CHAPTER 1: INTRODUCTION

It is true that humans have perhaps always been sensitive to the facial expression of pain. Classic era artists were able to capture the sense of suffering by the representations of the face. An example is the sculpture Laocoön, depicting the death throes of a Trojan priest, which is notable for the facial expression representing agonizing pain. Pain assessment proves difficult when the patient suffers from brain damage, dementia or some other condition that compromises the patient’s ability to engage in self-assessment and present a verbal report. In respect to the lack of pain assessment, clinicians may overlook new pathologies when they occur, resulting in failure to identify and alleviate the suffering of patients who actually experience pain that is not expressed verbally, and this may lead to higher costs of care [Chapman, 2008].

Charles Darwin characterized pain expression thus:

> “During the pain the mouth is compressed closely or the teeth are clenched, the lips are retracted, the eyes are wide spread as if in horrified astonishment” [Darwin, 1955].

Facial expressions, being complex in nature, are difficult to describe and quantify, as they evolves over time. Usually, they leave no record. These obstacles present a barrier to scientific analysis. Recent development in video technology which was affordable and accessible overcame this problem and stimulated growth of the field. However, technology does not, resolve the problem of quantification. Automatic pain recognition and its intensity estimation is an evolving research area with promising applications in health care. In this thesis, we propose an automatic approach to continuous pain intensity estimation from facial images.

The proposed framework is a major contribution to this thesis that has been tested for its validity and accuracy. This can play a significant role in the better design of intelligent computing systems, which at present is lacking.

Pain assessment using multidimensional perspectives is considered in this thesis. A brief introduction of pain as a multidimensional construct, along with a breakdown of those dimensions and their typical means of assessment has been presented here. The other major contribution to this thesis is the self- prepared database of patients collected in real time environment in clinical and lab settings. As we are aware that very limited database is available of facial pain expressions due to its spontaneous nature, making it difficult for researchers to proceed in this direction. We have showed on the recently published UNBC-McMaster Shoulder pain expression archive database and the Self-prepared database that using multidimensional constructs such as computational, medical, psychological and bioinformatics it was possible to assess pain reliably on a scale of 0-10 (0-no pain, 10-severe pain) giving better pain intensity estimation compared to feature-specific pain intensity estimation.

One goal of paramount importance to this work is the improvement of patient quality of life, which means improving the amount and quality of data available to doctors at minimum effort to the patients. The thesis also investigates the various available methods used in this domain.

The organization of the thesis comprises of:

Section 1.1 presents the background of pain assessment tools commonly used by physicians to assess the intensity level. The motivation and problem description for the present work in detection and estimation of pain has been discussed in section 1.2. In section 1.3, thesis objectives have been described. Section 1.4, present the main contributions of the thesis. Finally, Section 1.5 highlights the organization of the thesis.

1.1. Background

Pain is a commonly experienced unpleasant sensation that can be caused by both emotional and physical stimuli. It can be something as minor as an inconvenience or irritant, or in severe cases as the Handbook of Pain Assessment says “a serious threat to one’s freedom, to the significance of one’s life, and ultimately to one’s self-esteem.” [Jensen M.P. & Karoly P. 1992]. The American Academy of Pain Medicine (AAPM) gives a variety of statistics related to pain and pain management, including that chronic pain affects. The record constitutes of 1.5 billion people worldwide, and at least 100 million Americans. The American statistics indicate that roughly four times as many people suffer from chronic pain than do either diabetes or heart disease, and ten times as many when compared to cancer. However, before looking further at how pain affects people, it is important to define what pain is and how it is typically assessed.

The Handbook of Pain Assessment defines pain as a multidimensional construct and gives a breakdown of those dimensions and their typical means of assessment. The typical and most comprehensive pain assessment is the McGill Pain Questionnaire (MPQ) [Melzack R. 1975] which takes means of assessment from each of the four dimensions i.e., intensity, location, quality and affect to give medical personnel a complete picture of the pain the patient is experiencing. The intensity and location are perhaps the easiest dimensions to define; they express how much pain an individual is in and where the pain is on their body. Three common methods exist to assess pain intensity; the Verbal Rating Scale (VRS), the Numerical Rating Scale (NRS) and the Visual Analogue Scale (VAS). All three of these methods ask the patient to report their own pain ranging on a scale from no pain to the worst pain imaginable. VRSs [Edgar, E.O. & Rolf, A. 1975] are given verbally and present the patient with a list of adjectives which increase in perceived pain intensity. NRSs are mostly interchangeable with VRSs, as they simply ask a patient to supply a number on the same relative scale. VASs present a patient with a series of images corresponding to more and more pain and ask them to select the image that corresponds to their pain appropriately. Again, this method can be mapped to an NRS with the same scale. A sample VAS is provided in Figure 1.1.

Figure 1.1: A sample Visual Analogue Scale [Jensen, M. P. & Karoly, P. 1992]

Pain location can be assessed via two methods: a simple verbal question is presented to the patient, asking where the pain is located. Otherwise, a pain drawing can be given to the patient, who is then asked to give the location(s) of the pain based on the drawing. A sample pain drawing is provided in Figure 1.2.

The remaining two dimensions of pain can be more difficult to define. Pain quality refers to how the pain feels, independently of how much it hurts. These can also be called sensory qualities, and are assessed with several descriptors, such as sharp, dull, hot, cold, sensitive, deep, itchy and surface.

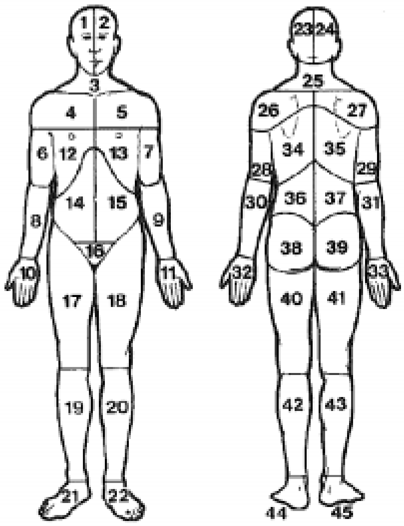


Figure 1.2: A sample pain drawing [Jensen, M. P. & Karoly, P. 1992]

It is not unknown to assign an NRS to each of these descriptors, having patients rate each descriptor on a numeric scale, but this is not a common practice. The final dimension, pain affect, is the most intangible dimension but also the most impactful. Pain affect measures how the pain someone is experiencing affects them on an emotional level. It is important to distinguish that this is not an emotional pain, but rather how the patient is coping with the pain, how disruptive the pain is to their everyday life, how bearable the pain is and how the pain is affecting their emotional wellbeing. Pain affect is correlated with pain intensity, although different people are able to deal with it differently. For example, someone dealing with consistent, high levels of pain will be more likely to be affected more than someone with low, intermittent levels of pain, but this is not necessarily the case. Pain affect is typically accessed via a VRS, although VASs also exist for assessment. A sample 15-point VRS presents the following descriptors to the patient: distracting, bearable, uncomfortable, unpleasant, distressing, oppressive, miserable, awful, frightful, horrible, dreadful, agonizing, unbearable, excruciating, and intolerable.

Two more important definitions associated with pain are acute pain and chronic pain. Acute pain is the typical pain people feel when injured, it is relatively brief and typically milder, although it can reach the heights of pain intensity scales. Chronic pain, however, is pain that lasts for weeks, months or years. The causes of chronic pain are incredibly varied, everything from a sprained back to cancer. This work will focus predominantly on chronic pain. It is also important to note the subjective nature of pain [Jensen M.P. & Karoly P. 1992], each individual's pain intensity and pain affect can differ dramatically, regardless of the similarities of the causes. While individuals experience pain individually, it is still something that affects a significant portion of the population, is unpleasant, and costs society as a whole. As mentioned previously, roughly 100 million Americans suffer from chronic pain, meaning that a third of Americans experience joint pain, swelling or a limitation of movement at any given time [Woolf, A.D. & Pfleger, B. 2003]. Pain also puts a substantial burden on our society due to the inability to perform daily activities, loss of work productivity [Stewart, W.F. *et al*., 2003] and increased healthcare costs [Mantyselka, P. *et al*., 2001]. Continuous monitoring of pain intensity in intensive care units improves patient outcomes and quality of life tremendously [Lucey, P. *et al*., 2012].

This point and the following quote are what this work strives to do: "Pain is a dynamic, developmental process, not a single event or simple quantifiable product. Thus, when we and others talk of 'objective' measures or 'quantifiable' indices, the reader should understand that we do not intend to depict pain as a static, all-or-none, uni-dimensional, body-centered occurrence that exists somehow independently of time, place, the patient's states of consciousness, or the observer's presuppositions. We have elsewhere noted: 'As pain assessors, we are co-participants, not merely observers and, therefore, although there is no single best way to interpret pain, we can probably serve our patients better if we acknowledge that we are jointly engaged in creating the pain dimensions we seek to measure.' The purpose of this work is the development of a computational pain intensity algorithm based on facial images that could be useful in design of clinical decision support systems. It focuses primarily on chronic pain and strives to provide additional, easy to obtain information on pain to medical personnel, allowing them to provide better care, pain management, and hopefully improve the patient's quality of life.

All of that said, it is our dream that health care facilities may someday employ a pain monitoring system evocative of modern day vital sign monitors as standard equipment in patient rooms. The nature of this work naturally gives rise to several criticisms that demand answers. First is the fear that this work aims to replace medical personnel in the pain management process. Medical personnel are instrumental in pain management. This work does not in any way mean to replace or remove medical personnel from pain management. Instead, the goal is to provide medical personnel with additional information to allow them to make more informed decisions. In remote monitoring contexts, providing daily information to medical personnel gives them more information than they would typically receive at a scheduled appointment with a patient so that in those scheduled appointments medical personnel can make better decisions with more information.

The question that needs to be answered is what can a facial pain image accomplish or accomplish better that an NRS does not? Both accomplish the same goal of providing more pain information to doctors. The difference is in how that goal is accomplished. One goal of paramount importance to this work is the improvement of patient quality of life, which means improving the amount and quality of data available to doctors at minimum effort to the patients.

Automated Facial Expression Recognition

Initially brief information regarding the definition of facial expression recognition (FER) is given [Zhang, Z. 1999]. Then, one of the most fundamental systems used for FER which is facial action coding system (FACS) is explained. Afterwards, the importance of FER and potential areas regarding FER are discussed. Finally, the limitations and challenges regarding FER are shown.

What is Automated Facial Expression Recognition?

It is a widely known fact that vast majority of what one says does not come from his/her words. Analyzing the body language of others is almost instinctual to humans. Humans are extremely capable of seeing if one is in pain, sad, angry, happy etc. However for computers, the analysis of human body language is not as simple as it is for humans. Automated FER is defined as the analysis and classification of facial muscle movements. The facial movements are coded by a certain standard and via computational methods, these facial actions are classified.

Different coding systems

Multiple coding methods have been suggested so far to analyze the facial actions of people. Maximally discriminative facial movement coding system (MAX) [Izard, C.E. 1983], a system for identifying affect expressions by holistic judgment, FACS [Ekman, P. *et al*., 1978], and emotional facial action coding system (EMFACS) [Ekamn, P. 1982] are amongst these coding. Even though multiple facial action coding methods have been suggested so far, the commonly preferred one is the FACS. Therefore, to make this work relevant and comparable to other studies, it is used in the proposed system as well.

Computational methods

The discussed system is an automated system, and, therefore, multiple areas of computational sciences need to be applied so as to achieve such system. One can divide computational methods for automated FER into three groups; computer vision, digital image processing and machine learning. By definition, computer vision is the analysis of multidimensional data (such as images) to produce numerical or symbolic information. Since the research area is strictly based on coded facial actions, computer vision is fundamental for any researcher willing to exploit automated FER.

The other aspect of automated FER is digital image processing (DIP). Digital image processing is a sub-field of signal processing that works with two-dimensional signals (digital images). This computational field is very fundamental for automated FER because it is quite crucial for image normalization and feature extraction. The last part of automated FER is machine learning. Since the extracted features from digital images contains fuzzy data, a static algorithm is impossible to devise. Therefore, a statistical modeling method is crucial.

Facial Action Coding System

Facial Action Coding System (FACS) is a facial action analysis system that is commonly accepted amongst researchers. The system was first developed for psychological purposes rather than automated FER [Ekman, P. & Friesen, W.V. 1978].

Table 1.1: Face areas and definitions [Ekman, P. & Friesen, W.V. 1978].

Facial Area	**Definition**
GLABELLA	Area of the forehead between the eyebrows.
ROOT OF NOSE	The beginning of the nose between the eyes, also called the nasal root.
EYE APERTURE	The degree to which the eye is open; the eye opening.
EYE COVER FOLD	The skin between the eyebrows and the palprebral part of the upper eyelid (the part that contacts the eyeball), which folds into the eye socket.
LOWER EYELID FURROW	A place below the lower eyelid where a line or wrinkle may appear. A line or wrinkle may be permanently etched into the face; if so, it will deepen with certain AUs. If not, it should appear when these AUs are contracted.
INFRAORBITAL FURROW	A place where a line or wrinkle may appear parallel to and below the lower eyelid running from near the inner corner of the eye and following the cheek bone laterally.
NOSTRIL WINGS	The fleshy skin of the side of the nose that forms the outside of each nostril.
NASOLABIAL FURROW	A place where a line or wrinkle may appear which begins adjacent to the nostril wings and runs down and outwards beyond the lip corners. In some people it is permanently etched in the face; if so, it will deepen with certain AUs. If not, it will appear on most peoples' faces with certain AUs.
PHILTRUM	The vertical depression in the center of the upper lip directly under the tip of the nose.
CHIN BOSS	The skin covering the bone of the chin.
SCLERA	The white part of the eyeball.

The fundamental principal of the system is to divide facial muscle areas into 11 parts (Table 1.1, Figure 1.3), and muscle movement in those parts into action units. The initial system had 44 AUs ranging from 1 to 46 (numbers 3 and 40 were not used). Later on, a revised version of FACS was developed with additional 12 AUs involving head and eye movements. Facial action coding system is one of the most commonly used methods for automated FER for it is detailed, clear and robust.

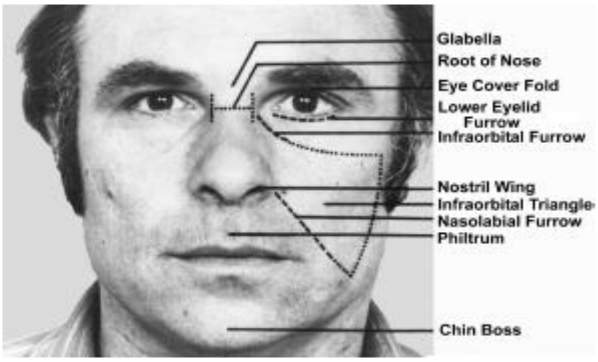


Figure 1.3: Facial areas defined in Table 1.1 [Ekman, P. & Friesen, W.V. 1978].

Action Units and Intensities:

Action units are numerical codes for the movement of face muscles. The system divides AUs into three sets; upper face, lower face, and miscellaneous (head-eye movement) AUs. Action units 1-7 are accepted as an upper face, 8-46 represents lower face AUs. The remaining 12 are miscellaneous AUs. Table 1.2 represents the homology of pain expression across the various stages of human life. Table 1.3 shows some of the AUs selected for this research. Figure 1.4 shows the muscular anatomy under a partition of a face and AUs related to given partition.

Analysis on human face regarding the presence of AUs is fundamental, yet detecting the presence of AUs is naturally not enough to analyze a face in detail. Therefore, AUs are not only defined as present or absent but are defined to have a level of presence as well, which is called intensity.

The level definitions of AU intensities are given in Table 1.4, and Figure 1.3. As it can be seen AU intensities are not linearly distributed. It cannot be claimed that level E is five times the intensity of level A. This is quite natural for human body language is not something that can be analyzed linearly, yet it makes any study regarding FACS AU intensity more complicated.

Table 1.2: Homology of pain expression across the various stages of human life

Muscular Basis	**Adult (FACS)**	**Neonate (NFCS)**	**Child (CFCS)**	**Elderly (FACS)**
Corrugator	Brow Lower (AU4)	Brow bulge	Brow lower	
Orbicularis oculi	Lids tighten, cheek raise (AU6, AU7)	Eye Squeeze	Eye Squeeze, squint, cheek raiser	Lids tighten, cheek raise (AU6,AU7)
Levator	Nose wrinkle, upper lip raiser (AU9,AU10)	Nasolabial furrow, vertical mouth stretch	Nose wrinkle, nasolabial furrow, upper lip raiser	Nose wrinkle, lip raiser (AU9, AU10)
Zygomatic	Lip corner pull (AU 12)	Lip corner puller		Lip corner pull (AU12)
Risorius	Horizontal mouth stretch (AU 20)		Horizontal mouth stretch	
Plerygoid			Vertical mouth stretch	
Nasalis			Flared nostril	

Descriptors are from the system used to code expressions. AU- Facial Action Coding System (FACS) action unit; CFCS- Child facial coding system; NFCS- Neonatal facial coding system. (Prkachin, K.M. 1992)

Action Unit Combinations

As the main subject of FACS is to analyze human behavior through facial actions, it is natural to expect facial actions to occur in combinations. For example AU26 (jaw dropped) is impossible to occur without AU25 (lips parted). Over the years of analyzing facial actions through FACS, over 7000 AU combinations have been observed. Said combinations are not only defined by having multiple AUs present, but by intensities as well.

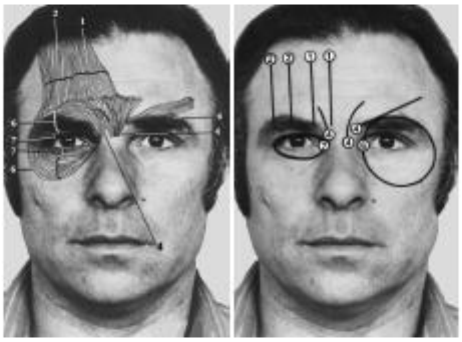
Table 1.3: FACS AUs selected for this research [Lucey, P. *et al.*, 2012]

AU	Used Muscle	Description of Muscle Movement
4	Corrugator supercilii, Depressor supercilii	Eyebrows drawn medially and down
6	Orbicularis oculi, orbitalis	Cheeks raised; eyes narrowed
7	Orbicularis oculi, pars palpebralis	Lid tightener
9	Levator labii superioris alaquae nasi	Nose wrinkle
10	Levator labii superioris	Upper lip raiser
25	Depressor labii inferioris or relaxation of Mentalis, or Orbicularis oris	Lips part
43	Relaxation of Levator palpebrae superioris; Orbicularis oculi, pars palpebralis	Eyes closed

Action units combinations are applicable to many different areas, and one aspect of FACS to human behavior is the analysis of emotions. Emotions are defined by EMFACS which is directly derived from FACS AU combinations. There are seven accepted emotions which are happiness, sadness, surprise, fear, anger, disgust, and contempt. All of these emotions are successfully definable by FACS AU combinations. Table 1.5 shows the various emotions and their definitions by FACS AUs.

Table 1.4: FACS AU intensity level descriptions [Ekman, P. & Friesen, W.V. 1977]

Intensity	Definition
Normal	A
Mild	B
Moderate	C
Severe	D



(A) Muscular anatomy (B) Relative AU

Figure 1.4: Muscular anatomy under a face region and the corresponding AUs to that region [Ekman, P. & Friesen, W.V. 1977].

Importance and Potential Areas

The vast majority of what humans say does not come from their mouths. An automated facial action detection system can potentially lead up to a lot of advancements in a lot of fields. One potential application would be a system that analyzes the user's face as he/she is using an application on his/her computer and reacts accordingly. One potential field would be automated pain detection via patient’s faces. The suggested application would be a breakthrough in the patient-care system because even now, medical professionals are bound by under-developed pain charts. In 1992, Prkachin associated pain with multiple FACS AUs. The associated AUs are brow lowering (AU4), orbital tightening (AU6 and AU7), levator contraction (AU9 and AU10) and eye closure (AU43).

Furthermore, in 2002, Prkachin and Solomon developed the PSPI scale [Prkachin, K. 1992]. Prkachin and Solomon pain intensity scale suggests that the summation of pain related AUs' intensities would give the intensity of pain. They suggested PSPI scale by analyzing the facial images of patients with shoulder pain and currently PSPI is a commonly accepted method for pain assessment other than patient’s self-diagnosis.

Table 1.5: Eight emotions including pain with their FACS AU combinations [Ekman, P. & Friesen, W.V. 1977].

Intensity	**FACS AU combination**
Happiness	6+12
Sadness	1+4+15
Surprise	1+2+5B+26
Fear	1+2+4+5+7+20+26
Anger	4+5+7+23
Disgust	9+15+16
Contempt	R12A+R14A
Pain	4+ max(6 or 7) + max(9 or10) + 43

1.2 Motivation

The following were the issues that motivated us to carry our research in this particular domain. They are listed as:

- Lack of pain database.
- There is no objective measurement of pain. No observational tool evaluates pain with reliability, validity, sensitivity and specificity.
- Clinicians are in dilemma while taking decisions.
- Infants and non-communicative patients cannot communicate their pain.
- Real-time human-to-human interaction analysis and improvement of human-computer interactions.

1.3 Objective of the thesis

The major objective of this research is to design and develop a methodology for pain assessment using interdisciplinary methods i.e., to develop an efficient and robust computational intelligence techniques for prediction of pain based on the pain intensity level. The success of design and development of efficient and robust computational intelligence techniques relies on the design and development of an appropriate feature extraction, feature selection and pattern classification techniques for the said task.

1.4 Contributions

The contributions of this thesis are fourfold: First and foremost, this thesis provides a novel approach to computational pain quantification. Secondly, this thesis investigates the medical practitioner perception to pain along with the readings of the various tools available. Thirdly, psychological aspect was taken into consideration to predict how pain was perceived by observers and experts (physicians) especially in the case of non-communicative patients. Fourthly, what kinds of genes are involved in pain and no pain conditions along with the dominance of a particular gene at various pain intensity levels followed by classification of pain and nonpain genes using machine learning algorithms. Finally, this thesis will provide a distinct dataset of facial pain images with correlated pain intensity values, of approximately 100 images. This database does not exist elsewhere.

The man-machine interface is one of the promising areas from the beginning of computing machines and plays a crucial role for designing a system that could accurately distinguish and understand the human behavior. The research also focuses on one specific property of pain behavior i.e. automatic pain detection through facial expression.

To meet up the specific necessities, a framework has been designed (Figure 1.5) for extraction of features from the face for automatic pain detection and intensity estimation through facial expression.

Proposed framework:

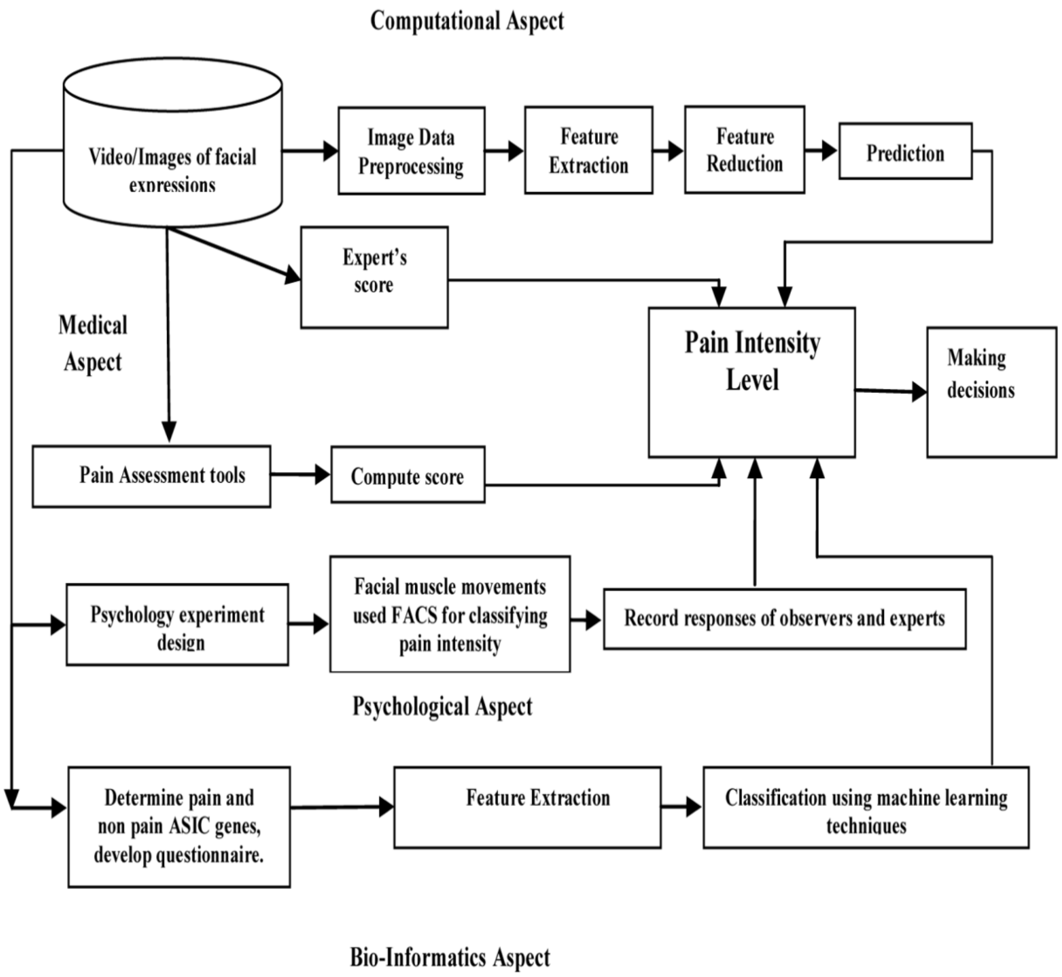


Figure 1.5: Proposed framework for estimating Pain Intensity

This framework illustrates the overall effort involved in specifying the pain intensity level. As we know that pain could not be assessed considering a single parameter, one has to go into background details such as heredity, time, location, severity etc. These restrictions motivated us to take the multidimensional approach towards pain assessment. Here, facial expressions have been taken into consideration. In the given model, pain is looked upon by four different perspectives: computational aspect, medical aspect, psychological aspect and lastly through bio-informatics aspect (genes and their interactions).

A total of 100 participants (59 male, 41 female) who were self-identified as having a problem with back, neck and knee pain were video recorded in the Pain department of IMS (BHU), Varanasi, India. Facial expressions were recorded with a standard webcam (Logitech) at 30 frames per second located in front of the subject and connected to a laptop when their affected area was pressed by the practitioner. The video was converted into frames. The computational approach used feature extraction, reduction and classification techniques to predict the intensity level of pain.

Secondly, in medical aspect the self-report of the patients were obtained using VAS and the feedbacks of the physicians were taken which were then correlated. Next in the psychological aspect an experiment was designed and coded in Superlab 4.0. Here the response of the observer and the expert (physician) were recorded and analyzed. Lastly, amino acid sensing ion channels for pain and non-pain genes were taken; features extracted and classified using machine learning algorithms.

The results thus obtained using all the methods displayed the pain intensity level. The results were further correlated and analyzed giving a more specific pain intensity level. This provided a great assistance to the physicians in taking sound decisions and prescribing drug accordingly which ultimately improved the quality of life of the patients.

1.5 Organization of the thesis

The overall thesis is organized into six chapters as follows:

Chapter 1 provides the introduction, background, motivation and problem description for the present work. It also includes the thesis objectives, and contributions comprising of the proposed framework for pain intensity detection and estimation. Finally, this chapter concludes with the organization that illustrates the coverage of chapters in the thesis.

Chapter 2 provides introduction and survey of the computational aspects of pain assessment, to acquire knowledge from the clinical data received by patients or experts are focused in this review. The computer technologies identified were grouped together into following four categories comprising of artificial neural networks, rule-based algorithms, statistical learning algorithms and nonstandard set theory.

In **Chapter 3** for computational approach binary pain detection and pain intensity estimation, self-prepared database along with the standard McMaster shoulder pain achieve is used as an input. Scale-invariant feature transform and speeded up robust features are used for feature extraction along with principal component analysis for dimensionality reduction and multi-class support vector machine used for classification.

In **Chapter 4** for psychological approach an experiment is designed for prediction of pain intensity from facial expressions using facial action coding system including observers, self report of patients provided on visual analogue scale along with experts decision. Computational techniques were used to analyze and correlate the results for better accuracy.

Chapter 5 presents an efficient approach for the feature extraction, classification of pain and no pain genes representing amino acid sensing ion channels using machine learning methods along with detecting gene-gene interaction and network pathways.

In **Chapter 6** we have summarized main findings of this thesis and give future perspectives of the research in this thesis.