Emotion detection on Myanmar texts

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ABSTRACT

At this age, World Wide Web is growing faster. Many companies have built and launch social media networks. People so widely use social media to get the latest news, to express their emotions or moods, to communicate with their friends and so on. Emotions of social media users are needed to analyze in order to apply in many areas. Many researchers do research on emotion detection using different techniques with their languages. Currently, there are no emotion detection systems for Myanmar (Burmese) language. So, this paper describes the emotion detection system for Myanmar language. This system uses our pre-constructed M-lexicon, a Myanmar word-emotion lexicon, in the detection process. This system detects six basic emotions such as happiness, sadness, anger, fear, surprise, and disgust. In order to determine certain emotion from the text, we also apply rule-based decision making on sentence nature. We use Facebook users' status, which has been written in Myanmar words. Emotions of user groups are also summarized in this system. Our approach achieves 86% accuracy for emotion detection in Myanmar texts.

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1. INTRODUCTION

Between ours, social media are most popular as a communication median. Most people spend their time on using the social media (such as Facebook, Twitter) in so many ways, such as posting videos, images and texts, sharing the others' post to express their emotions, interested information and getting up-to-date news around the world. The emotions of the social media users are most important in so many areas such as medical status, treatment, development process, pre-elections results, and so on.

Emotion involves feelings, experience, physiology, behavior, cognitions and conceptualization [1, 2]. According to WordNet Search 3.0, an emotion is "any strong feeling". An emotion is "a mental state associated with a wide variety of feelings, thoughts, behavioral responses, and a degree of pleasure or displeasure" [3]. Emotions are an important part of human nature that can be considered as heredity [4]. The expression of a particular emotion by different user is identified.

Researchers did researches to detect emotions from text using different techniques. Most of them are performed in English and their languages (Korean [5], Turkish [6], France [7], Arabic [8] etc.). Some of them apply existing lexicon (for example, NRC, EmoLex) and use Google translator for their languages. There is no research work to detect emotions from the text which are written in Myanmar language. Thus, we make this research to develop an emotion detection system for Myanmar language. In order to detect emotion, we apply lexicon-based emotion detection. We firstly construct a new word-emotion lexicon, namely M-lexicon [9]. This lexicon has six basic emotions are happiness (joy), sadness, anger, fear, disgust, and surprise as defined by Ekman [10-12]. We now apply M-lexicon in our emotion detection system. The system finds emotion words from the text post using M-lexicon and then determines emotion from the text post based our pre-defined rules. This system also determines the emotions of a post with feelings status. This system gathers all emotions values of the user and determines the users' emotional status from the collected emotions values. This system also produces the emotional status on group with different categories. The rest of this paper is organized as follows: section 2 discusses on the related works, while section 3 shows the research methodology in detail. Results are found in section 4 before concluding remarks in section 5.

2. RELATED WORKS

Most of the existing emotion analysis works focused on English language while some are addressed for other different languages. The works can be done by applying two main approaches which are lexicon-based and machine learning based approaches [13]. This section will provide a short review of research efforts put towards building and applying lexicon in detection from text.

A novel and totally automated extracting a high coverage and high precision emotion lexicon is presented in [14]. They used cross-sourced affection annotation from a social media network *rappler.com*. They built their emotion lexicon using distributional semantics, with the numerical scores associated with each emotion. They applied naive approach in classifying the emotion class. Although their method can significant improvement over the state-of-the art unsupervised approaches, they did not propagate emotion values for similar words.

A lexicon-based approach for emotion analysis from the Arabic text are developed [15]. They construct EmoLex lexicon manually by crowdsourcing on Mechanical Turk. They also apply the automatic machine translation (AMT) service, Google Translate, to translate original English language lexicon words to Arabic words. Then they also built a lexicon-based tool for emotion analysis. Their tool simply segments the text into a set of terms and counts how many terms belong to each lexicon. The emotion whose count is maximum becomes a detected emotion. Their method can easily detect emotion with high accuracy results. Nevertheless, the dataset was small and their results could not be trusted.

Lexicon-based approaches rely on previously generated lexical resources. The creating process of lexicon for less popular languages are difficult and time consuming. A lexicon-based method for sentiment analysis with Facebook data for Vietnamese language is proposed in [16]. They build Vietnamese emotion dictionary (VED) which contains noun, verb, adjective, and adverb and proposed features. In VED, each word has corresponding emotional values ranging from each most negative (-5) to the most positive (+5). They used six features to classify whether the sentence is emotional or not. They classified the emotions in subjective classification and sentiment classification steps. Their method has a good accuracy results but they cannot solve the big data problem.

Current sentiment analysis fails to describe the exact feelings of customers and the intensity of their reaction because it only informs whether the public reaction is positive or negative [17]. They proposed a method to classify texts to Paul Ekman's six standard emotions. Their model has two approaches: Natural language processing and emotion-words set, using several textual features and machine learning classification algorithms. They finally combined the approaches and proved that their model provides significant accuracy in classifying tweets but it only works on one lined headlines, messages and posts.

A new lexicon named EmoLex which contains 14,182 words in total was created by [18]. EmoLex is created by considering eight emotion types which are anger, disgust, fear, expectation, joy, sorrow, surprise, and trust and two sentiments (positive and negative). EmoLex, also known as NRC lexicon, listed English words. They show that the combined strength and wisdom of the crowds could be applied to construct a large, high-quality, term-emotion lexicon quickly and inexpensively. They also provided new version of lexicon for other languages. The lexicon contains over hundred language words which got by translating English terms using Google translate. NRC lexicon [19] could not say that it is correct for other language because they only focus on English texts.

Rule-based approach to sentiment analysis allows deep analysis of the emotion or opinion from content of the post or review. This provides enough information to single out separate positive and negative points about an entity or event. A review can include both positive and negative comments about a certain entity. In order to classify more deeply, a rule-based approach to clause-level sentiment analysis of reviews in Ukrainian language is demonstrated in [20]. Romanyshyn proposed twenty rules for sentiment classification of user reviews under two main rules: context-independent and context-dependent rules.

3. RESEARCH METHODOLOGY

This paper describes the emotion detection from text which is written in Myanmar language. This system is named as emotion detection on Myanmar texts (EDMTs) system. EDMTs detects the emotion from

Facebook users' posts and examines the emotional status of the users. The system also examines which kinds of emotion are indicated by the posts with feeling status. In order to do so, the system development includes four processing steps which are data collection, data pre-processing, emotion detection uses M-lexicon, and rules-based emotion examining. The overall system design is shown in Figure 1.

The system starts filtering the status depend on the specified user from the collected Facebook posts. The system then performs pre-processing step to extract words from each post. Each extract word is determined whether it is an emotion word or not by using M-lexicon. Finally, the system examines the emotional of the status by using our pre-defined rules. In addition, the system also generates the emotions of different types of user group. In this section, it is explained the results of research and at the same time is given the comprehensive discussion. Results can be presented in figures, graphs, tables and others that make the reader understand easily. The discussion can be made in several sub-chapters.

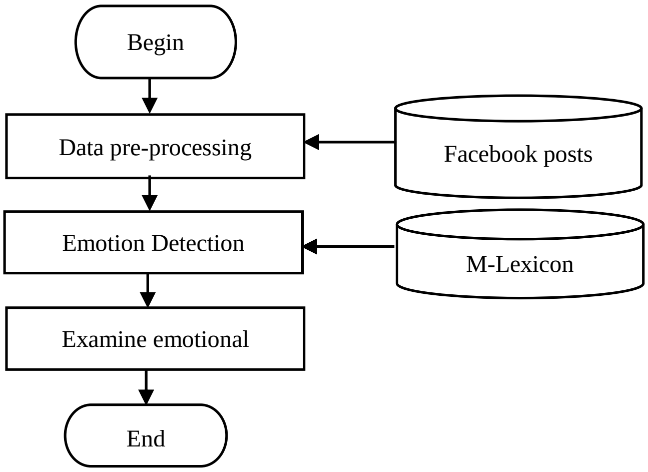


Figure 1. Architecture of EDMTs system

3.1. Data collection

Facebook is the most flexible social network sites (SNS) than others. Facebook allows their users to select the specific "networks" which they belong, such as geographic location, works, education. Each network many contain couples of users. Each Facebook user has a personal profile that shows their posts and content [21]. Each user maintains a "profile", which expresses the basic information such as the individual's year of graduation and hometown, as well as personal information, such as his or her name and whether he or she is single or in a relationship (i.e., "relationship status").

This system gets the users' available graduation, works, date of birth, gender from their profile information. They will be used in making the user grouping before generating the emotion. The detail of the user grouping process will be discussed later. Facebook also provides several ways of communicating between users. Users can interact with each other by sending private message. The user can also post the message on each other's "Walls" [4]. Facebook also offers the user to add the feeling status on the message. Reactions are Facebook's line-up of emoji that allow you to interact with the posts by giving on six different animated emotions which are Love, Haha, Wow, Sad, Angry, and the classic Like. This system collects Facebook users' post where texts are written in Myanmar (Burmese) language. Although there may have images or video posts, this system only takes text posts with feeling status or not. The system also collects user basic information such as age, gender, education, work to be used in group's emotion result.

3.2. Data pre-processing

In order to detect the emotion from the collected posts which is written in Myanmar language, the posts are needed to work on the pre-processing steps. Before doing pre-processing step, we briefly explain about the Myanmar language. Myanmar (Burmese) language [22], an official language in the Republic of the Union of Myanmar, is the Sino-Tibetan language spoken by 30 million people. According to history, Myanmar script draws its source from Brahmi script which flourished in India from about 500 B.C. to over 300AD [23, 24]. In Myanmar script, the sentences are written from left to right and clearly delimitated by a sentence boundary marker. There is no regular inter-word spacing, although the inter-phrase spacing may sometimes to be used [25]. Myanmar written style does not use white spaces between words or between syllables. Due to this, the word segmentation process of another language is not straightforward for Myanmar language. In our system, the posts are segmented by two steps. First of all, the syllable segmentation step is performed by using rule-based heuristic approach. The segmented syllables are then merged with the help of using a dictionary-based statistical based approach. Table 1 describes these steps.

The collected posts are segmented by using one of the Myanmar word segmentation tools, Word-Breaker [26] and the segmented posts are stored in our database. After doing the segmentation process on all collected posts, the system retrieves the selected Facebook user' posts from the database. Then the system works on each retrieved post. The post may have feeling status or not. Thus, the system first checking the post. If the post is with feeling status, the system will mark it as 'feeling post'. If not, the system finds unnecessary words because the posts may contain them. In other words, the system searches and removes stop-words from the posts. Stopwords, by definition, are meaningless words that have very low discrimination value [27]. Stop words are usually pronouns, prepositions, conjunctions, and particles. Those words carry no emotional information and are not necessary to find it in the M-lexicon. The stop-words are removed from the pre-processed post so that the computation of intensity is done with the appropriate words. After finishing the stop-words removal process, the extracted words are listed. Table 2 shows the pre-processing on a post.

Table 1. Segmented process

Original Post	နေကြတ်လိမ့်မယ် (Eclipse will happen)
Syllable Segment	နေ_ကြတ်_လိမ့်_မယ်
Merged words	နေကြတ်_လိမ့်_မယ်

Table 2. Data pre-processing output

Segmented post	မုန်းတီး_ဖွယ်ရာ_တွေ_ပါ_ပဲ (They are hateful)
Stop words	ဖွယ်ရာ, တွေ, ပါ, ပဲ
Extract words	မုန်းတီး (hateful)

3.3. Emotion detection

As described in section 2, many researchers developed emotion detection from text using lexicon-based and machine learning-based approaches. EDMTs use lexicon-based emotion detection approach for Myanmar texts. This approach utilizes a dictionary of words annotated with their emotional orientation and simply counts the words or aggregates the according values presented in texts. The emotion detection techniques are keyword based, learning based and hybrid-based approach. In this system, we apply simplest technique, keyword-based detection, in the emotion mining area.

Before we implement this detection system, we have previously created a Myanmar-word emotion lexicon namely M-lexicon. Now, we apply the lexicon in our EDMTs system. The M-lexicon contains words with associated six emotions values as shown in Table 3. The matched word with the extracted one is searching in the M-lexicon. If the word is found, the corresponding six emotions values will be also got. The values will be used in next examining step. If the posts have no emotion word, this step will be final step and the post will be labelled as 'No emotion is detected'. Table 4 describes the sample of emotion detection.

Table 3. Sample data of M-lexicon

	Word	Happiness	Sadness	Fear	Anger	Surprise	Disgust
1	ကျေနပ် (satisfied)	1	0	0	0	0	0
2	စိတ်နာ (hurt)	0	0	0	1	0	0
3	အံ့အားသင့် (amazing)	0	0	0	0	1	0
4	ထိတ်လန့် (afraid)	0	0	1	0	0	0
5	စိတ်ညစ် (sad)	0	1	0	0	0	0
6	မုန်းတီး (hate)	0	0	0	0	0	1
7	စိတ်အားငယ် (depressive)	0	1	0	0	0	0
8	ပျော်ရွှင် (joy)	1	0	0	0	0	0
9	စိတ်တို (angry)	0	0	0	1	0	0
10	သာသာယာယာ (happy)	1	0	0	0	0	0

Table 4. Emotion detection sample

Segmented Posts	အခု_ငါ_ပျော်ရွှင်_ရ_တာ_ကျေနပ်_တယ် (Now I'm satisfied to be happy)
Stop words	အခု, ငါ, ရ, တာ, တယ်
Extract words	ပျော်ရွှင် (happy), ကျေနပ် (satisfied)
Founded Emotions	ပျော်ရွှင် (1, 0, 0, 0, 0, 0)
	ကျေနပ် (1, 0, 0, 0, 0, 0)

3.4. Rules based emotion examining

Although the extracted words are found as emotion words, those words may be opposite emotion words or even become not emotion words due to the post nature. And, there may have more than one emotion in a post. In such cases, there is needed to examine which emotion word is certain for the post. Some problems are discussed in Table 5.

To solve these problems as in Table 5 and to improve the emotion detection, we apply rule-based classification and define a set of rules. Rule-based classification is used to classify the emotions in user posts using a set of "if-then" rules [28], the "if clause" is called "rule antecedent", and the then clause is called "rule consequent". We currently define twelve-rules for this process as in Table 6. The detected emotion words and original segmented posts are put as input to each rule. If the emotions are true with one of them, then the decision made upon the rule. For example, first sample post in Table 5 is true with the Rule 1, the last emotion 'Sadness' is selected as emotion for the post and the system denotes that user is in 'Sadness'. If emotions are not conditioned with every rule, the system detects that user does not have an emotion.

Table 5. Emotion detection problems

Sample Posts	Emotion words	Problems
အရမ်း_ပျော်_နေရာ _က_နေ_စိတ်ညစ်_ သွား_တယ် (I lost my sense of humor)	ပျော် (Happiness) စိတ်ညစ် (Sadness)	The post has two emotion words. Need to examine that the post expresses 'Happiness' emotion or 'Sadness'.
ကျွန်တော်_ပြော_လိုက်_လို့_သူ_ငို_သွား_တယ် (she is crying because I said)	ငို (Sadness)	Although this post has one emotion word, the post cannot be set as 'Sadness' structure. Because of the post talks about another.
ဒီနေ့_မ_ပျော်_ဘူး (I'm not happy today)	ပျော် (Happiness)	The post has one 'Happiness' emotion. Nevertheless, it does not express that emotion because there is negative word together with the emotion one.

Table 6. Emotion examination rules

Rules	Conditions and decision
I	If there are more than two emotions in a sentence, the last emotion value will be taken.
II	Although the word is an emotion in the lexicon, it may be not an emotion word. In such case, the word will be not an emotion word.
III	If there are emotions and the sentence is not referred to post owner, the emotion(s) will not be defined as emotion word(s).
IV	If there is more than one sentence and each sentence has emotion(s), the sentence which refers to post owner will only be considered.
V	If the word is more than one emotion, the emotion is determined on Pronoun.
VI	If the word is an emotion word and the sentence is having no pronoun, the hidden pronoun refers to post owner.
VII	If the word is emotion and tends to negative word, the emotional value is converted to opposite emotion. (Happiness <-> Sadness)
VIII	If the word is a negative word and the lexicon has no direct such word, the negative word in word phrase will be removed and search. If there exists, the emotion value is converted to opposite.
IX	If the word expresses two emotions, one of the emotions will be selected on the related end word.
X	If the word is negative together with negative, the word will not be considered as negative.
XI	If the word expresses an emotion and it is together with past tense, the word will not be considered.
XII	The word expresses emotion and above rules are not satisfied. In such case, the closest subjective words are found in two portions (before and after the word). The second portion is lastly found if there is no such word in the first portion.

The system finally denotes that each user is in which emotion by using maximum-based decision making process. The decision process is as shown in Figure 2. The algorithm accepts the user as 'filter_on' and the associated detected emotion values of posts. The algorithm sums values and finds the maximum value and then generates emotion of the user upon the value. For instance, a user has sum values 15, 19, 5, 6, 7, and 3 for happiness, sadness, anger, fear, surprise, and disgust emotion respectively. The maximum value is 19 (sadness), therefore the algorithm will produce 'User is in Sadness emotion'.

```
Input:  filter_on, detected_emotions [1…n]
Begin
            Happiness ← 0, sadness ← 0, fear ← 0, anger ← 0, surprise ← 0, disgust ← 0;
For each detected_emotions do
            Sum detected emotion count value into corresponding emotions_array
End For
            max_emotions ← findMaxEmotions(emotions_array);
            Generate Detected Emotions string using max_emotions
End
```

Figure 2. Emotion detection for user

3.5. Group users' emotion detection

This system also detects the emotions of users on different groups. The groups will be age-range, education, gender, and works at. The group members will be chosen depending on user profile information. Facebook users are divided into two groups on gender such as male group and female group. There may have sub-group on their degrees, student, and non-graduate. The system estimates the emotions of teachers, doctors, students, and other works user group. The emotions of the age-range group, as listed in Table 7, are also detected and generated.

The detection process of these groups emotional status is worked as in Figure 3. The algorithm takes the user list, the detected emotions of the users, and the type of group as described earlier. The filtered user groups are getting upon the type of group. Upon the filtered result group, the related emotions values of each user in group are added and found the maximum emotion in six emotion values.

Table 7. Age-range groups

Group	Age-Range	
	Min	Max
A	13	15
B	16	20
C	21	24
D	25	30
E	31	35
F	36	40
G	41	50
H	50	55
I	56	60
J	61	65
K	66	70
L	71	75
M	76	80

```
Input:  users [1...n], emotions [1...n], group_type
Begin
            user_group [1...m] ← find users on group_type
            emotions_array ← 0;
For each user_group do
            For each emotion do
               Sum detected emotion count value into corresponding emotions_array
    End For
End For
            max_emotions ← findMaxEmotions(emotions_array);
            Generate Detected Emotions for group_type using max_emotions
End
```

Figure 3. Emotion detection for groups

The algorithm finally generates the emotional status of the selected user group. For instance, the system creates a user group whose age in the range 13 to 15, and adds the emotions values of each user in the group. The added values are values 335, 159, 125, 146, 97, and 83 for happiness, sadness, anger, fear, surprise, and disgust emotion respectively. The maximum value is 335 (happiness), therefore the algorithm will produce 'Users whose age in the range 13 to 15 years are in Happiness emotion'.

4. EXPREIMENTAL RESULTS

To evaluate our detection approach, we collect a dataset of Myanmar text posts from Facebook. We collected 10389 posts with 98 Facebook users. The number of reactions of those posts are shown in Figure 4. The total 'Like' count is 4251 while 'Love' count is 3169. The 'HaHa' reaction count is 1025. The number of 'Wow', 'Sad', and 'Angry' reactions are 613, 827, and 198 respectively. The 'Disgust' and 'Fear' reaction counts are 39 and 72 each. Precision, recall, and F-measure are used to evaluate the classification performance for each emotion type. For each post, we manually labelled emotion type by human to compute accuracy results.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

In both equations, the true positive (TP) is the number of status correctly labelled as belonging to particular emotion class, false positive (FP) number of status incorrectly labelled as belonging to a particular emotion class, and false negative (FN) is the number of status were not labelled as belonging to the particular emotion class but should be labelled. Precision (1) is the number of correctly labelled posts retrieved by the approach divided by all the posts retrieved by the approach. Recall (2) is the number of correctly labelled posts retrieved by the approach divided by the posts annotated as correct. After calculating the precision and recall, the values are used to calculate the F-measure, the harmonic mean of precision and recall taking both metrics into account in (3):

$$F - measure = 2 * \frac{Precision * Recall}{Precision + Recall} \tag{3}$$

The results of measuring the accuracy of our approach to automatic detection with the collected Facebook posts are shown in Figure 5. Our method obtained average 86% of f-measure for detecting the six basic emotions from Myanmar text written posts.

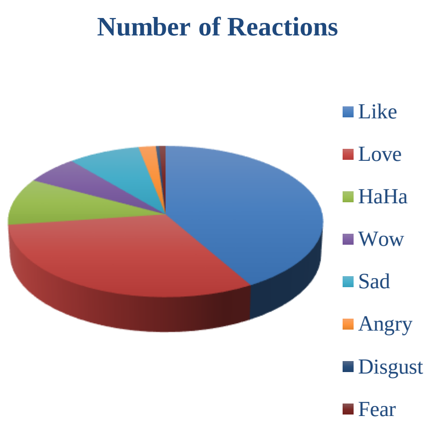
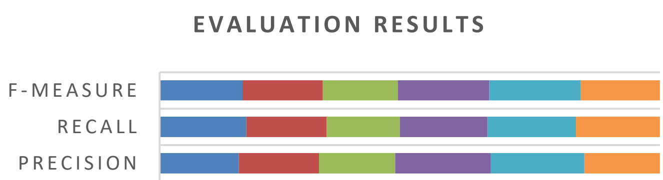


Figure 4. Reactions count



	Precision	Recall	F-measure
Happiness	0,813	0,966	0,883
Sadness	0,829	0,892	0,859
Fear	0,783	0,818	0,8
Anger	0,988	0,97	0,978
Surprise	0,962	0,987	0,975
Disgust	0,778	0,933	0,848

Figure 5. Evaluation results

5. CONCLUSION

In this work, we have introduced lexicon-based emotion detection system for Myanmar language called EDMTs. Before this system developed, we firstly created M-lexicon using Matrices, TF-IDF scheme.

M-lexicon is used in the EDMTs system to detect emotion words in the given Facebook user posts. We additionally applied rule-based emotion examining to correctly detect the emotions of user on each Myanmar text posts. We described the rules for emotion detection and also stated that the system could summarize the emotions on the same users' group. This system is successfully annotated emotion for Myanmar language at 86% of overall accuracy of 98 Facebook users. In this paper, we evaluate the performance of our detecting system on 98 users with 10,389 posts. This system does not contain the emoticon, slang words, and other abnormal words in current. In future, new rules may be appended to the existing rules to have more correct detection and this system can be also extended to get more correct emotion values.

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