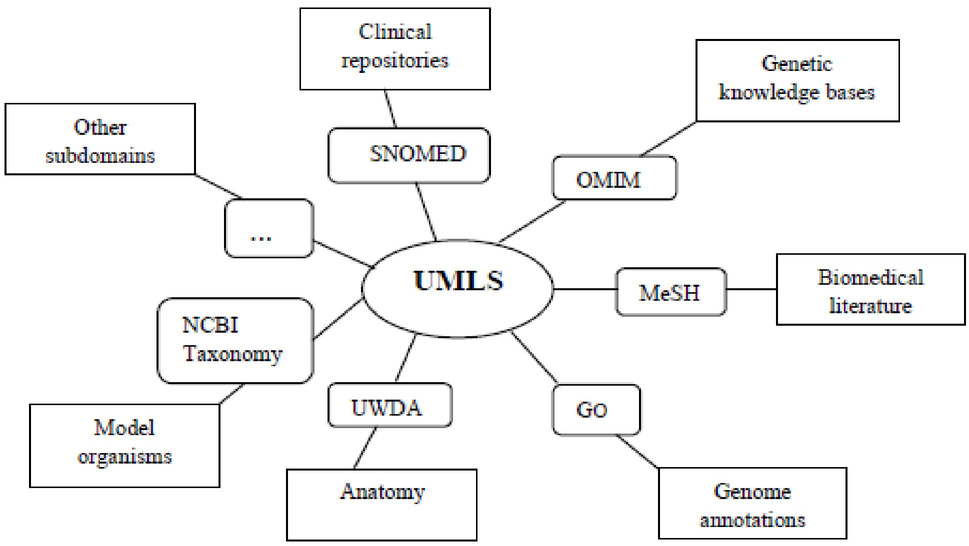


**Figure 2.1:** Illustrates how the UMLS metathesaurus, by integrating these various terminologies, can serve as a link between not only the vocabularies, but also the sub domains they represent.

The UMLS knowledge sources are updated quarterly. The metathesaurus also covers the biomedical literature with the MeSH, the controlled vocabulary used to index MEDLINE. Core sub domains such as anatomy, used across the spectrum of biomedical applications, are also represented in the metathesaurus with the digital anatomist symbolic knowledge base. Finally, the sub-domain represented best is probably the clinical component of biomedicine, with general terminologies such as SNOMED International (and soon SNOMED-CT), Clinical Terms Version 3 and the International Classification of Diseases, to name a few.

**Terminology integration principles**

In the UMLS, knowledge is organized by concept (i.e. meaning). Synonymous terms are clustered together to form a concept and concepts are linked to other concepts by means of various types of relationships, resulting in a rich graph. Inter-concept relationships are either inherited from the structure of the source vocabularies or generated specifically by the editors of the metathesaurus. Symbolic relationships can be hierarchical (e.g. `is a kind of' or `is a', `part of') or associative (e.g. `location of', `caused by'). Statistical relations between concepts from the MeSH vocabulary are also present, derived from the co-occurrence of MeSH indexing terms in MEDLINE citations. Finally, each Metathesaurus concept is broadly categorized by means of the semantic types (i.e. the 135 high-level categories found in the Semantic Network), assigned by the Metathesaurus editors.

Such a structure makes it easy for users to perform tasks such as:

(i) Collecting the various terms used to name a concept.

(ii) Extracting the relations of one concept to other concepts, either hierarchical or associative, symbolic or statistical.

(iii) Obtaining a set of concepts for a given category, using the list of concepts that were assigned a given semantic type.

More formally, synonymy is the lexical relation used to cluster biomedical terms into concepts. Hyponymy (`isa') and meronymy ('part of') relations provide the hierarchical framework on which the concepts are organized. Associative relations, including co-occurrence relations, extend this framework laterally, providing links across various sub domains. The categorization by semantic type can be thought of as redundant with some of the hierarchical relations. In practice, because the categorization is independent of the structure of the source vocabularies, it provides a simple and stable means of semantic orientation in the metathesaurus.

**Questionnaires**

Electronic questionnaires for pain assessment are becoming increasingly popular. The McGill Pain Questionnaire (MPQ) is a well-known, valid and reliable tool that guides patients in providing the information necessary for clinicians to diagnose pain etiology and select appropriate analgesic therapies. Some clinicians, however, have been reluctant to use the MPQ in clinical practice, stating that the reading level of the verbal descriptors is too high and that the tool is too long and complex. Research, however, has demonstrated the MPQ can be completed in 15 to 20 minutes.

**Table 2.5:** Content Processing: Terminologies, questionnaires and scores

| Condition | Study | Year | Number of records | Terminology |
|---|---|---|---|---|
| **Terminologies** | | | | |
| Abdominal pain | Eich et al. | 1997 | 10233 | SNOMED-CT |
| Palliative care | Kuziemsky et al. | 2003 | - | UMLS |
| Abdominal pain | Lu et al. | 2008 | 2256 | UMLS |
| Post-operative pain | Abas et al. | 2011 | - | UMLS |
| Chest pain | Farooq et al. | 2011 | - | SNOMED-CT |
| **Questionnaires** | | | | |
| Cancer pain | Wilkie et al. | 2003 | 213 | MPQ |
| Palliative care | Chang et al. | 2007 | - | Patient-tailored |
| **Scores** | | | | |
| Chest pain | Westfall et al. | 2006 | 1861 | ACI-TIPI |
| Rheumatoid arthritis pain | Simonic et al. | 2011 | 175 | DAS, HAQ |

To avoid the hectic task of collecting and analyzing the data of patients manually through McGill pain questionnaire (MPQ), its computerized version is launched

[Wilkie, D.J. 2003] and [Chang, C.H. 2007] suggests an ICS based on this concept involving computerized adaptive testing (CAT). The limitations found were basically related to time involved in filling up the questionnaire.

**Scores**

The authors proposed ICS based on scores that were a result of the various characteristics analyzed. In order to optimize the patient's treatment, the disease activity score (DAS) along with the health assessment questionnaire (HAQ) was proposed. The drawback of this lies in the time required to obtain the required information (Table 2.5)**.** As observed from the above Table 2.5 it was found that the terminologies were applied in five studies (16%) and in two studies questionnaires and scores were included (6%). This clearly illustrates that because of the difficulty in concept extraction and generally due to the large amount of time involved in collecting and processing the data, this content processing aspect is not so popular amongst the patient and expert's community. As represented in the table, one can conclude that terminologies are much more prominent and are mostly used in comparison to questionnaires and scores. This area needs to be further explored by researchers and practitioners in order to obtain objective results which are more relevant and accurate. However this limitation may diminish in the future as information technology becomes more widely adopted.

## 2.5 Results

The results focused on the following clusters of computer technologies: artificial neural networks, rule-based algorithms, nonstandard set theory, and statistical learning algorithms. It is clear from the Table 2.1-2.4, the commonly used computer technology is the SLA applied in the design of ICS which contributed to almost 38% (in 12 of 32 studies), followed by NST and RBA with seven studies

(22%) and ANN with six studies (19%). Finally, terminologies were applied in five studies (16%) and in two studies questionnaires and scores were included (6%) (Table 2.5). Hence terminologies are more in use in comparison to questionnaires and scores. The range of median accuracy ranged from 57% to 87.5%. The period from beginning of 2007 till the end of 2014 was characterized by complete absence of studies involving ANNs. During the same period terminologies and RBAs, with three studies each appeared falling just behind SLA. Based on these observations it is clear that the SLAs are the most promising computational technology in comparison to the others which are basically used in ICSs applied to pain. In addition to this, several methodologies were found in connection with content processing which are terminologies, questionnaires, and scores. Further, it was concluded that Bayesian network and Logistic regression gave very much accurate results for diagnosis of knee pain.

## 2.6 Discussion

Through proper design of computerized methodologies, taking the multi-modal dimensionalities into consideration e.g. data of patients including demographic, social, behavioural, psychological traits, pain expression along with objective measures using tools like Numerical Rating Scale (NRS), Visual Analogue Scale (VAS) were collected. The next step is the information fusion, which helps to analyze the data based on various parameters and assists in arriving at more accurate results. This would streamline the process of patient assessment, increasing its accessibility to physicians and improving quality of care.

## 2.7 Conclusion

ICS involving the details of the patients symptoms and analgesia have significantly contributed to bringing a drastic change in the old traditional concept of pain assessment making it more reliable and fast in clinical decision making but however this too has its own limitations when talking about system's accuracy, reduced integration with mobile devices, web-based interfaces and above all huge scarcity of pain related databases. On searching the literature it was observed that the current state of the art focuses on the real-time aspects of pain assessment through facial expressions, demanding the design of ICSs to incorporate these issues which provided higher accuracy. This chapter presents clearly the ICSs for patients suffering from either chronic or acute pain by identifying, categorizing and describing computer technologies in use.

The main findings summarized from the selected studies are as follows:

• Machine learning and content processing are the two computer technologies that have been used in ICSs. Machine learning is grouped into ANN, RBA, NST and SLA whereas content processing includes terminologies, questionnaires and scores.

• The highest median accuracy (87.5%) was presented by ANN followed by NST (77%), SLA (72.5%) and RBA (57%). The risk assessment was best-taken care by CART algorithm. The fuzzy logic, logistic regression and Bayesian network gives the highest accuracy of medical diagnoses.

• Few studies (20%) provided results based on practitioner performance whereas (80%) focused on further improvement in this area. The essence is that clinical practice could be improved if ICSs is developed keeping in view the patients symptoms and not on the particular computer technology applied. A few limitations of this review were: firstly, only selected studies of pain were considered which used the computer technology for diagnosis. Secondly, lack or absence of the number of records regarding learning and test sets used in ICSs was not clearly defined and lastly, only English language published papers were included.

These findings may contribute towards the development of a computer-assisted system using machine learning techniques to be used as a tool for reliable, uncomplicated and effective clinical decision-making for pain assessment.

This ICS is also intended to assist the nurses to perceive the intensity of patient's pain successfully and to manage it effectively.