ENHANCING SOCIAL PRESENCE IN ONLINE ENVIRONMENTS

AFFECTIVE MODELING APPROACH

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Enhancing Social Presence in Online Environments

Affective Modeling Approach

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DECLARATION

This thesis is my original work and has not been presented for a degree in any other university.

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DEDICATION

I dedicate this thesis to my loving parents, my dad, the late John Mwangi Theuri, and my mother Nelius Muthoni Mwangi.

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ABBREVIATIONS

AI	Artificial Intelligence
BOW	Bag of Words
CMC	Computer-Mediated Communication
HCI	Human-Computer Interaction
IM	Instant Messaging
ISEAR	International Survey on Emotion Antecedents and Reactions
LSA	Latent Semantic Analysis
ML	Machine Learning
MUDs	Multi-User Dungeon
NLP	Natural Language Processing
PMI	Point wise Mutual Information
SIP	Social Information Processing
SVM	Support Vector Machines
TTS	Text to Speech

ABSTRACT

In face to face communications, people often rely on nonverbal cues such as body language, facial expressions, gestures, physical proximity, and dress to communicate and establish relationships. Recently computer mediated communication became a popular way of interaction. Unfortunately nonverbal elements are normally absent in online communications.

This thesis presents an affect recognition model that assesses the emotional states of online users from textual messages. The study is based on the Social Information Processing (SIP) theory argument that "when most nonverbal cues are unavailable, as is the case in text-based computer mediated communication, users adapt their language, style, and other cues to such purposes". The focus is on emotion recognition from online nonverbal textual symbols/patterns of vocalics (e.g. the use of capitals and use of punctuation "!" and "!!s!" or "?" and "???", length of response e.t.c), and those of chronemics (e.g. time to respond to an email or to a discussion posting or a reply to a chat message e.t.c) that are used in text.

The model uses Naïve Bayes classifier to recognize six basic emotions (anger, disgust, fear, happiness, sadness and surprise). The training set was developed based on the results of an online study named "Emotion Recognition from Nonverbal Symbols for Enhancing Social presence in Online Environments", that was carried out to determine the level of use and the meaning of various nonverbal textual symbols used by students during their online communications. Two sets of training data were prepared, a dictionary of words

associated with different categories of mentioned emotions and messages labeled with the six basic emotions collected from student's online chats and posts. The messages were annotated by three student raters independently, the level of agreement was measured using Fleiss Kappa (k), and the reliability of agreement among the raters was moderate with a k of (0.7).

Results of a user study comparing a chat system integrated with the affect recognition model with a conventional chat system suggest that an online interface that conveys emotional information helps online users to interact with each other more efficiently thus providing an enhanced social presence.

CHAPTER ONE

1.0 INTRODUCTION

1.1 Background Information

With the prevalence of 'web 2.0' software (e.g. Email, Twitter, Blogs, Facebook, WhatsApp) a great deal of today's social interaction happens online. This has substantial benefits for online users but it also raises problems. The online interfaces in use today, such as chat systems, are far more primitive than face-to-face conversation, making it difficult to convey many basic cues, such as emotions. This makes online environments impersonal. This feeling of impersonality can be characterized as a lack of 'social presence' .Considered a design guideline, social presence theory advocates that the design of Computer mediated communication (CMC) should be as proximate to face-to-face communication as possible (Pavlou et al., 2007).

Bovee and Thill (2000) explain that, while we communicate verbally by using words in a face-to-face conversational mode, nonverbal cues provide 93% of the meaning exchanged in the interaction, 35% from tone and 58% from gestures, expressions and other physical cues. These observations demonstrate the importance of non-verbal information, such as emotions, which are essential for human cognition and influence different aspects of peoples' lives.

In recent years computer science research has shown increasing efforts in the field of software agents which incorporate emotion (Picard, 2007).A wide range of modalities have been considered, including affect in speech, facial display, posture, and physiological activity (Picard,2007;Neviarouskaya et al, 2007). Sufficient amount of work has been done regarding to speech and facial emotion recognition but text based emotion recognition system still needs attraction of researchers. Emotions influence rational thinking and therefore should be part of rational agents as proposed by artificial intelligence research. From a user perspective, emotional interfaces can significantly increase motivation and enhance interaction which is of high relevance to the games and e-learning industry (Zhang et al., 2006). To improve the user experience in Computer-Mediated Communication (CMC) and Human-Computer Interaction (HCI), it is significant to develop affective intelligent interfaces that are more natural and social.

1.2 Problem Statement

Everyday human communication involves a level of affective communication .In face to face communications people tend to communicate with each other through a number of channels. In online environments people tend to interact in a social way too. The online world is an environment where people exchange opinions, keep in touch with friends and contribute to ongoing topics. However computer mediated communication lacks such signals of face to face communication, such as body language, facial expressions, gestures, physical proximity, intonation and gaze. Online users are more limited in the ability to communicate nonverbal cues and to express their emotions e.g. smiling, laughing, poking, teasing, and winking. These expressions which are traditionally visual are essentially cut off. Successful deployment of computer-supported communication require consideration of social factors, such as getting to know other people's feelings, emotions, etc. These environments might greatly benefit from consideration of emotions (Cowie,R.,et al,2001)

1.3 Proposed Solution

In this research, the focus is on affect recognition from text to enhance social presence in computer mediated communication. This study proposes emotion recognition as one way to curb the social challenge in online interactions. The ability to communicate emotions in text is very important in social environments. Trends show that textual messages are often enriched with symbolic cues (e.g exclamations marks, question marks, capital letters, and emoticons) to make it more expressive. Studies indicate that these textual cues/patterns cues can serve as nonverbal substitutes for visual cues in face to face communications. (Derkd, D., 2007).The studies also state that these cues have an impact on the way online messages are interpreted.

The key focus of this work is on textual emotion communication with online nonverbal textual patterns of vocalics (e.g. the use of capitals and use of punctuation like "!" and "!!s!" or "?" and "???", length of response e.t.c), and those of chronemics (e.g. time to respond to an email or to a discussion posting, the length of the response e.t.c.) to enhance social presence. The study is based on natural language processing and machine learning techniques for automatic emotion detection. The study proposes a model that is able to assess the affective status of users based on the textual symbols /patterns in online environments.

1.4 Research Objectives

In order to enhance interaction in online environments, this research explores how university students communicate emotions in a text based online environment, the way they interpret certain stylistic textual symbols/patterns used in text and contextual cues to understand others emotions.

The main objectives of this study are:

i. To explore use and meaning of certain nonverbal textual symbols/patterns used in text to communicate emotions in online environments

ii. To identify a mapping of nonverbal symbols of(chronemics (timing) and vocalic textual symbols (styles of writing) to particular affective states

iii. To develop an affect recognition model capable of detecting the affective status from text based on textual nonverbal symbols/patterns in (ii)

1.5 Thesis Outline

This thesis presents a broad range of work investigating emotion expression in text:

Chapter Two: Gives a review of related literature that formed the basis of the research.

Chapter Three: Describes the methodological approach in regard to affect detection from text, data selection requirements and methods.

Chapter Four: Describes how data was labeled with various emotion interpretations. The chapter also describes the process of feature selection for the model building.

Chapter Five: Describes the affect recognition model design: the process of emotion estimation, the training module and the algorithm implementation.

Chapter Six: Describes a chat system integrated with the affect recognition model, details the evaluation framework for the affect recognition model.

Chapter Seven: summarizes the work presented in this thesis and the main contributions are drawn. An outline of future work is also presented.

CHAPTER TWO

2.0 LITERATURE REVIEW

2.1 The Concept of Social Presence

The concept of presence has been used in studying telecommunication, and virtual environments. A widely accepted definition of presence is “a perceptual illusion of non-mediation” that occurs “when a person fails to perceive or acknowledge the existence of a medium in his/her communication environment and responds as he/she would if the medium were not there” (Lombard and Ditton, 1997).Successful social engagement often centres on understanding what others are experiencing and then acting appropriately. The focus of this study is the social aspect of presence, or social presence, as this type of presence is considered to be the central design principle for social computing technologies, e.g., Multi-User Dungeon (MUDs), Email, Online Chat, and online communities (IJsselsteijn and Riva, 2003).

Social presence theory took on new importance with the rise of computer-mediated communication (CMC) and later online learning (Lowenthal, in press, 2009). Researchers and practitioners continue to try out different ways to establish and maintain social presence in online environments. For instance, Aragon (2003) identified over a dozen different ways to create social presence in online courses (e.g., incorporating audio and video, posting introductions, frequent feedback).DuVall, Powell, Hodge, and Ellis (2007) investigated using text messaging to improve social presence. Also, Keil and Johnson (2002) investigated using Internet based voice mail to increase social presence.

Considered a design guideline, social presence theory advocates that the design of CMC should be as proximate to face-to-face communication as possible (Pavlou et al., 2007).

2.2 Human Communication and Emotions

Human beings express emotions in day to day interactions, the ability to assess and respond to another person's emotional state is very significant for successful interactions. (Cowie, et al. 2001) demonstrate that when interacting in technologically-mediated environments with few available cues, people are still able to make fairly accurate judgments of others' emotional states (to varying degrees of specificity). Human affect sensing can be obtained from a broad range of behavioral cues and signals that are available via visual, acoustic, and tactual expressions or presentations of emotions. Affective states can thus be recognized from visible/external signals such as gestures (e.g., facial expressions, body gestures, head movements, etc.), and speech (e.g., parameters such as pitch, energy, frequency and duration), or invisible/internal signals such as physiological signals (e.g., heart rate, skin conductivity, salivation, etc.), brain and scalp signals, and thermal infrared imagery (Picard, R.W., 2007).Visible features that can be observed by others through day-to-day interactions for example facial expression can help us to determine whether someone is distracted, frustrated, or happy just through facial expression.

Some researchers have used sophisticated face-tracking software to analyze facial expressions to infer the emotional state of the user .Work by Khan et al.(2006) extended this idea but used thermal imaging to identify changes of blood flow patterns in the face that correspond to different facial expressions. The major problem with the physiological approaches to measuring affect is the intrusive nature of the technology. Affixing sensors to user's skin would not be realistic in a real-world context (e.g. casual interactions with mobile phones). Sensors take time to attach to the user, conductive gels might be used, shaving may be necessary, and the sensors can be sensitive to movement and could fall off with activity. Furthermore, the presence and constant reminder of the sensors may alter the emotional state that the user would have been in, if the sensors were not present.

Several ways have been defined for describing emotions. Some use categorical approach and some use dimensional approach. Categorical approach is labeling emotions with some languages or words (Ekman, 1992). Dimensional approach uses two orthogonal axes called arousal and valence to describe emotions (Rusell, 2003).

Researchers have investigated several aspects of human emotion (Picard, 1997). Several works in this direction have been reported in the literature (Izard, 1977; Plutchik, 1980; and Ekman, 1992). Below lists the most common emotions used in emotion detection:

Table 2. 1.Common lists of Emotions used in Emotion detection

List of Basic Emotions	
Ekman (1992)	Anger, disgust ,fear, joy, sadness and surprise
Izard(1977)	Anger, contempt, disgust, distress, fear, guilt, interest, joy, shame and surprise
Plutchik(1980)	Anger, anticipation, disgust, fear, joy, sadness, surprise and trust

This work uses Ekman's emotion categories (see Table 2.1) as they are the most widely accepted by the different researchers. Previous researches based on computational approaches to emotion recognition have also used Ekman's emotion categories (Liu et al., 2003; Alm et al., 2005; and (Neviarouskaya et al., 2007, Saima, 2007).

2.3 Non Verbal Communication: Chronemics and Vocalics

Previous Research in the area of computer-mediated communication (CMC) based on Social Presence Theory have argued that non-verbal communication in the absence of face-to-face interaction is severely restricted and that, using an online platform, 'any form of non-verbal communication, like gestures or facial expressions, cannot be perceived by the other group member' (Zumbach J, Hillers A, Reimann P,2004).Others maintain that CMC 'differs from face-to-face communication in striking, interpersonally related ways'(Walther JB, Tidwell ,1995)in that 'relationally-rich nonverbal cues are absent'.

A body of literature based on Social Information Processing (SIP) Theory which takes a less extreme position (Walther JB, 1995) counters this view. A review of this literature points out that non-verbal cues are also available in the online setting which cater for communication with a social-emotion-orientation (Liu Y, Ginther D, 2001).

These cues comprise, for example, the time to respond to an email or to a discussion posting; the length of the response (short/long; too short/too long); the frequency of communication (Liu Y.,2000)the style of the response (e.g. the use of capitals to denote shouting, and use of punctuation like "!" and "!!!" or "?" and "???" to convey difference in the degree of feeling .Another group of researchers have documented how the social-emotion-oriented model has been taken to a new level with the increasingly widespread use of 'relational icons' or pictographs , or what are commonly referred to these days as 'emoticons' (Walther J et al.,2004).

The Social Information Processing (SIP) theory argues that “when most nonverbal cues are unavailable, as is the case in text-based CMC, users adapt their language, style, and other cues to such purposes” (Walther, Loh, & Granka, 2005). When participants communicate with text-only e-mail, the timing of response, silence, or non-response provides researchers with chronemic nonverbal data. When people chat or text message in real time the length of time between post and response provides pacing and turn-taking in the conversation. This study is based on Social Information Processing (SIP) theory and the notion that traditional categories of sociometry, such as proximics (physical arrangement of individuals), kinesics (physical interaction between individuals), chronemics (use of time within group interaction) and environment (layout of space), may have slightly different meanings or manifestations online than they do in real life.

Some important questions need to be addressed for designing affective interaction in online environments. Perhaps the most vital is whether distinct nonverbal patterns (chronemics and vocalics) can be associated with particular expression of emotions. Although the common answer is an enthusiastic “yes”, the scientific research is much more controversial, what is clear, however, is that some nonverbal correlations of the “basic” emotions can be identified more reliably than others. Below is a discussion of the two nonverbal patterns that are the focus of this study and their association with some affective states

In face to face communications nonverbal code of vocalic includes tone of voice, loudness of voice, shouting, and vocal pauses (Hall, 2006). Table 2.2 below shows vocal behavior & emotions in face to face communication (Vinciarelli et al. 2009)

Table 2. 2 Vocal behavior & emotions

	Joy	Boredom	Neutral	Sadness	Anger	Fear	Surprise	Stress	Depression	Happiness	Disgust	Annoyance	Frustration	Anxiety	Dislike
Pitch	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Intensity	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Rhythm	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓
Formants		✓	✓	✓	✓	✓	✓	✓	✓	✓				✓	✓
Cross sectional Areas								✓							
MFCC		✓	✓	✓	✓	✓	✓	✓		✓					✓
LFPC				✓	✓	✓	✓			✓					✓
LPC	✓		✓	✓	✓	✓	✓				✓				
Spectral-band Intensity			✓	✓	✓	✓		✓	✓	✓	✓				
Cepstral Coefficients												✓	✓		
Voice Quality Parameters		✓	✓	✓	✓					✓				✓	

Research suggests that users can also communicate nonverbal vocalic cues via CMC e g using capital letters and repeated punctuation (i.e., hyperbolic punctuation) has proven to be effective in instant messaging/chatting environment when a user is compensating for lack of nonverbal cues (Walther, 2005). Recipients often perceive this type of message as a form of shouting or yelling (Wilson & Zigurs, 2001) .Because of this, whereas use of all capital letters can be used to indicate joy, it can also be interpreted as an expression of anger. Most messages sent via CMC in all capital letters are perceived to have a negative implication (Byron & Baldridge, 2007). Moreover, when e-mail content is emotionally ambiguous, the use of all capital letters leads to more negative impressions of senders. (Byron & Baldridge, 2007). Senders often use repeated punctuation such as multiple exclamation points or question marks to emphasize a point or to create greater effect.

Chronemic is a nonverbal code pertaining to time. It is considered an important aspect of face to face communication. Thus, time stamps on e-mails or text messages can be considered a nonverbal cue of chronemics. It has been found that a slow reply to a message can convey greater intimacy than a fast one (Liu et al., 2001). Another sub-dimension of chronemics in CMC is that of response time or response latency. Short response times can be interpreted as nonverbal cues of interpersonal Closeness, immediacy, care, presence, and even submissiveness. (Doering & Poeschl, 2007).

2.4 Emotion Detection from Text

The aim of textual affect detection is to understand how people express emotions through text, or how text triggers different emotions .A great deal of research has been done in the area of affective computing and a number of modalities have been considered (Picard, 2007). The written expression of emotion lacks nonverbal cues employed to communicate emotions in face to face communications such as gestures, tones, and facial expressions, and instead relies on creative use of words for communicating emotion. The focus of this thesis is on learning specific emotions from text with a great focus on textual symbols/patterns. In this perspective, this section presents a review of the research work done to wholly recognize expressions of emotions in text.

Strapparava and Mihalcea (2008) have reported results for emotion analysis of news head-lines and blog posts using a range of techniques including keyword-spotting, Latent Semantic Analysis (LSA), Naïve Bayes, rule based analysis and Pointwise Mutual Information (PMI). Neviarouskaya et al. (2007) propose a system for augmenting online conversations with a graphical representation (avatar) of the user, which displays emotions and social behavior in accordance with the text. This system performs automatic estimation of affect in text on the basis of symbolic cues such as emoticons, popularly used IM (Instant Messaging) abbreviations, as well as word-, phrase-, and sentence-level analysis of text. To support the handling of abbreviated language and the interpretation of affective features of linguistic concepts, a special Affect data base, containing emoticons and abbreviations, interjections, modifiers, direct and indirect emotion-related words (adjectives, adverbs, nouns, and verbs), and words standing for communicative functions, was created. For accumulation of relevant and most often used emoticons and abbreviations, they employed five online dictionaries dedicated to and describing such data. Words conveying affective content directly or indirectly were taken from the source of affective lexicon, WordNet-Affect. Each database entry was annotated, depending on its role, with the emotion category with intensity, or communicative function category, or modifier coefficient. Such a system can help improve the experience of online social interactivity by allowing expression of emotion in real-time online conversations.

Alm et al. (2005) explored the text-based emotion prediction problem empirically, using supervised machine learning with the SNoW learning architecture. The goal is to classify the emotional affinity of sentences in the narrative domain of children's fairy tales, for subsequent usage in appropriate expressive rendering of text-to-speech synthesis. Initial experiments on a preliminary data set of 22 fairy tales show encouraging results over a näıve baseline and BOW approach for classification of emotional versus non-emotional contents, with some dependency on parameter tuning. They however distinguish between positively surprised and negatively surprised emotions resulting in two classes instead of one surprise class in the original set identified by Ekman. In the preliminary work reported in (Alm et al., 2005), the authors have conducted experiments to classify sentences into emotional versus non-emotional, as well as according to valence into – positive emotion, negative emotion, and no emotion. In the former case, all emotion classes, that is, happy, sad, angry, disgusted, fearful, positively surprised and negatively surprised are coalesced into one emotion class. In the latter case, happy and positively surprised were coalesced into the positive emotion class, while sad, angry, disgusted, fearful, and negatively surprised were coalesced into the negative emotion class.

Rubin et al. (2004) have performed a study of the manual classification of texts drawn from blogs and product reviews on the basis of Circumplex Theory of Affect Owsley et al. (2006) have proposed automatic techniques for affective classification of the blog posts belonging to specific domains (e.g, movies, politics, etc.) into positive and negative affect categories.

Holzman and Pottenger (2003), have reported very encouraging results on emotion analysis of internet chat using Text to Speech (TTS) conversion and subsequent learning based on phonetic features. In their approach, they first automatically convert textual chat messages into speech using the Microsoft Speech SDK12, and then use frequency counts of the phonemes extracted from the speech version of the text messages for ML-based emotion classification. This approach is advantageous in case of chat data, as it is immune to the presence of such noise as misspellings, grammatical errors and abbreviated form of words used in chats.

Some researchers have focused on visualizing the affective content in text Liu, et al (2003) introduce an approach for graphically visualizing the affective structure of a text document. In their work a document is first affectively analyzed using a unique textual affect sensing engine, which leverages commonsense knowledge to classify text more reliably and comprehensively than can be achieved with keyword spotting methods alone. Using the engine, sentences are annotated using six basic Ekman emotions. Colors used to represent each of these emotions are sequenced into a color bar, which represents the progression of affect through a text document. Smoothing techniques allow the user to vary the granularity of the affective structure being displayed on the color bar. The bar is hyperlinked in a way such that it can be used to easily navigate the document.

Liu and Maes (2004) introduce a computational model of attitudes. Their work present a novel method for automatically modeling a person's attitudes and opinions, and a proactive interface called "What Would They Think?" In the application, each person is represented by a "digital persona," generated from an automated analysis of personal texts (e.g. weblogs and papers written by the person being modeled) using natural language processing and commonsense-based textual-affect sensing.

2.5 Methods

Emotion detection is considered a subfield of sentiment analysis. In the literature, there are a number of approaches to textual emotion detection. Emotion recognition approaches can be broadly classified into keyword-based, linguistic rules-based and machine learning techniques.

Keyword-based approaches are applied at the basic word level. Such a simple model cannot cope with cases where affect is expressed by interrelated words. The keyword pattern matching problem can be described as the problem of finding occurrences of keywords from a given set as substrings in a given string (Chun et al, 2009). In the context of emotion detection this method is based on certain predefined keywords. These words are classified into categories such as disgusted, sad, happy, angry, fearful, surprised etc.

Lexical approaches also called “sentiment lexicons” (opinion lexicons or tagged dictionaries).WordNet-Affect, a linguistic resource for the lexical representation of affective knowledge, was created by Strapparava and Valitutti ((2004) with the aim to support applications relying on language recognition and generation. Lexical affinity techniques classify the emotion of a linguistic unit based on the affinity of the linguistic unit and an affective keyword. For example, if a phrase appears closely much more often with the work “happy” than “sad”, it is reasonable to believe that the emotion associated this phrase is happy.

2.5.1 Machine Learning Approaches

Originally the problem was to determine emotions from input texts but now the problem is to classify the input texts into different emotions. Unlike keyword-based detection methods, learning-based methods try to detect emotions based on a previously trained classifier, which apply various theories of machine learning such as support vector machines (Teng,Z.,2006) and conditional random fields (Yang,C.,2007)to determine which emotion category should the input text belongs.

Pure machine learning approaches do not rely on lexicons but invoke other features to accomplish sentiment detection. Supervised learning and unsupervised learning approaches have been used to automatically recognize expressions of emotion in text such as happiness, sadness, anger, etc. In supervised learning, an algorithm is provided with a label for every example, and this information is used to learn a mapping from examples to labels. In unsupervised learning, no labels are provided at all in advance and consequently no training is provided. The goal of machine learning is to learn the following simple function

$$\mathcal{F}: ! \longrightarrow !$$

where ! is a set of examples {!! … !!}. Each example may be associated with a label from the universe of possible labels ! with pairs <x, y>. When the set of labels! is discrete and finite, the labels are called target classes. Each example has one or more properties, which are called features. These features describe the properties of the examples, and can be used in learning as predictors of the target class. The features used in this study are described in Chapter Four. Mixed approaches combine lexical with machine learning techniques.

Supervised machine learning classification techniques have been applied to automated affect detection, such as Naïve Bayesian, Support Vector Machines (SVM), Neural Networks, etc. These techniques have been exploited to classify movie reviews into two classes, positive and negative (Li, Bontcheva, & Cunningham, 2007; Pang, Lee, & Vaithyanathan, 2002).

Supervised and unsupervised techniques have been compared before. Strapparava and Mihalcea (2008) describe the comparison between a supervised (Naïve Bayes) and an unsupervised (Latent Semantic Analysis - LSA) method for recognizing six basic emotions.

Turney (2002) and Turney and Littman (2003) use unsupervised methods to classify movie reviews based on the similarity of the phrases in the review to the words "excellent" and "poor".

Pang et al. (2002) have used n-gram and part-of-speech information in their feature set. They have tested three machine-learning techniques, namely, Naive Bayes, Maximum Entropy classification, and SVM learning algorithms, and found SVM to give the best performance.

Owsley et al. (2006) use adjectives as training features in Naïve Bayes classifiers. In their machine learning experiments, they characterize each document with a vector representing the number of times each adjective feature occurred in the document.

Beineke et al. (2004) refine Turney's work (Turney 2002) by applying a Naïve Bayes model which they train on a labeled and an unlabeled corpus.

2.5.2 Naïve Bayes Classifier

In this study the Naïve Bayes algorithm was selected for automatic classification mostly due to its conceptual simplicity and comparably good efficiency. Naive Bayes classifier is one of the simpler methods of automatic categorization that has been applied to text classification. Consequently, it has also been utilized in attempting to solve the problem of sentiment analysis. In this algorithmic setting, the lexical units of a corpus are labeled with a particular category or category set, and processed computationally. Strapparava et al. (2006) note that in discourse, each lexical unit, whether it be a word or phrase has the ability to contribute potentially useful information regarding the emotion that is being expressed. However, it is typically a combination of these lexical units which motivates the communication and understanding of an emotional expression.

Naïve Bayes classifier is a classification method that is used for categorical data based on applying Bayes' theorem. By the classical Bayes approach, for a record to be classified, the categories of the predictor variables are noted and the record is classified according to the most frequent class among the same values of those predictor variables in the training set.

A rigorous application of the Bayes theorem would require availability of all possible combinations of the values of the predictor variables:

$$= p(C)\ p(F_1, \dots, F_n|C)$$

$$= p(C)\ p(F_1|C)\ p(F_2, \dots, F_n|C, F_1)$$

$$= p(C)\ p(F_1|C)\ p(F_2|C, F_1)\ p(F_3, \dots, F_n|C, F_1, F_2)$$

$$= p(C)\ p(F_1|C)\ p(F_2|C, F_1)\ p(F_3|C, F_1, F_2)\ p(F_4, \dots, F_n|C, F_1, F_2, F_3) \tag{2.1}$$

$$= p(C)\ p(F_1|C)\ p(F_2|C, F_1)\ p(F_3|C, F_1, F_2)\ \dots p(F_n|C, F_1, F_2, F_3, \dots, F_{n-1}).$$

The Naïve Bayes method overcomes this practical limitation of the rigorous Bayes approach to classification.

The major idea of it is to use the assumption that predictor variables are independent random variables. This makes it possible to compute probabilities required by the Bayes formula from a relatively small training set. Now the "naive" conditional independence assumptions come into play: and the joint model can be expressed as:

$$\begin{aligned} p(C, F_1, \dots, F_n) &= p(C)\ p(F_1|C)\ p(F_2|C)\ p(F_3|C)\ \cdots \\ &= p(C) \prod_{i=1}^{n} p(F_i|C). \end{aligned} \tag{2.2}$$

This means that under the above independence assumptions, the conditional distribution over the class variable C can be expressed like this:

$$p(C|F_1, \dots, F_n) = \frac{1}{Z} p(C) \prod_{i=1}^{n} p(F_i|C) \tag{2.3}$$

where Z (the evidence) is a scaling factor dependent only on $F_1, \dots, F_n$, i.e., a constant if the values of the feature variables are known.

In spite of their naive design and apparently over-simplified assumptions, naive Bayes classifiers have worked quite well in many complex real-world situations. In 2004, analysis of the Bayesian classification problem has shown that there are some theoretical reasons for the apparently unreasonable efficacy of naive Bayes classifiers. (Caruana, R. and Niculescu-Mizil, A., 2006)

An advantage of the naive Bayes classifier is that it only requires a small amount of training data to estimate the parameters (means and variances of the variables) necessary for classification. Because independent variables are assumed, only the variances of the variables for each class need to be determined and not the entire covariance matrix.

2.6 Emotion Labeled Datasets

Machine learning approaches require affect-annotated data for training purpose. Emotions labeled datasets are blocks of text that have been annotated with emotion tags. Manually annotating datasets of text is expensive and time consuming. However, because comparing results to annotated texts is the most stabilized method of checking the accuracy of an algorithm, annotated datasets have been established and consistently used throughout emotion detection studies. The agreement between judges is generally measured using Kappa statistic (Cohen, 1960; Fleiss, 1981).

A common dataset, used in many emotion detection studies, is SemEval 2007-Task, an affective text that consists of newspaper headlines. The annotations are labeled with Ekman's six basic emotions along with a neutral category. Another annotated dataset is the International Survey on Emotion Antecedents and Reactions (ISEAR). The ISEAR is a compilation of 7,666 sentences provided by 1,096 culturally divergent participants who were questioned about experiences and reactions that related to the emotions of anger, disgust, fear, joy, sadness, and guilt.

The third emotion-labeled dataset is fairy tales. The fairy tales collection is compiled of stories by (Potter et al,) with stories annotated on the sentence-level. Varying annotation processes have been conducted by Alm (2005) that provides a larger set of specific emotions. A dataset of 1580 sentences compiled in 2005 is labeled with Izard's set of ten basic emotions; and a dataset, including 176 stories, compiled in 2009 is labeled with emotion classes: angry-disgusted, fearful, happy, sad, and surprised. The latter dataset is composed of only sentences that have a high kappa value.

There are also blog datasets. The natures of some web-blogs, like Live Journal, allow the blogger to attach a mood or an emotion to an entry. The data is then self-annotated by the author and annotated at the entry-level as opposed to sentence-level. One corpus of LiveJournal entries compiled by Mishne (2005) is available for use and contains 815,454 entries.

Rubin et al. (2004) involve human judges in the classification of online product reviews and blogs into eight categories of emotion. The unit of text to be classified is a segment ranging from 2 to 20 sentences. Hiroshima et al. (2006) use a corpus, which was manually annotated for opinion sentences and subjective clues, for training an SVM-based machine learning classifier. Hu and Liu (2004) manually annotate descriptions of product features in customer reviews for training classifiers.

Mihalcea and Strapparava (2006) have collected positive and negative examples from the Web to train their humor classifier. Positive examples consist of humorous one-liners, which were collected using automatic bootstrapping process, beginning with a short seed list of manually identified one-liners.

Read (2005) has performed sentiment analysis experiments on a dataset drawn from newsgroup messages, and labeled with smileys or emoticons. No manual labeling of affect information is required in this case as these labels are provided by the writers of the message themselves.

2.7 Conclusion

From the review a number of researchers have employed machine learning methods to affect detection .A number of data sets have been created as described in section 2.6. Researchers have also experimented using different features. A variety of text genres, including product and movie reviews, news stories, editorials and opinion articles and, more recently, blogs have been considered. This study is based on supervised machine learning algorithm, Naïve Bayes method was chosen because it is simple to implement but still delivers good results.

CHAPTER THREE

3.0 METHODOLOGY

This research addresses the task of emotion recognition from textual messages in online environments and specifically in environments where informal language is used .The study focus is on the use of nonverbal textual patterns/symbols to communicate emotions in online environments.

3.1 Textual Affect Recognition Approach

Figure 3.1 shows the framework of the approach taken to detect emotions from textual symbols/patterns in this research:

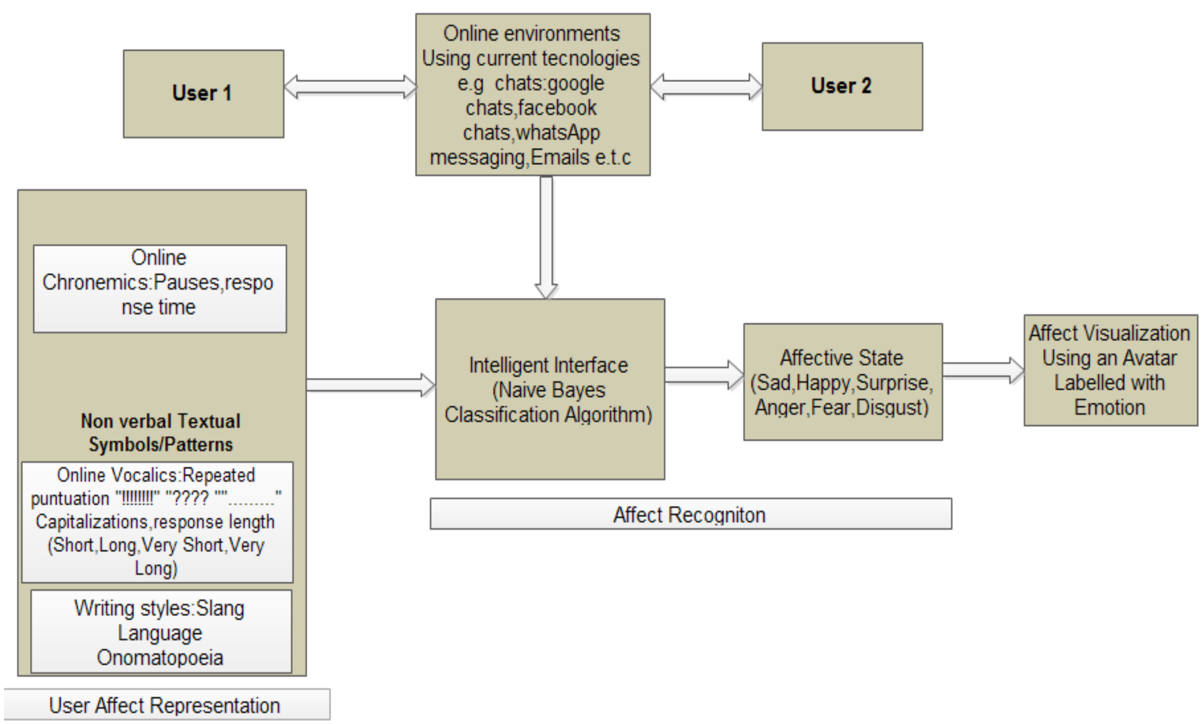


Figure 3. 1 Textual Emotion Recognition Approach

In order to enhance interaction in online environments (e.g. Google chats, Facebook chats, Whats App messaging) this study introduces a machine learning approach towards affect detection from textual messages .The developed model uses naïve Bayes algorithm to recognize the six basic emotions (anger, disgust, fear, happiness, sadness and surprise). The model was designed to handle informal textual messages as a way of dealing with the evolving language in online communications. Feature selection for the model was based on two factors: emotions keyword and textual patterns/symbols which are the focus of this study. The message goes through sequential steps in order to be analyzed for an emotion. These include analysis for keywords, and for features based on textual symbols.

The main features of the model include:

i. Analysis of six basic emotions by Ekman (Happy, Anger, Sad, Fear, Surprise, Disgust)
ii. Dictionary of Keywords associated with each emotion in i
iii. Use of nonverbal textual symbols/patterns of online vocalics and chronemics for textual affect representation.
iv. A supervised learning classification approach using naïve bayes algorithm
v. Use of textual patterns and emotion keywords as features for training the model
vi. A database of Slang language, and abbreviations: This allows the model to handle the evolving language in online communication

3.2 Data Collection

In order to investigate the use of nonverbal textual symbols to communicate emotions in online environments an online questionnaire was selected as the tool for data collection.

An advantages of an online survey tool is automatic processing of the surveys. The tool was convenient and easy to prepare compared to interviews which take a lot of time and are hard to process. Since the study targeted young university students with skills for computer use and online experience, this guaranteed their ability to use the online questionnaire. The questionnaire focused on the following aspects: (Appendix A)

i. Frequency of use of various textual symbols/patterns to express feelings/emotions in a text based environment
ii. Mapping textual symbols/patterns and basic emotions
iii. Modes of communication: The preference and frequency of use of modes used by students to communicate in online environments.

The survey targeted university students who have interacted and used text messaging environments such as facebook chats, WhatsApp applications e.t.c. The study target size was 60 participants, representing learners in various stages in regard to online use experience.

3.2.1 Data Selection Criterion

When developing machine learning systems, it is a requirement to have an annotated data for training and evaluation of the learning system. In regard to the approach taken in this research to detect emotions from text, three aspects were taken into consideration in regard to data selected for this study:

i. The data should be rich in emotion expressions of online nonverbal textual symbols

ii. The evolving nature of language in online conversations

iii. Data should comprise ample instances of all the emotion categories considered in this research that is six basic emotions by Ekman (happy, sad, anger, fear, disgust, surprise).

3.3 Emotion Annotation Experiment

Based on the three mentioned requirements described in 3.2, student's chat and post messages found in applications such as Facebook, WhatsApp applications were chosen as data sources .The goal of this experiment was to manually add emotion information to the chat messages collected from student online chats and posts. The messages were annotated with the six emotions that is happiness, surprise, fear, sadness, anger, disgust. Three students participated in the annotation exercise and had an independent judgment on the emotion classes of sentences. Agree Stat which is Software for analyzing the extent of agreement among Raters with MS Excel was used to compute chance corrected Agreements coefficients among raters. The tool is readily available online and easy to work with.

CHAPTER FOUR

4.0 DATA ANALYSIS

This chapter describes the entire process of data selection and annotation adopted in this study. Section 4.2 details the preparation of the affect dataset. The process of defining the features used in model building is described in section 4.6.

4.1 Communicating Emotions in Text

This section describes the results of a study carried out to determine the level of use of nonverbal textual symbols to communicate emotions in online environment. The study focused on the use of online nonverbal textual symbols of vocalics (e.g. the use of capitalizations and use of punctuation "!" or "!!s!" or "?" or "???" and"……"), and online chronemics (e.g. time to respond to an email) to communicate emotions. Informal styles of writing e.g. use of slang language, onomatopoeia (repetition of sounds) were also taken into consideration.

The questionnaire was sent to 61 participants. A total of thirty (30) student respondents from the university (17 Male (57%), 13 Female (43%)) took part in the study. All of them were computer literate.93% of the participants indicated they use computers for study purposes and all participants had an internet experience of more than a year. Section 4.1.1 describes the frequency of use of modes of communication, and a mapping between the nonverbal symbols/patterns and emotions is discussed in section 4.1.3.

4.1.1 Communication Modes: Frequency of use

One aim of the study was to identify the mode frequently used by students while communicating in online environments: Emails, Text chats, Instant Messengers and Micro blogs were the modes frequently used as indicated in Table 4.1.

Table 4.1 Frequency of Use of modes of Communication

Modes of Online communication						
Mode	Less Often	Quite often	Often	Very often	Don't use at all	Maximum No of Responses
Emails	1	5	4	20	0	**20**
Text only chats	2	2	11	14	0	**14**
Discussion Forums	13	4	5	2	3	**13**
Wikis	7	7	5	7	3	**7**
Blogs	12	1	7	6	3	**12**
Micro Blogging	12	3	5	5	5	**12**
News feeds	4	5	8	11	2	**11**
Instant messenger	5	5	7	13	0	**13**
Voice chat	9	5	7	3	5	**9**
Online conferencing	8	4	1	2	10	**10**
Social Book Marking	11	5	5	6	2	**11**
Journaling	12	4	6	3	5	**12**
Frequency of Use	13	7	11	**20**	**10**	

4.1.2 Online Non Verbal Elements & Emotions

Based on sample chat messages exchanged by students ,the study focused on the following textual symbols: Multiple exclamation marks (!!!!!!),Multiple question marks (???????),Multiple full stops (……),Discourse markers such as but ,Capitalization, Abbreviations or shorthand such as brb (be right back),ASAP ,Length of the response(very short, short, long, very long), Slang language "LOL", Onomatopoeia e.g. "whizz", “aaarrr”, and the response time. Table 4.2 shows the forms that students frequently use to communicate their emotions.

Table 4.2 Frequency of use of nonverbal textual symbols

Styles of expression frequency of use

Symbol	Less Often	Quite Often	Often	Very Often	Maximum No of Responses
Capitalizations	6	5	12	7	12
Multi !!!!!(Exclamations)	3	6	5	16	16
Multi ????(Question marks)	0	6	7	17	17
Multi……(Full stops)	4	7	5	14	14
Length of response	5	6	11	7	11
Pauses/silence	6	5	11	8	11
Discourse markers	9	7	5	9	9
Onomatopoeia	0	5	7	17	17
Slang Language	1	2	9	17	17
Abbreviations & shorthand	3	5	7	15	15

Slang language, Multi question marks and onomatopoeia were the most frequently used patterns of communication by students to express emotions. 53% indicated to have very often used Exclamation marks (!!!!!) to communicate their emotions. Other forms that were frequently used included: repetition of full stops and abbreviations.

4.1.3 Mapping Non Verbal Textual Symbols and Emotions

The main aim of this study was to find out if the textual symbols of focus can be mapped to particular basic emotions. 90% of respondents agreed to have felt and communicated emotions while interacting in online environments .Table 4.3 illustrates how the respondents mapped various textual symbols/patterns to basic emotion states.

Table 4. 3 Mapping between non Verbal symbols and Emotions

Mapping between non verbal elements and Emotions

Symbolic Expressions	Happy	Surprise	Fear	Sadness	Disgust	Anger	MaxResponses
Capitalizations	13	17	7	5	13	21	21
Exclamation Marks	18	27	19	11	14	16	27
Repetition of full stop	9	6	10	9	2	6	10
Very long response	3	6	2	4	4	7	7
Very short response	8	4	4	11	5	4	11
Pauses/silence	5	7	10	15	7	9	15
Question Marks	4	8	5	5	7	5	8
Discourse Markers	3	1	4	6	3	5	6
Onomatopoeia	16	14	8	8	8	11	16
Slang Language	21	10	7	9	9	10	21
Abbreviations& Shorthand	8	4	5	8	5	6	8

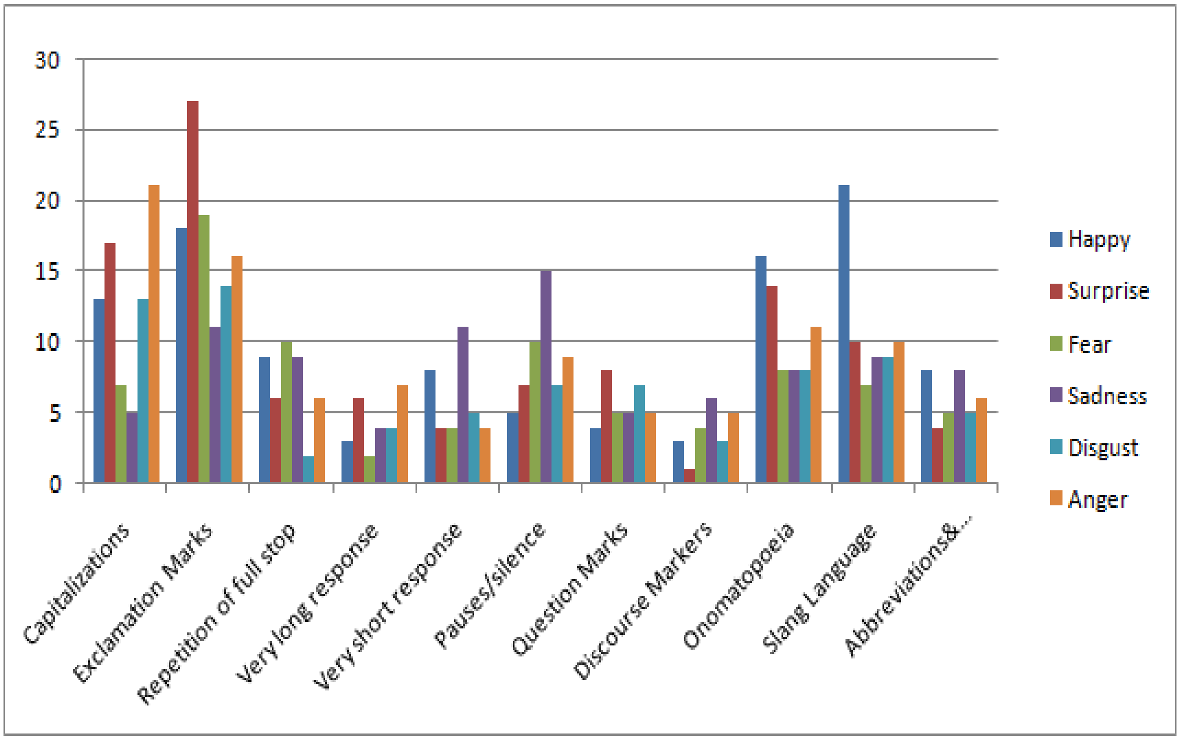


Figure 4. 1 Mapping between non Verbal symbols and Emotions

Slang language, exclamations and onomatopoeia were the forms mostly associated with the happy emotion with 70% of the participants mapping Slang Language with the happy emotion.60% also mapped exclamation marks to Happy. 53% of the participants mapped onomatopoeia with happy emotion. Pauses, short and very short response were the forms mostly mapped with the sad emotion with 50%, 37%, and 37% respectively. Exclamation marks, pauses /silence were the forms mostly associated with fear with 63% and 33%respectively. 70% participants mapped Capitalization with anger. 90% participants associated exclamation marks with surprise.57% of the participants also associated capitalization with Surprise. Disgust inclined towards anger with capitalizations and exclamations being more used by participants to indicate it.

4.2 Training Data Set

This section details the preparation of the dataset. Two sets were prepared:

4.2.1 Word Set

This entails creating a dictionary of a set of keywords for each of the following categories:

Table 4.4 Sample Words and Categories

Categories	**Key Words**
Happiness	Glad,amused,love,pleased,cheerful,amazing,excited,Lol,fun,Good,happy, nice, awesome,funny,great,excited
Sadness	Lonely, depressed, unhappy, sorrow, Hurt, miss, sorry,sad,lost,cry,stress,wept, longing
Anger	Annoyed,gloomy,Angry,furious,annoyed,pissed,yelling,upset,mad,shut up
Disgust	Hate dislike, sucks, stupid,disgusting,crap
Surprise	Confused, Surprised, amazing, astonished,incredible,suddenly,wonder,unexpected,can't believe, shocked, perplexed, what?
Fear	Horrified, nervous, scared, insecure, frighten, Afraid, scared, nervous, worry, security ,fear, what if, threat, freak, dangerous
Abbreviations	Hi,ASAP,2MOR,2NTE,2MI,ATM

Slang Word	LOL,wow,yep,yeah,sawa,hey hey heyhahhaha,

In creating the dictionary of word sets this study drew from the publicly available lexical resource WordNet-Affect (Strapparava and Valitutti, 2004), Word Net assigns a variety of affect labels to each synset in WordNet (Fellbaum, 1998). There are six lists corresponding to the six basic emotion categories identified by Ekman (1992). A detailed description of these lists appears in Table 4.5. In addition to the six emotion categories; slang words and abbreviations were also included.

Table 4. 5 Sample words and categories from WordNet

Category	#synsets	Sample Words
Happiness	227	joy, love, rejoicing, glee, happiness, euphoria, enthusiasm, admiration, cheerful, content, happy, merrily
Sadness	123	sorrow, misery, woe, gloom, grief, depression, heartbreak, mournful, hapless, guilty, sadly, remorsefully, repent, bored
Anger	127	wrath, fury, rage, angry, annoyed, pissed, mad, sore, livid, displeasingly, aggressive, hateful, hostile, malice, spite, resentfully
Disgust	19	repulsion, nauseous, foul, abhorrent, fed_up, abominably, revolt, sicken
Surprise	28	wonder, fantastic, marvelous, baffle, bewilder, astonishing, awestruck, stupefy, dumbfound, staggering
Fear	82	scary, fright, panic, terror, chilling, frightful, terrible, intimidate, dread, anxiously, apprehension

4.2.2 Messages with Known Emotions

The messages were drawn from online chats and posts exchanged by students in applications such as Facebook, WhatsApp and labeled with emotions. Initially 1050 sentences/messages were collected. It was a requirement for this study that the messages collected should have adequate expressions of emotion in text that are the focus of this study. The chat indicates extensive emotion expression in text by use of Non-Verbal textual symbols/ patterns.

M1: Person 1☹ Hi (Happy)

M2: Person 1: Hey. Are you there... ()

M3: Person 1: Hmph! :-((Angry)

M4: Person 2: Hi Sandra!   (Happy)

M5: Person 2: Sorry, my phone was off the whole day. My charge died somewhere along the way.

M6: Person 1: It's ok.(neutral)

M7: Person 2: Did the lecture happen?(Neutral)

M8: Person 1: the whole freaking full time. 3 HOURS!!!!!   (Angry),

M9: Person 2: Hahaha. But you just hang in there.   (Happy)

M10: Person 1: I'm now off to another class...... :-| (Sad)

M11: Person 2: What time does it end?

M12: Person 1: Imagine 7pm!   (Sad)

M13: Person 2: WHAAATT!!! (Surprised) M15:

Person 2: that lecturer doesn't realize its a friday? (Surprised)

M16: Person 1: Hahaha.Maybe. (Happy)

M17: Person 2: Ooooooooh. Hehehe (happy)

M18: Person 1: What plans do you have today?

M19: Person 2: We're going out for a movie with Dan and Loise. You could tag along... (Neutral)

M 20: Person 1: What time does it start?

M21: Person 2: 6:30

M22: Person 1: I can't. My lecture ends at 7, remember? Sigh. (Sad)

M23: Person 2: Yeah. That sucks. Sorry. (Sad)

M24: Person 1: :-((sad emoticon)

M25: Person 2: But tomorrow you're free, right?

M26: Person 1: Yeah, why?

M27: Person 2: We'll be going to Safaricom Sevens. It'll be great if you could come along.

M28: Person 1: Yaaaaaaay!!!!! (Happy)

M29: Person 2: So i take it that's a yes?

M30: Person 1: Hahaha. I won't even justify that with an answer. (Happy)

M31: Person 2: Hehehe. *clear throat* Ahem. Ahem. (Happy)

M32: Person 1:. It's about to start. Lemme leave you with all your speculations.

M33: Person 2: Speculations? LOL. We both know better, don't we?

(Happy)

M34: Person 1: Haha. No, we don't. (Happy)

M35: Person 2: Whatever you say. We'll chat more after your class. (Neutral)

Figure 4. 2: Sample Chat Conversation

From the chat the following textual expressions have been employed to indicate the emotion:

M3:Hmph! :-((Angry); Use of onomatopoeia to indicate emotions

M8: Person 1: the whole freaking full time. 3 HOURS!!!!! (Angry), this indicates use of capitalizations and multi exclamations to show anger.

M19:M2, M30, M31, M33: Person 2: Oooooooooh. Hehehe (happy).In the mentioned sentences, the students have used slang symbols/language to indicate happiness

M13: Person 2: WHAAATT!!! (Surprised): use of capitalizations and exclamation marks to indicate happiness

4.3 Message Annotation

Three students participated in the annotation process (Appendix B).While labeling the sentences, the annotators were required to pay special attention to keywords associated with identified emotion categories and the textual symbols/patterns discussed in the previous section and the mapping identified in Table 4.3.The raters independently labeled the sentences with emotions.

The reliability of human raters was measured using Fleiss Kappa Coefficient. Fleiss Kappa works for any number of rates giving categorical ratings to a fixed number of items. It can be interpreted as expressing the extent to which the observed amount of agreement among raters exceeds what would be expected if all raters made their ratings completely randomly. Shortly Kappa gives a measure for how consistent the ratings are. The Kappa coefficient k is defined as:

$$k = \frac{\overline{P} - \overline{P}e}{1 - \overline{P}e}, \tag{4.1}$$

where $\overline{P}$ is the proportion of the times the raters agreed, and $\overline{P}e$ is the proportion of the times the agreement would be made by chance. If two raters always agree, the kappa value is 1, and if they agree only at the rate given by chance, the value is 0. The negative kappa means that annotators are worse than random. The Kappa scoring ranges between 0 and 1, poor and complete agreement respectively. On a sample of 350 annotated sentences the agreement measurements were as follows:

Table 4.6: Distribution of Subjects by Rater and Score/Category

Category

Raters	ANGER	DISGUST	FEAR	HAPPY	NEUTRAL	SAD	SURPRIS	Total
Rater 1	73	26	25	118	30	58	13	343
Rater 2	55	41	28	106	41	52	19	342
Rater 3	52	44	24	111	55	45	15	346
Average	60	37	25.7	111.7	42	51.7	15.7	343.70

From the sample majority of the sentence were labeled with the happy emotion with an average of 111, Followed by Anger with an average of 60 and Sad Emotions with an average of 51.

Table 4.7: Annotator agreement measurements

Unweighted Analysis

METHOD	Coefficient	Inference/Subjects StdErr	Inference/Subjects 95% C.I.	Inference/Subjects p-Value	Inference/Subjects & Raters StdErr	Inference/Subjects & Raters 95% C.I.	Inference/Subjects & Raters p-Value
Conger's Kappa	0.71044	0.02217	0.667 to 0.754	1.894E-105	0.06324	0.586 to 0.835	3.641E-25
Gwet's AC1	0.72952	0.02166	0.687 to 0.772	4.310E-111	0.05927	0.613 to 0.846	4.164E-29
Fleiss' Kappa	0.70991	0.02231	0.666 to 0.754	1.208E-104	0.06356	0.585 to 0.835	6.220E-25
Krippendorff's Alpha	0.71308	0.02245	0.669 to 0.757	1.861E-104	0.06387	0.587 to 0.839	6.504E-25
Brenann-Prediger	0.72688	0.02172	0.684 to 0.77	2.269E-110	0.05983	0.609 to 0.845	1.620E-28
Percent Agreement	0.76590	0.01862	0.729 to 0.803	4.223E-135	0.05128	0.665 to 0.867	2.989E-39

As shown from table 4.7, the level of agreement between annotators is moderate (0.7)

4.4 Sample Annotated Sentences

Below are sample annotated sentences in the dataset that have a high kappa value in regard to the agreement measurements between annotators on the emotion categories assigned.

Table 4. 8: Sample annotated Sentences from Training Set

	Messages	Emotion
1	I don’t know what will happen……	FEAR
2	I DON’T LIKE THAT!!!	ANGER
3	Am so happy for u!!	JOY
4	He left without saying.	SADNESS
5	He drowned in the swimming pool	SADNESS
6	I fear dealing with such….	FEAR
7	Are you serious???	SURPRISED
8	DON’T EVER CALL ME AGAIN!!!	ANGER
9	Am glad you are my friend, don’t know what I would have done without you	HAPPY
10	I just made a loss!!	SADNESS
11	I just got the job!!	HAPPY
12	Can u believe him????? ….	SURPRISED
13	I don’t want to go out at night….	FEAR
14	I WONT DO THAT!	ANGRY
15	She is a great friend, I like her company	HAPPY
16	Am lost without you	SADNESS
17	LEAVE ME ALONE	ANGER
18	You mean you would do such a thing tto me??????	ANGRY

19	Am afraid, I can't make it to ur graduation party	SAD
20	My Kid is bright, am so proud of her	HAPPY

4.5 Defining the Feature Set

In defining the feature set for automatic classification of emotional sentences, the study focused on those features, which noticeably characterize emotional expressions, the most appropriate features that distinguish distinct emotion categories are emotion key words. Emotion key words, are those words that are quite unambiguously affective. Beyond emotion-related word features, this study focused on emotion expression in text through the use of textual symbols. From the study described in chapter four a mapping was identified between these symbols and the six emotion categories by Ekman. Sentences collected from student online chat indicate that online communication is changing rapidly, in such communications emotion is quite frequently emphasized through repeated usage of punctuations (as in "How is that possible!!!!!!!!!). Many kinds of texts are characterized by increased use of punctuations, this justifies their use as features in emotion classification. Table 4.9 summarizes the features that were used in the following classification experiments; the length of response feature was classified into long, short, very short, very long response.

Table 4. 9: Summary of feature set used in Emotion Classification

Word Features (From Dictionary)	**Textual Symbols /Patterns of Communication**

Happiness Keywords	MultiQuestionMarks (???????)
Sadness Keywords	Length of Response (Long,short,Very short,very Long)
Anger Key words	Capitalizations
Fear Key words	Full stop repetition (………)
Disgust Key words	Abbreviations “ASAP”
Surprise Keywords	Exclamation marks (!!!!!!!)
	Discourse Markers “but”
	Slang Language “LOL”

CHAPTER FIVE

5.0 MODEL DESIGN

This chapter describes the work flow of the affect recognition model. In section 5.1 the Training module is discussed. Section 5.3 describes the emotion estimation process. The model logic implementation was written in clojure, a functional language that runs on the Java Virtual Machine(JVM) (Appendix C) .The database was created using My SQL 5.0.

5.1 Training Module

The training module includes two sections:

5.1.1 Dictionary

This part of the training module presents the dictionary set which is a set of words and their associated categories; this allows one to enter a word and assign it to a category e.g. amused to happy category. In order to cater for the evolving language in online communication the categories of Slang language and abbreviations were included.

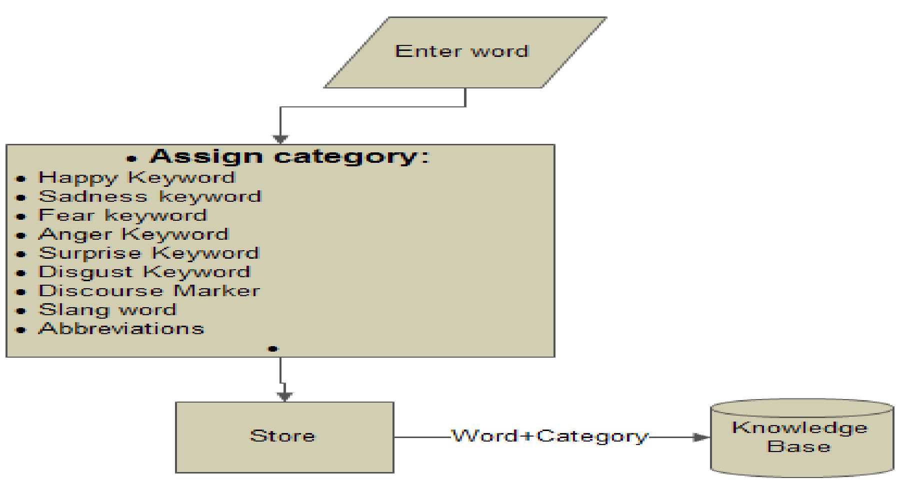


Figure 5. 1: Dictionary

5.1.2 Training Set: Messages with known Emotions

This part of the training module allows one to input messages labeled with emotions discussed in chapter four.

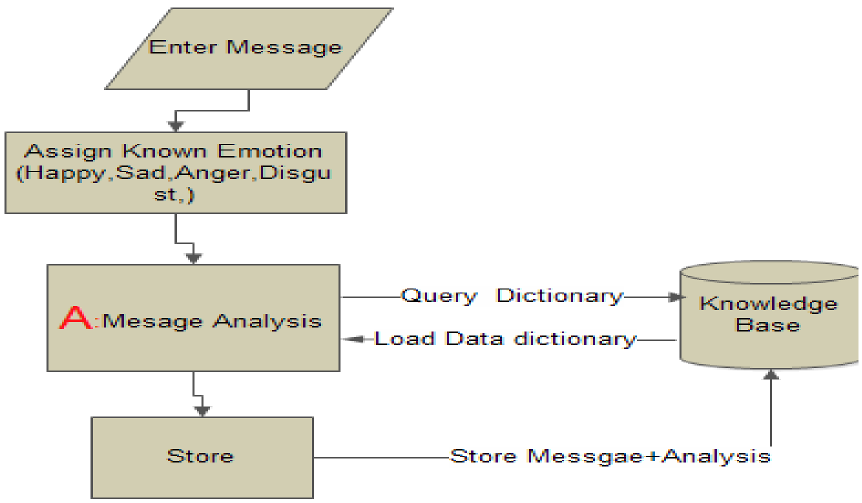


Figure 5.2 Training Set

5.2 Message Analysis Process

As indicated in Figure 5.2 in the section labeled A, this process involves extracting the features from the annotated messages.

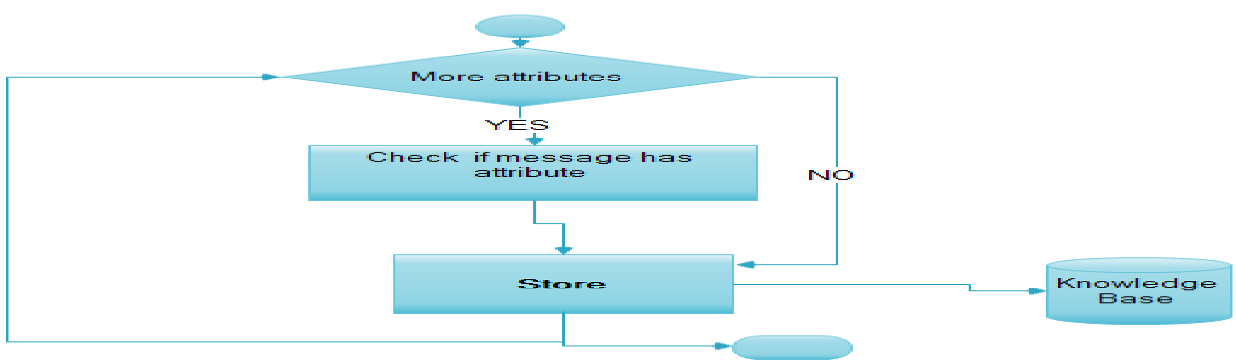


Figure 5. 3: Message Analysis Process

The first step is to load the data dictionary for analysis of keywords associated with a category in the database. Following is an illustration of the process of extracting keywords:

Function to check for Happy Keyword: Consider an array of happy Keywords

happyKeywords=[a,b,c,d…]

```
Function has_happyKeyword (Message)
        {
        For word i in happy keyword
        {
If message. Contains (word)
        Return 1
Else
        Return 0
}
```

The message is then analyzed for the rest of the features

```
For each attribute ai           a represents an attribute e.g Capitalizations
        If message has ai
```

Add ai to the attribute array

End if

Loop //loop for all attributes

The result of the analysis is a message map shown in Figure 5.4. Features are implemented as Boolean values of true or false.

Message	Has Capitalizations	Has Abbreviations	has Discourse Markers	has Anger Keyword	Has Exclamation Marks	Has Fear Keyword	Has FullStop Repetition	Has Happy Keyword	Has Question Marks	Has Sad Keyword	Has Slang word	Has Surprise Keyword	Is Long Response	Is short Response	is Very long Response	is Very short Response
Msg (Values)	True	False	True	False	False	True	True	False	False	True	True	True	True	True	True	False

Figure 5. 4 Message map

The resulting message map shown in Figure 5.4 is then stored in the training data table in the Affect Model DB .The affect DB has two tables as shown in Figure 5.5

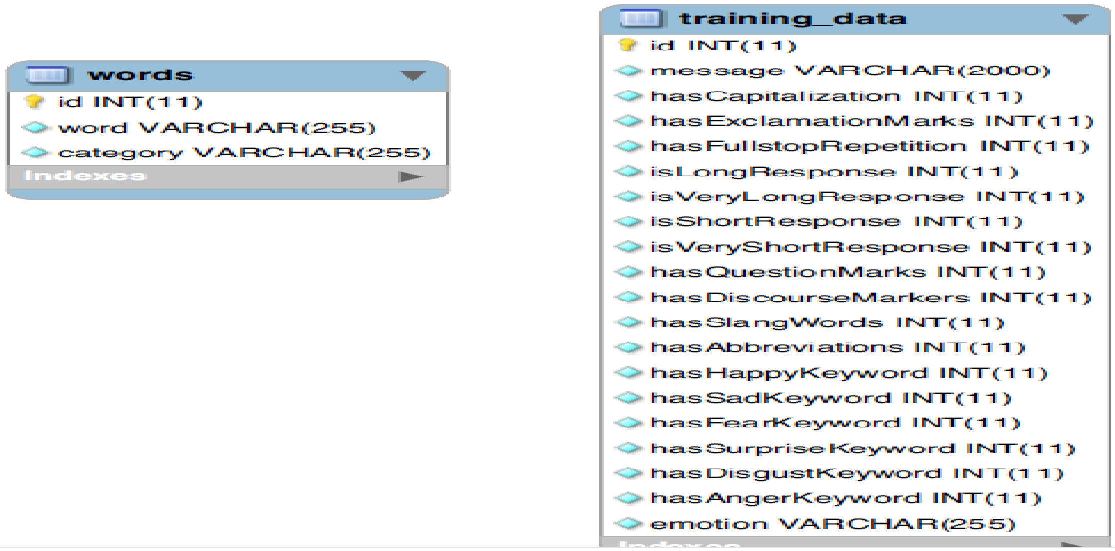


Figure 5. 5 Affect Database

5.3 Emotion Estimation Process

This section explains the logic of estimating the emotion given the message. The algorithm uses the sentence as a recognition unit. The process of emotion estimation is treated as a classification problem. Naïve Bayesian Classifier based on the Bayes rule is used to compute the probabilities of emotions given the message. The input message is analyzed to derive features described above. In order to determine which emotion is expressed in the input text, the algorithm computes the probability P (for each emotion) given the message e.g. P (Happy/Message) or P (Sad/Message).

The process is as follows:

- Input: a sentences (d)
- A fixed set of classes C={c1,c2,…,cJ} Emotions as Classes
- A training set of m hand –labeled sentences (d1, C1…..dm,Cm)
- Output: a predicted class c∈C

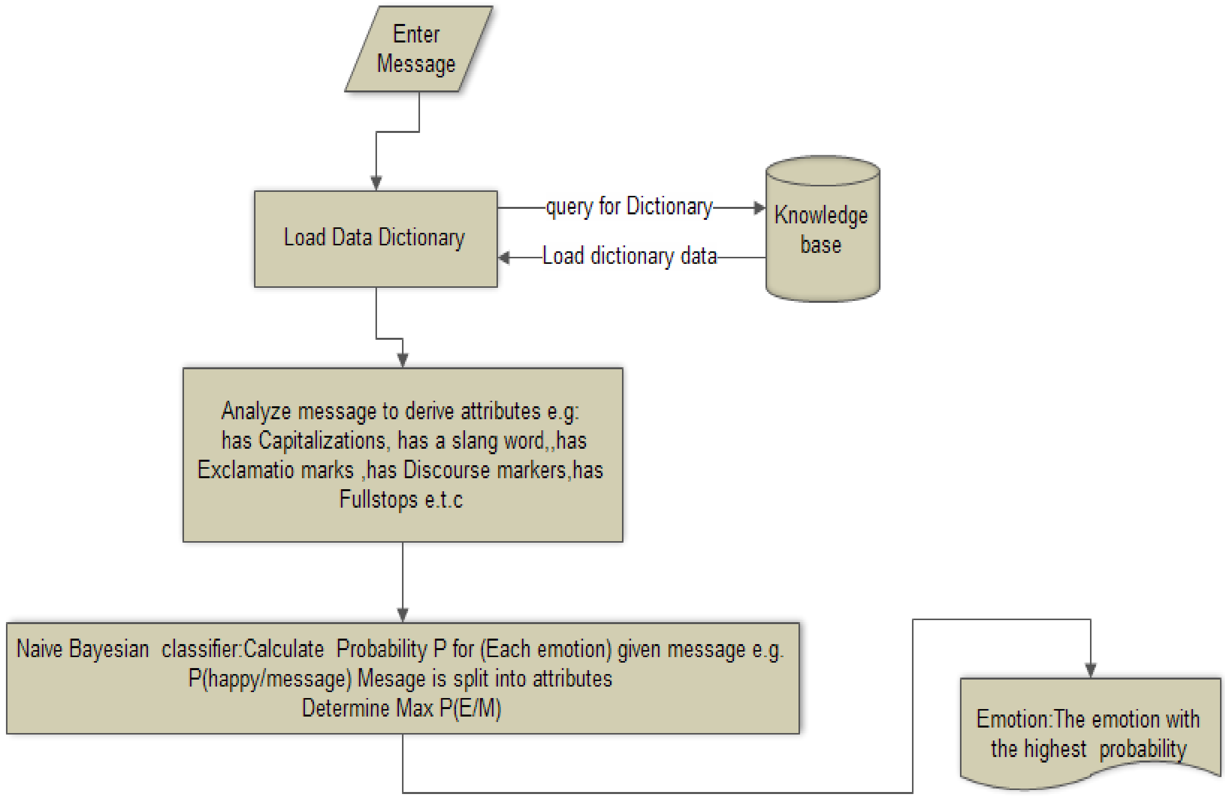


Figure 5. 6 Emotion Estimation Process

Bayes Theorem: P (A/B) = P (B/A).P (A)

/P (B) (5.1)

General

P (Emotion/Message) = P (Message/Emotion).P (Emotion)/ (5.2)

P (Message)

Applying the Naïve Bayes: Dropping the Denominator

P (Happy/Message)=P(Message/Happy).P (Happy) (5.3)

The message is split to a number of features: x1-xn represents features

$$P(x1\ldots xn \mid c) = P(x1 \mid c) \cdot P(x2 \mid c) \cdot P(x3 \mid c) \cdot \ldots \cdot P(xn \mid c) \tag{5.4}$$

Return the class with maximum Value

$$cMAX = \text{argmax}c\ P(x1, x2, \ldots, xn \mid c)P(c) \tag{5.5}$$

$$= \text{argmax}\ (P\ (\text{Capitalizations, shortResponse}\ldots\ xn \mid c)\ P\ (\text{Emotion})$$

5.4 Algorithm Implementation

The following are the main steps the algorithm follows to compute the probabilities of an emotion given message:

Step I: Compute the Probability of a certain emotion P (Emotion)

count-all : "SELECT count(*) AS count FROM training data"

count-emotion: "SELECT count (*) AS count FROM training data WHERE emotion=E1" emotion

P(Emotion) = (count-emotion)/ (count-all)

Step II: Emotion property value: The probability of Property/feature given emotion

"SELECT count (*) AS count FROM training data WHERE emotion =E1 AND "property "=F1 //Property indicates features

P-property-emotion = (property value)/ (count-emotion)

Compute for all the properties/features

Step III: Emotion-value= (P-Emotion *P- property-emotion/*…..*…*P- property)

Step IV: Repeat for all classes of emotions

Step V: Get-max-emotion: Compare Emotion-value:

Step VI: Return the emotion with the highest probability (P (Max))

CHAPTER SIX

6.0 MODEL IMPLEMENTATION AND EVALUATION

This chapter describes a chat system integrated with the affect recognition Model. The chat application was written in JavaScript using node.js platform.

6.1 System Architecture and User Interfaces

The architecture of the chat system is depicted in Fig. 6.1.

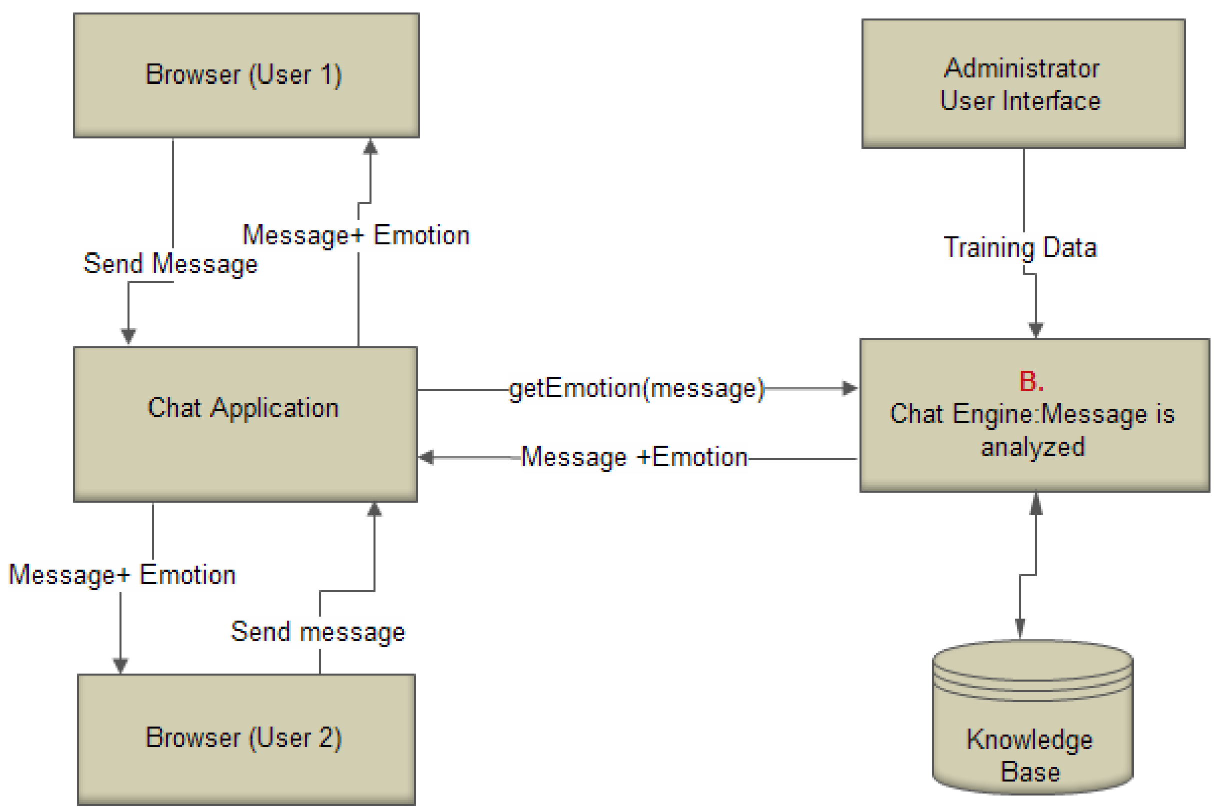


Figure 6. 1 Chat System Architecture

On the server side, the Chat Engine module is used to listen to the clients' connection and incoming messages. The module analyzes the emotion tendency of the incoming messages and returns the result back to the Chat Application module. Once the emotion of a message is estimated, the facial emoticon appears with affective expression i.e. Sad, Happy e.tc. As shown in Figure 6.3, the analysis of emotion is based on a ChatApp database and the algorithm described in Chapter Five.

6.2 Chat Engine Module

The chat engine has two interfaces as described in 6.2.1 and 6.2.2.

6.2.1 Dictionary: Word Categories

The interface allows the administrator to enter words and their categories; the categories include Happiness keyword, Sadness keyword, Disgust keyword, Fear Keyword, Anger Keyword, Surprise Keyword, Discourse markers, slang word and abbreviations. In order to cater for the evolving language in online communication the categories of Slang language and abbreviations were included.

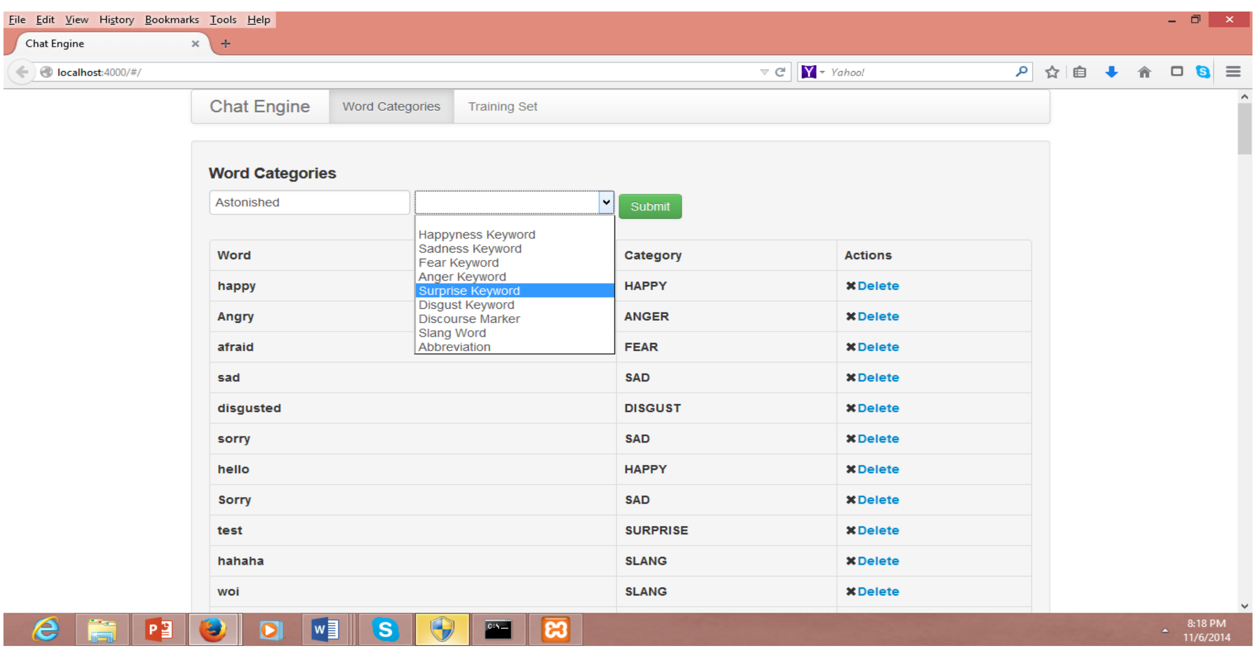


Figure 6.2 Word categories interface

6.2.2 Chat Engine: The Training Set

This interface allows the training messages to be submitted to the training data table with the associated emotions .The messages are then analyzed for training features as shown below, this is then saved to the training data table in the chat App database. This helps in computing the probabilities of emotions given the message as described in emotion estimation section in Chapter Five.

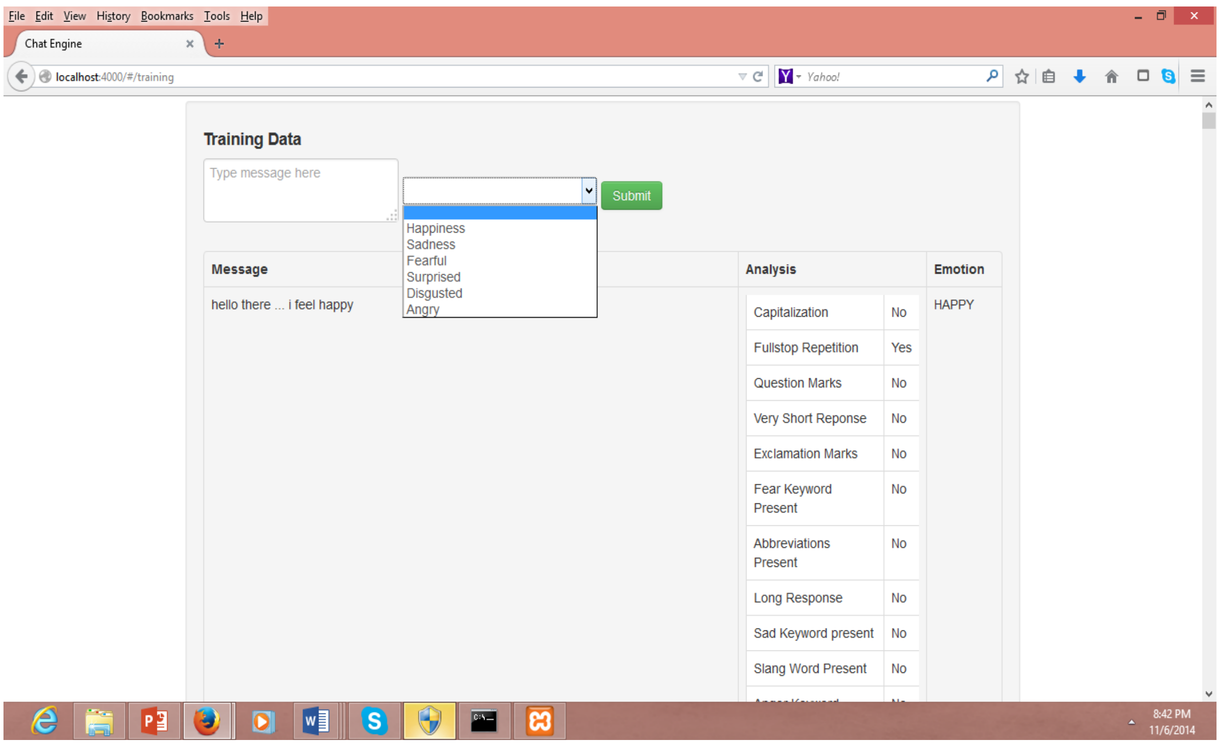
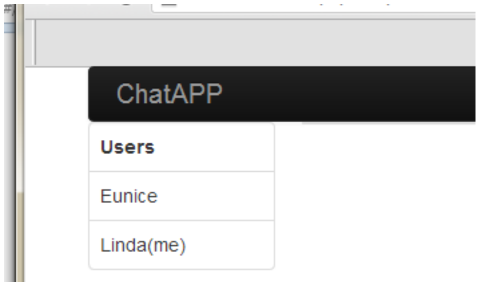


Figure 6.3 Training Interface

6.3 Chat Application

The user joins the chat by entering their handle, the chat is a broadcast, and the messages sent can be seen by everyone that is logged to the chat application, the text input at the bottom allows users to type and send the messages by clicking the send button.



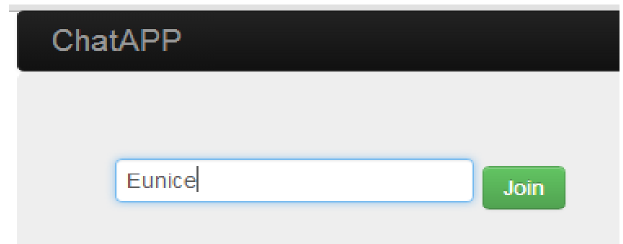


Figure 6.4 Logging Interface

The main window of the chat system while in online conversation is shown in the Figure 6.5. The Chat Application interface consists of three frames:

i. Text Input

ii. Output of Affect recognition Model

iii. Visualization

The Chat Application provides affect estimation of typed text/message during online communications, provides an emotional feedback as shown in Figure 6.5 and complementary visualization using a facial emoticon indicative of the result emotion. The sentences for affect recognition are typed in the field of Text Input.

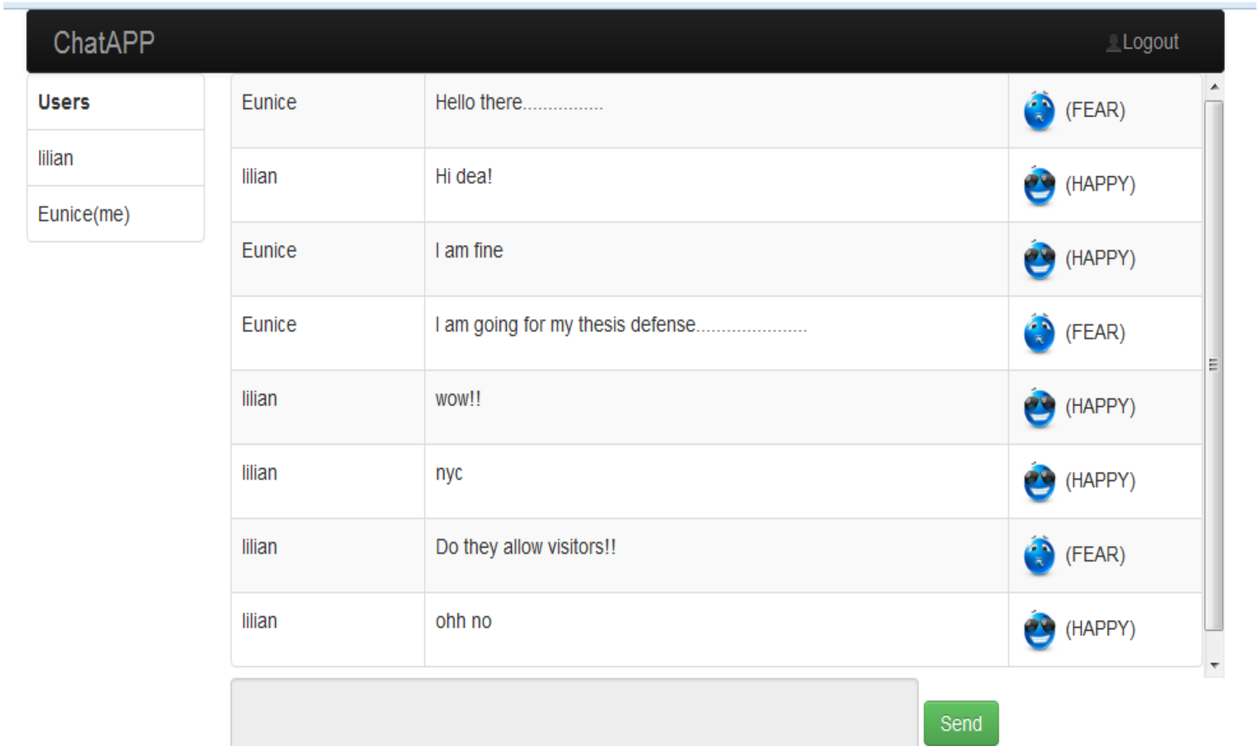


Figure 6. 5 User Demonstration

The inputs are in form of messages which are then analyzed into the discussed features used in the study. Each sentence is processed by the Affect Recognition Model, the results of which emotion and an associated facial emoticon corresponds to the emotion results of the affect recognition model.

In Figure 6.5 shows a communication scenario:

Eunice: Hello There…….:.Eunice: I am going for my thesis defense……….

The system interprets these two messages as fear; this indicates that many sentences used to train the system with repetition of full stops (……) are annotated with fear.

Lilian: wow, nyc; these are slang terms interpreted as happy: this indicates that many sentences used as training to the system with slang words are annotated with the happy emotions

6.4 Evaluation Framework

The affect recognition model was evaluated by use of the chat application described above. A user study was carried out to measure the level of experience and the intelligence of the system in regard to affect detection. The study focus was on enhancing the level of social presence through emotion recognition. The system was tested against likely everyday use rather than against a formal corpus.11 users interacted with the system and participated in a user study. The user study was in form of an online survey. Before filling the online questionnaire, each user was required to interact with the developed chat application. “User study evaluation shows that this approach works well enough to make a practical impact on the design of affective user interfaces”

The questionnaire covered the following major aspects: interactivity, social presence, affect intelligence, Users judged the chat application with the affect engine to be more intelligent than the previous chat they have interacted with before as shown in the bar graph in Figure 6.6:

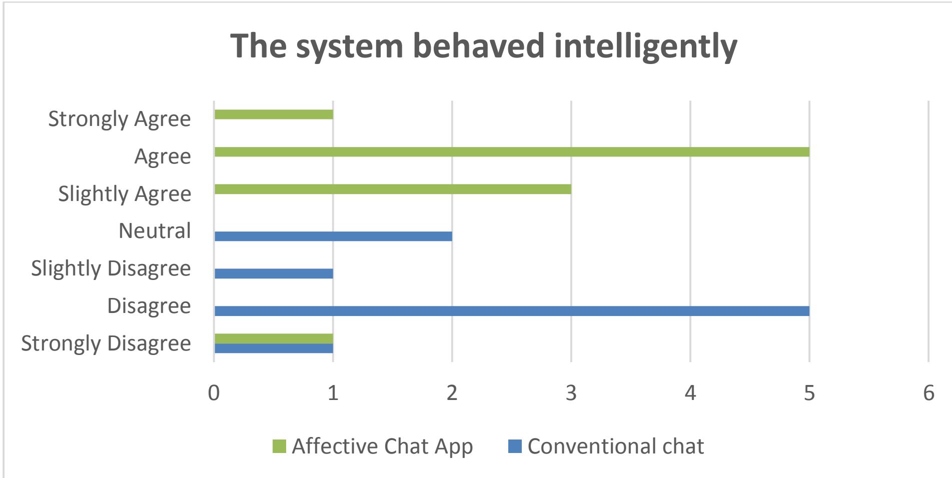


Figure 6. 6: Evaluation for affective intelligence

The questionnaire items covering the aspect of togetherness and interactivity were intended for the evaluation of the aspect of social presence. From the two bar graph in Figure 6.7 and Figure 6.8, the users found the affective chat application to give an enhanced level of social presence compared to a conventional chat.

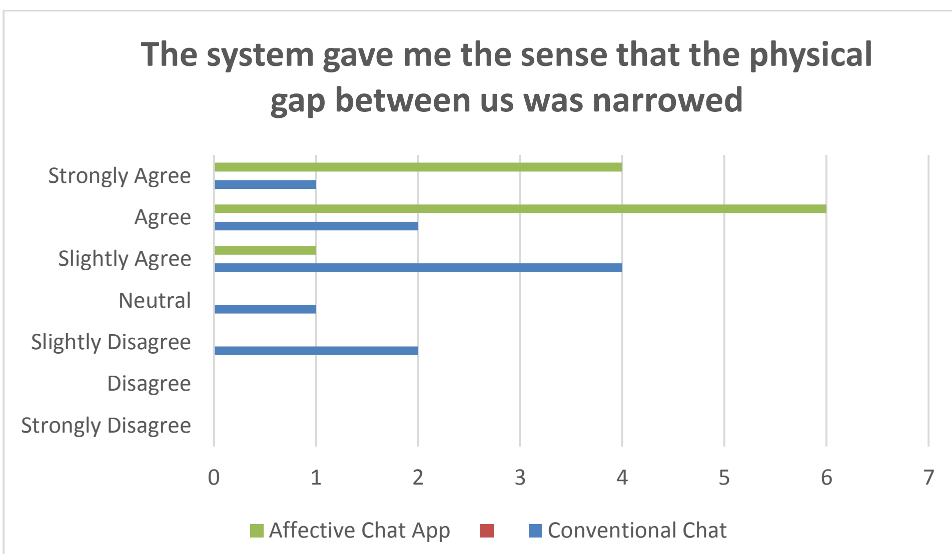


Figure 6.7 Evaluation for social presence

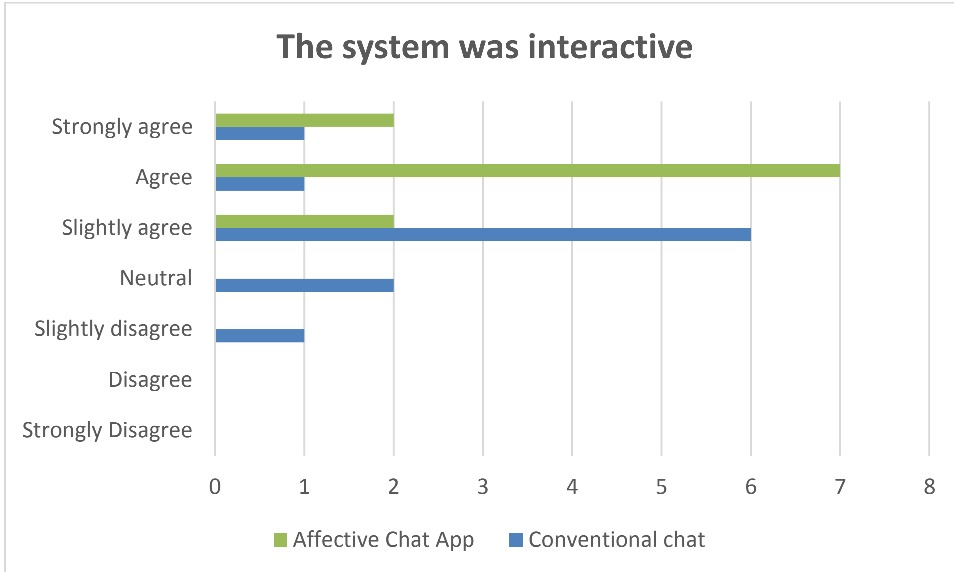


Figure 6.8 Evaluation for interactivity

CHAPTER SEVEN

7.0 CONLUSIONS AND RECOMMENDATIONS

The purpose of the presented work is to enhance interaction in computer mediated communication through automatic emotion recognition from text. Emotion research is an inter-disciplinary area and draws upon earlier works in Psychology, Linguistics, and Natural Language Processing.

For training machine learning systems and for the evaluation of any automatic learning system, it is pre-requisite to have annotated data. Most applications of automatic emotion recognition deal with real world text. Online communication is rapidly changing and people employing so many cues/patterns to communicate their feelings/emotions in online environments and hence deeper research is needed to investigate online communication of emotions in text based environments. Such text often contains noise, such as misspellings, onomatopoeic elements and slang.

Most of existing affect datasets are not appropriate for training systems to recognize emotions in environments where informal styles of communication are used. In order to come up with a training set, messages were collected from student chat and posts based on a study carried out to determine the use and meaning of nonverbal textual patterns used in text. Initially 1050 sentences/messages were collected from student online chat exchanges. The sentences were annotated for emotions by three independent student raters. The level of agreement between human annotators was moderate with Fleiss kappa of (0.7) .

The affect database was built from the two sets of training data established for this research: Dictionary of words and messages with known emotion; the process of defining the features was based on two factors, use of textual symbols and emotion keywords.

In order to enhance the user's experience in online communication, make it enjoyable, exciting and fun as it is the focus of this study, a chat application, integrated with the Affect Recognition Model was developed. To realize visual reflection of textual affective information, facial emoticons were used corresponding to individual emotions .This contributes to greater interactivity. Facial emoticons with labeled emotions are helpful in understanding the partner's emotions and giving some sense of social presence. Users reported that their experience with the affective chat narrowed the social gap and they enjoyed conversing in such an environment.

The research in this thesis contributes to an important ongoing topic, namely emotion modelling applied to affect detection. The subject is addressing an active area of research with substantial implications for online communication .The study introduces a new approach to affect recognition from textual messaging and reports an investigation of emotion expression in text by use of nonverbal textual symbols. The developed affect recognition model can be used to detect emotions in environments where informal styles of communication are used e.g in Facebook chats, WhatsApp applications. Building a database of slang words and abbreviations, an upcoming issue that has been addressed is the evolving language in online communication, or the language developing in instant messaging, chat rooms, and text messages. Following a mapping identified between online nonverbal textual symbols and the six basic emotions that is anger, happy, sad, surprise, disgust and fear, the ability to use textual patterns to communicate emotions in online environments is demonstrated.

In regard to future work, there are still many interesting and challenging aspects that still need to be investigated in regards to the area of affective computing.

One of the limitations of the current approach is that the affect sensing operates rather independently of the user and story contexts, instead, In future work, this work would be extended to overcome some of these limitations by investigating how the approach can be extended to incorporate a user model, and perform some tracking of story context.

The data prepared as part of this work is rich in emotion annotations and offers several exciting possibilities for further research. Future work may attempt to automatically identify the emotion indicators in sentences. Annotating more sentences to add on the training set, would also increase the level in which the system is able to interpret informal messages.

Affect visualization is another aspect that is key in the area of affective computing. Use of emoticons is the most widely used approach to visualize emotions with a great deal of research in the area. However due to cultural differences and many other factors these emoticons do not always give accurate visualizations. Based on this study future work would involve investigating use of nonverbal textual symbols/patterns for affect visualization and explore new approaches towards affect visualization.

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APPENDICES

Appendix 1: Emotion Recognition Questionnaire

Emotion Recognition from Nonverbal textual Symbols for

Enhancing social presence in online Environments

Questionnaire

Part 1: Basic Information

1.1. You are: ☐ Male ☐ Female

1.2. Please indicate your age group

☐ Under 20 ☐ 21-25 ☐ 26-35 ☐ 36-45 ☐ 46-55 ☐ 55+

1.3. You are:

☐ A Certificate student ☐ A Diploma student ☐ A Degree student

☐ A Master student ☐ PhD student

1.4. How long have you been using a computer?

☐ No experience ☐ Less than 1 yr ☐ 1-5 yrs

☐ 6-10 yrs ☐ 11-15yrs ☐ 16-20yrs 20+yrs

1.5. What do you mainly use your computer for?

☐ Work ☐ Games ☐ Study ☐ Communication ☐ Hobby

☐ Other (Please specify)

…………………………………………………………………………………………

…………………………………………………………………………………………

……………………

1.6. How long have you been using the Internet (years)? (Please √ only one answer)

☐ Less than 1 Year ☐ 1-5 years ☐ 6-10 years ☐ More than 10 years

1.7. How would you rate your skills as an Internet user? (Please √ only one answer)

☐ Very Basic ☐ Basic ☐ Average ☐ Advanced ☐ Very Advanced

Part 2: Emotion Recognition

2.1. Please indicate how often you use the following modes of online communication?

	Less Often	**Quite Often**	**Often**	**Very Often**	**Not at All**
Discussion forums					
Emails					
Text only chats					

Wikis					
Online chats					
Social Book marking					
News Feeds					
Micro online chats					
Journaling					
Instant messenger/VOIP, e.g., AOL, Yahoo, ICQ, Skype					
Voice Chat					
Online Conferencing					

Others (Please Specify)

………………………………………………………………………………………………

………………………………………………………………………………………………

………………….

2.3 .While communicating in online text based environments did/do you feel any emotions?

☐ Yes ☐ No

2.4. If Yes, How often do you use the following symbols/style of communication to express your feelings/emotions in a text based environment (e.g. Instant Messaging chat, emails etc)?

Style of response	**Less Often**	**Quite Often**	**Often**	**Very Often**
Capitalizations				
Exclamations Marks!!!!				
Pauses/silence				
Full stops……				
Question marks e.g.????				
Abbreviations or shorthand				
Discourse markers e.g. but				
Length of the Response				
Slang Language e.g. oops				
Onomatopoeia e.g. eeh				
Other (……………………)				
Other (……………………)				
Other (……………………)				
Other (……………………)				
Other (...…..………………)				
Other (……………………)				

Other (…………………….)				

2.5. Which set of the following symbols/style of response/communication do you use to indicate the following emotions in a text based environment? Please specify another emotion which is not specified on the (Other) section below.

	Capitalizations	Exclamations Marks	Question marks	Repetition of full stops	Slow response	Quick response	Short response	Long response	Too Long response	Too Short response	Pauses/silence	Abbreviations or Shorthand	Discourse markers	Onomatopoeia	Slang language	Other(Please specify)
Happy																
Sadness																
Fear																
Surprise																
Disgust																

Anger																
Other																
Other																
Other																

2.6. Any other views on this research topic

……………………………………………………………………………………………

………

Appendix 2. Sample Annotated Sentences

The goal of the emotion annotation was to manually add emotion information to each sentence in a dataset of chat messages collected from student online chats and posts. This work employs six basic emotions identified by Ekman (1993). Annotators were required to read each sentence and identify which of the following emotion categories can be assigned to the sentence:

i. Happiness
ii. Sadness
iii. Anger
iv. Disgust
v. fear
vi. surprise

Sample Annotated Sentences

	Dominant Emotion			
	Sentences	**Rater 1**	**Rater 2**	**Rater 3**
1	I am contented with your work.	**Happy**	**Happy**	**Happy**
2	I GET MY TRANSCRIPT TODAY!!!	**Fear**	**Fear**	**Happy**
3	I am going home!!!	**Happy**	**Happy**	**Happy**
4	I AM GOING HOME!!!	**Happy**	**Happy**	**Happy**
5	AND IM NOT SINGING HAPPILY TODAY	**Anger**	**Disgust**	**Sad**

6	S/he is like WOW	**Happy**	**Happy**	**Surprise**
7	I do not want to go to school…………..	**Sad**	**Disgust**	**Anger**
8	Why does this have to be so hard?!	**Anger**	**Sad**	**Disgust**
9	Oh No I forgot the exam was today!	**Fear**	**Sad**	**Sad**
10	Why must this be so painful??	**Sad**	**Sad**	**Disgust**
11	I bought her four pairs of socks coz all the others have holes LOL	**Happy**	**Surprise**	**Neutral**
12	I don't know what will happen……	**Fear**	**Fear**	**Fear**
13	I DON'T LIKE THAT!!!	**Disgust**	**Disgust**	**Disgust**
14	Am so Happy for u!!	**Happy**	**Happy**	**Happy**
15	He left without saying	**Sad**	**Sad**	**Disgust**
16	He drowned in the swimming pool	**Sad**	**Sad**	**Sad**
17	Am afraid, I cant make it to ur(your) graduation party …. (:	**Sad**	**Sad**	**Sad**
18	I dreamed I was being chased by a lion	**Fear**	**Fear**	**Fear**
19	I am very tired today………….very tired	**Neutral**	**Anger**	**Anger**
20	I am afraid of the unit we are doing today	**Fear**	**Fear**	**Fear**
21	You mean you would do such a thing tto me??????	**Anger**	**Disgust**	**Disgust**
22	LEAVE ME ALONE	**Anger**	**Anger**	**Anger**

23	Are you serious!!!!!!!	**Surprise**	**Surprise**	**Surprise**
24	Am lost without you	**Sad**	**Happy**	**Disgust**
25	Can u believe him????	**Surprise**	**Fear**	**Surprise**
26	She is a great friend, I like her company	**Happy**	**Happy**	**Happy**
27	I WONT DO THAT!	**Anger**	**Anger**	**Neutral**
28	I don't want to go out at night….	**Fear**	**Fear**	**Fear**
29	I just got the job!! Wow	**Happy**	**Happy**	**Happy**
30	I Fear dealing with such….	**Fear**	**Fear**	**Fear**
31	DON'T EVER CALL ME AGAIN!	**Anger**	**Anger**	**Anger**
32	I just made a loss	**Sad**	**Sad**	**Sad**
33	I am helpless in this situation and I don't know what to do	**Sad**	**Fear**	**Fear**
34	I hate Cockroaches	**Disgust**	**Disgust**	**Disgust**
35	WHAAATT!!!	**Surprise**	**Surprise**	**Surprise**
36	Yeah. That sucks. Sorry	**Disgust**	**Disgust**	**Disgust**
37	Eeww!!! Enyewe that was boring	**Disgust**	**Disgust**	**Disgust**
38	Oh!!! That's cool	**Happy**	**Happy**	**Happy**
39	That is soooo Sad ;)	**Sad**	**Sad**	**Sad**
40	IT AINT HAPPENING	**Anger**	**Anger**	**Anger**

41	Hahahaha ooh yeah!hahahaha ...:)	**Happy**	**Happy**	**Happy**
42	I broke up with my boyfriend	**Sad**	**Sad**	**Sad**
43	I am Fearing to go to the hospital for tooth extraction	**Fear**	**Fear**	**Fear**
44	Its hard finding a job today in Nairobi…..	**Sad**	**Sad**	**Sad**
45	All I can do is sit and pretend…	**Sad**	**Sad**	**Neutral**
46	Oohh no, I forgot the exam was today	**Fear**	**Fear**	**Sad**
47	I can't. My lecture ends at 7, remember?	**Neutral**	**Sad**	**Neutral**
48	That lecturer doesn't realise its a friday?	**Anger**	**Disgust**	**Disgust**
49	I'm now off to another class....	**Sad**	**Sad**	**Neutral**
50	Maybe he has a plot less Friday. Maybe his time with you is the hallmark of his day. Hahaha	**Happy**	**Happy**	**Happy**
51	Hahaha. Maybe. And it's a 'she', not a 'he'.....	**Happy**	**Happy**	**Happy**
52	Hahaha. I won't even justify that with an answer.	**Happy**	**Happy**	**Happy**
53	Person 2: Hehehe. *clear throat* Ahem. Ahem	**Happy**	**Happy**	**Happy**
54	I jus got the job!!	**Happy**	**Happy**	**Happy**
55	I DON'T LIKE THAT!!!	**Anger**	**Anger**	**Anger**

56	So he took you out last night?	**Surprise**	**Surprise**	**Surpris e**
57	The results will be out tomorrow! I hope to have done well.	**Fear**	**Fear**	**Fear**
58	Happy birthday dear! May you grow old to be toothless. Where are we partying tonight?	**Happy**	**Happy**	**Happy**
59	I am already home, it was great spending time with you, you made my afternoon.	**Happy**	**Happy**	**Happy**
60	Hi, how was your day? Mine was just amazing!!!!	**Happy**	**Happy**	**Happy**
61	What! She is getting married? I am Happy for her.	**Happy**	**Happy**	**Happy**
62	Thanks alot, I really appreciated your hospitality	**Happy**	**Happy**	**Happy**
63	How tight is your afternoon? Can we go swimming? I found it being fun.	**Happy**	**Surprise**	**Neutral**
64	I can't take it, it is the hardest thing I can accept	**Anger**	**Fear**	**Anger**
65	I just love it! It is the best thing I have ever received.	**Happy**	**Surprise**	**Happy**

66	What happened? He could be such an animal?	**Anger**	**Anger**	**Anger**
67	Your roommate was so cool, I enjoyed her company.	**Happy**	**Happy**	**Happy**
68	I met you sister and she is really nice.	**Happy**	**Happy**	**Happy**
69	I can’t make it today I feel really sick.	**Sad**	**Sad**	**Sad**
70	Mhhhh,,,, dear should I say this?	**Surprise**	**Surprise**	**Surpris e**
71	Have a lovely day ahead I am looking forward to seeing you tomorrow. longing	**Happy**	**Happy**	**Happy**
72	All will be well. Wishing you quick recovery.	**Sad**	**Neutral**	**Neutral**
73	Just tell me if you won’t make it, if you are busy we can schedule it for next time.	**Sad**	**Sad**	**Neutral**
74	Wakie! Wakie! Still sleeping? The sun has already risen.	**Happy**	**Happy**	**Happy**
75	My dad passed...I hope to cope soon with what seems to be reality.	**Sad**	**Sad**	**Sad**
76	Almost starting my first paper.	**Fear**	**Fear**	**Fear**
77	There is something that has been really troubling me	**Fear**	**Fear**	**Fear**

78	When are you free we really need to talk, I am troubled.	**Fear**	**Sad**	**Fear**
79	I would really need to take a photo with you because I will really miss you.	**Sad**	**Neutral**	**Sad**
80	Please find it in your heart to forgive me. I am really sorry.	**Sad**	**Sad**	**Sad**
81	Why is she always commenting on your pictures in facebook?	**Anger**	**Fear**	**Surprise**
82	I am just too Happy for you, congratulations!	**Happy**	**Happy**	**Happy**
83	Wow! How did you do that so well? inspired	**Happy**	**Happy**	**Happy**
84	I did not expect to get these low grades	**Sad**	**Sad**	**Surprise**
85	Arrrg! He is a real jerk	**Disgust**	**Disgust**	**Disgust**
86	Oh my God! Did everyone see me doing that?	**Surprise**	**Sad**	**Sad**
87	Thanks God its Friday! Where is the party	**Happy**	**Surprise**	**Happy**
88	I am finally free I am no longer answerable to anybody.	**Anger**	**Happy**	**Happy**

89	Why did you have to betray me? You are the last person I expected to do that	**Anger**	**Anger**	**Anger**
90	All will be well, learn to accept the situation as it is	**Sad**	**Neutral**	**Neutral**
91	Am sorry, I did not do that on purpose	**Sad**	**Sad**	**Sad**
92	I owe you one after what you did to me	**Neutral**	**Neutral**	**Neutral**
93	I can't wait to complete my studies	**Neutral**	**Surprise**	**Neutral**
94	Maybe I expected too much from you. I should have known it from the start	**Anger**	**Anger**	**Anger**
95	I will push it to the end!!!	**Neutral**	**Neutral**	**Neutral**
96	Wow! i passed the interview	**Happy**	**Happy**	**Happy**
97	Thanks dear, I take it as a complement	**Happy**	**Happy**	**Happy**
98	Are you okay at the moment?		**Neutral**	**Neutral**
99	Why did you refuse to pick my calls?	**Anger**	**Anger**	**Sad**
100	We are definitely gonna rock this party.	**Happy**	**Happy**	**Happy**

Appendix 3: Affect Detection Model Logic Implementation

```
(ns chatengine.engine
  (:require [clojure.string :as str]
            [clojure.java.jdbc :as j]
            [clojure.java.jdbc.sql :as s]))


(def mysql-db {:subprotocol "mysql"
               :subname "//localhost:3306/chat"
               :user "root"
               :password "root"})


(def discourse-markers (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='DISCOURSE'"]))] (:word x)))
(def slang-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='SLANG'"]))] (:word x)))
(def abbrevs (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='ABBREV'"]))] (:word x)))
(def happy-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='HAPPY'"]))] (:word x)))
(def sad-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='SAD'"]))] (:word x)))
```

```
(def fear-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='FEAR'"]))] (:word x)))
(def surprise-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='SURPRISE'"]))] (:word x)))
(def disgust-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='DISGUST'"]))] (:word x)))
(def anger-words (for [x (doall (j/query mysql-db ["SELECT * FROM words WHERE category='ANGER'"]))] (:word x)))

(defn has-capitalization?
  [message]
  (if (nil? (re-find #"[A-Z]" message)) 0 1))

(defn has-exclamations?
  [message]
  (if (nil? (re-find #"!!!*" message)) 0 1))

(defn has-question-marks?
  [message]
  (if (nil? (re-find #"\?\?\?*" message)) 0 1))

(defn has-fullstops?
```

```
  [message]
  (if (nil? (re-find #"\.\.\.*" message)) 0 1))

(defn is-long-response?
  [message]
  (if (> (count message) 101) 1 0))

(defn is-very-long-response?
  [message]
  (if (> (count message) 200) 1 0))

(defn is-short-response?
  [message]
  (if (< (count message) 100) 1 0))

(defn is-very-short-response?
  [message]
  (if (< (count message) 10) 1 0))

(defn has-discourse-markers?
  [message]
  (loop [current-str (first discourse-markers) str-list discourse-markers]
```

```
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list)))))))

(defn has-slang-words?
  [message]
  (loop [current-str (first slang-words) str-list slang-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list)))))))

(defn has-abbreviation?
  [message]
  (loop [current-str (first abbrevs) str-list abbrevs]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
```

```
        (recur (first str-list) (rest str-list))))))


(defn has-happy-keyword?
  [message]
  (loop [current-str (first happy-words) str-list happy-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list))))))


(defn has-sad-keyword?
  [message]
  (loop [current-str (first sad-words) str-list sad-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list))))))


(defn has-fear-keyword?
  [message]
```

```
  (loop [current-str (first fear-words) str-list fear-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list))))))

(defn has-surprise-keyword?
  [message]
  (loop [current-str (first surprise-words) str-list surprise-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
        0
        (recur (first str-list) (rest str-list))))))

(defn has-disgust-keyword?
  [message]
  (loop [current-str (first disgust-words) str-list disgust-words]
    (if (some #(= current-str %) (str/split message #"\s"))
      1
      (if (empty? str-list)
```

```
    0
    (recur (first str-list) (rest str-list))))))

(defn has-anger-keyword?
  [message]
  (loop [current-str (first anger-words) str-list anger-words]
   (if (some #(= current-str %) (str/split message #"\s"))
     1
     (if (empty? str-list)
       0
       (recur (first str-list) (rest str-list))))))

(defn analyze-message
  [message]
  {:message message
   :hasCapitalization (has-capitalization? message)
   :hasExclamationMarks (has-exclamations? message)
   :hasFullstopRepetition (has-fullstops? message)
   :isLongResponse (is-long-response? message)
   :isVeryLongResponse (is-very-long-response? message)
   :isShortResponse (is-short-response? message)
   :isVeryShortResponse (is-very-short-response? message)
```

```
  :hasQuestionMarks (has-question-marks? message)
  :hasDiscourseMarkers (has-discourse-markers? message)
  :hasSlangWords (has-slang-words? message)
  :hasAbbreviations (has-abbreviation? message)
  :hasHappyKeyword (has-happy-keyword? message)
  :hasSadKeyword (has-sad-keyword? message)
  :hasFearKeyword (has-fear-keyword? message)
  :hasSurpriseKeyword (has-surprise-keyword? message)
  :hasDisgustKeyword (has-disgust-keyword? message)
  :hasAngerKeyword (has-anger-keyword? message)})

(defn load-training-data
 []
 (try
   {:success true :data (doall (j/query mysql-db ["SELECT * FROM training_data"]))}
   (catch Exception e
     {:success false :message (.getMessage e)})))

(defn re-analyze
 []
 (let [data (:data (load-training-data))]
   (doseq [row data]
```

```
    (let [row-map row]
      (try
        (j/update! mysql-db :training_data (analyze-message (:message row-map)) ["id=?"
(:id row-map)])
        (catch Exception e
          (.printStackTrace e)))))))

(defn save-message
  [input]
  (let [training-data (merge (analyze-message (:message input)) {:emotion (:emotion
input)})]
    (try
      (println "saving " training-data)
      (j/insert! mysql-db :training_data training-data)
      {:success true}
      (catch Exception e
        {:success false :message (.getMessage e)}))))

(defn save-word
  [input]
  (try
    (j/insert! mysql-db :words input)
```

```
    (re-analyze)
    {:success true}
    (catch Exception e
      {:success false :message (.getMessage e)})))

(defn load-words
  []
  (try
    {:success true :data (doall (j/query mysql-db ["SELECT * FROM words"]))}
    (catch Exception e
      {:success false :message (.getMessage e)})))

(defn delete-word
  [input]
  (try
    (re-analyze)
    (j/delete! mysql-db :words ["id=?" (:id input)])
    {:success true}
    (catch Exception e
      {:success false :message (.getMessage e)})))

(defn delete-training-data
```

```
  [input]
  (try
    (j/delete! mysql-db :training_data ["id=?" (:id input)])
    {:success true}
    (catch Exception e
      {:success false :message (.getMessage e)})))

(defn count-all
  []
  (:count (first (j/query mysql-db ["SELECT count(*) AS count FROM training_data"]))))

(defn count-emotion
  [emotion]
  (:count (first (j/query mysql-db ["SELECT count(*) AS count FROM training_data
WHERE emotion = ?" emotion]))))

(defn count-property
  [emotion property value]
  (:count (first (j/query mysql-db [(str "SELECT count(*) AS count FROM training_data
WHERE emotion = ? AND " property "= ? ") emotion value]))))

(defn p-emotion
```

```
  [emotion]
  (if (zero? (count-all)) 0 (/ (count-emotion emotion) (count-all))))

(defn p-property-emotion
  [emotion property value]
  (if (zero? (count-emotion emotion)) 0 (/ (count-property emotion property value) (count-
emotion emotion))))

(defn emotion-value
  [emotion message]
  (let [message-map (analyze-message message)]
    {:emotion emotion
     :value (* (p-emotion emotion)
            (p-property-emotion emotion "hasAbbreviations" (:hasAbbreviations message-
map))
            (p-property-emotion emotion "hasAngerKeyword" (:hasAngerKeyword
message-map))
            (p-property-emotion emotion "hasCapitalization" (:hasCapitalization message-
map))
            (p-property-emotion emotion "hasDiscourseMarkers" (:hasDiscourseMarkers
message-map))
```

(p-property-emotion emotion "hasDisgustKeyword" (:hasDisgustKeyword message-map))

(p-property-emotion emotion "hasExclamationMarks" (:hasExclamationMarks message-map))

(p-property-emotion emotion "hasFearKeyword" (:hasFearKeyword message-map))

(p-property-emotion emotion "hasFullstopRepetition" (:hasFullstopRepetition message-map))

(p-property-emotion emotion "hasHappyKeyword" (:hasHappyKeyword message-map))

(p-property-emotion emotion "hasQuestionMarks" (:hasQuestionMarks message-map))

(p-property-emotion emotion "hasSadKeyword" (:hasSadKeyword message-map))

(p-property-emotion emotion "hasSlangWords" (:hasSlangWords message-map))

(p-property-emotion emotion "hasSurpriseKeyword" (:hasSurpriseKeyword message-map))

(p-property-emotion emotion "isLongResponse" (:isLongResponse message-map))

(p-property-emotion emotion "isShortResponse" (:isShortResponse message-map))

```
            (p-property-emotion emotion "isVeryLongResponse" (:isVeryLongResponse
message-map))
            (p-property-emotion emotion "isVeryShortResponse" (:isVeryShortResponse
message-map)))}))




(defn get-max-emotion
  [em1 em2]
  (if (> (:value em1) (:value em2)) em1 em2))


(defn get-emotion
  [message]
  (let [message-map (analyze-message message)]
    (let [emotion-values [(emotion-value "HAPPY" message)
                          (emotion-value "SAD" message)
                          (emotion-value "FEAR" message)
                          (emotion-value "SURPRISE" message)
                          (emotion-value "DISGUST" message)
                          (emotion-value "ANGER" message)]]
      (reduce get-max-emotion emotion-values))))
```

PUBLICATIONS

Eunice Njeri Mwangi, Stephen Kimani, Michael Kimwele. Textual Emotion Communication with Non-verbal Symbols in Online Environments. In Masaaki Kurosu, editor, Human-Computer Interaction. HCI International 2014, Proceedings, Part III. Volume 8512 of Lecture Notes in Computer Science, pages 42-48, Springer, 2014