A comparative analysis of detection mechanisms for emotion detection

Vimala Balakrishnan[1*], Marian Cynthia Martin[1], Wandeep Kaur[1], Amir Javed[2]

[1]Faculty of Computer Science and Information Technology, University of Malaya, Kuala Lumpur, Malaysia
[2]Faculty of Computer Science and Information Technology, Cardiff University, Wales, United Kingdom

*vimala.balakrishnan@um.edu.my

Abstract. This paper compared the performance of emotion detection mechanisms using dataset crawled from Facebook diabetes support group pages. To be specific, string-based Multinomial Naïve Bayes algorithm, NRC Emotion Lexicon (Emolex) and Indico API were used to detect five emotions present in 2475 Facebook posts, namely, fear, joy, sad, anger and surprise. Both accuracy and F-score measures were used to assess the effectiveness of the algorithms in detecting the emotions. Findings indicate string-based Multinomial Naïve Bayes to outperform both Emolex (i.e. 82% vs. 78%) and Indico API (i.e. 82% vs. 50%). Further analysis also revealed emotions such as joy, fear and sadness to be of the highest frequencies for the diabetes community. Implications of the findings and emotions detected are further discussed in this paper.

1. Introduction

Emotion Detection (ED) or analysis concerns the computational study of natural language expressions in recognizing various emotions from text, such as joy, trust, fear, surprise, and sadness, among others [1, 2] In recent years, more users freely share their opinions, suggestions and experience on social media platforms, and thus generating a lot of studies on sentiment and emotion analysis with applications in social sciences [3, 4], business [5], medical [6, 7], politics [8] etc.

Nevertheless, research on the use of social media for health-related purposes is limited, particularly in mining users' emotion. Emotion is deemed to be powerful elicitors and indicators of human motivational and perceptual states, with evidences documenting the contagious effects in social media are due to users' emotional states that are often transmitted from offline to online life [9]. For example, depression, anxiety and distress have been commonly reported among diabetics [10]. A study analysing 690 Facebook diabetes comments found almost 29% of posts featured an effort by the poster to provide emotional support to other members [11].

ED is often performed using two main techniques including Machine Learning (ML) which extracts features using a criterion or a combination of criteria, and lexicon-based approach that involves the use of dictionaries with mapped words (to emotions). Popular ML algorithms include Random Forest, Naïve Bayes and Support Vector Machine whereas other tools and mechanisms include the NRC Emotion Lexicon or Emolex [12], Microsoft Azure products and Indico API. The current study aims to compare the performance of three different types of mechanisms: (i) ML approach using string-based Multinomial Naïve Bayes, (ii) lexicon-based Emolex and (iii) Indico API which is a public tool.

We targeted the online Facebook diabetes community comprising of all three types of diabetes with the followers including patients and care-givers (e.g. parents, social workers etc.). Diabetes is one of the largest global health concern with almost 451 million people (age 18-99 years) diagnosed with the disease worldwide, and this number is expected to increase to 693 million by 2040 [13].

The remainder of the paper is structured as follows: Section 2 presents the background on ED, and the mechanisms related to the study. This is followed by the research methodology, which encompasses the corpus, ED approach and the evaluation of the proposed approach. Results and discussion are presented in Section 4.

2. Background

Emotion analysis is often performed using two main techniques, that is, lexicon-approach which involves the use of dictionaries that have mapped words to specific emotions (e.g. SentiWordNet) or the machine-learning approach. Examples of the former approach include works of [14] who compared various lexicons to detect four primary emotions (i.e. anger, fear, joy, and sadness) using textual sources ranging from fairy tales to news headlines, and authors who detected emotions based on social media sources [15, 16]. On the other hand, Reference [12] proposed a keyword-based emotion filtering mechanism that identifies posts containing some form of emotion using keywords based on the NRC Emotion Lexicon (Emolex). Emolex is a lexicon consisting of 14,181 words with eight basic emotions (i.e. anger, fear, anticipation, trust, surprise, sadness, joy, and disgust).

The machine-learning approach on the other hand, classifies text using syntactic and/or linguistic features [1], and is based on a set of collected data to train the classifiers. Therefore, the approach is highly dependent on the availability of labelled or annotated datasets. Popular machine-learning algorithms used in emotion analysis are Support Vector Machines [17, 18], logistic regressions [18] and Convolutional and Recurrent Neural Network [19, 20]. Studies that have used string vector with k-nearest neighbour (KNN) algorithm found improved text classification of 5% compared to using the traditional method of numerical vectors [21]. Reference [22] proposed a string-based MNB that converts each post into a string of vectors to map the words around the word identified as an emotion using bag of words concept, with results showing improved emotion classifications as well.

Alternatively, there are many established and freely available application programming interfaces (APIs) that support text, emotion and image analysis, often provided by giant corporations such as IBM and Google, among others. One such example is the Indico API, which uses advanced machine-learning techniques supporting various functions such as text analytics, sentiment analysis, image analysis and emotion recognition.

The present study aims to classify users' unstructured online communication into their respective emotions, and to compare the performance of three identified mechanisms, namely, Emolex, string-based MNB and Indico API.

3. Methodology

This study is part of a much larger study looking into the communication patterns of the online diabetes community. This section presents the processes required for the emotion analysis, emphasizing on the diabetes corpus preparation, emotion classification, and the evaluation process.

A. Diabetes Corpus

We gathered data from Facebook by targeting the online diabetes community, using Facebook Graph API. Pre-processing included the removal of spams, emojis, misspelled words, etc. resulting in a total of 82 120 posts. Of these, approximately 15 000 posts were selected for further Part of Speech (POS) tagging, tokenization, stop word removal and stemming, using the Standard Core NLP parser. Out of these, 6 000 posts were randomly annotated by seven annotators comprising of medical practitioners and linguists, with an inter-coder reliability of 89%.

B. Emotion Detection

Three mechanisms were tested based on the curated diabetes dataset. First, Emolex containing mapped words to emotions were used to detect five primary emotions, namely, anger, fear, joy, sadness, surprise. Second, the posts were passed through the string-based MNB (see further details in [22]). Emolex provides several emotions for a post, whereas the string-based MNB selects the emotion with the highest intensity for a final classification. Finally, Indico API works by detecting emotions and returning a set of five scores for a post, with the highest score indicating the strongest emotion.

Therefore, for sample post as below:

My body hasn't made insulin since 1973, but the government (Medicare) every year makes me have a blood test to see if my body is making any. How many times do I have to tell them I don't make any insulin.

Emolex detects ***anger, sad*** and ***surprise*** whereas string-based MNB classifies the post as ***anger***.

Indico API returns anger (0.539), joy (0.049), fear (0.321), sad (0.077) and surprise (0.014). We performed the final emotion classification by categorizing the said post based on the highest score, hence, the sentence above will be classified as ***anger***.

C. Evaluation

For evaluating the effectiveness of the emotion detection mechanisms, 800 posts were randomly selected. We used both accuracy and F-score (i.e. a harmonic balance between recall and precision) with a higher score for both the metrics indicating a better classification. Additionally, a web-based text reading and analysis environment, called Voyant was used to identify the top topics discussed in the form of word clouds.

4. Results and Discussion

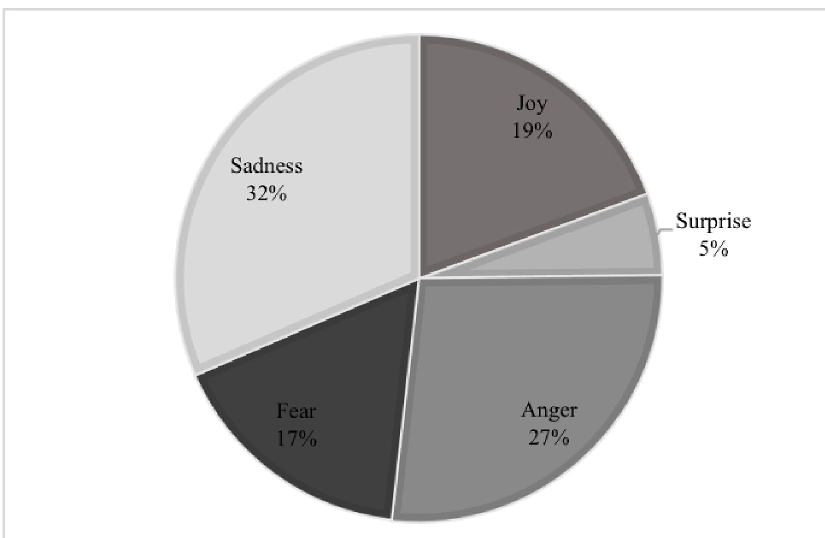

Figure 1. Emotion frequencies

Figure 1 illustrates the classification breakdown for the five emotions, based on the average classifications for all three mechanisms. Generally, it can be observed that sadness emerged as the top negative emotion followed by anger whereas joy ranked top for the positive emotions. Figure 2 and Table 1 below depict the top topics/words discussed among the community.

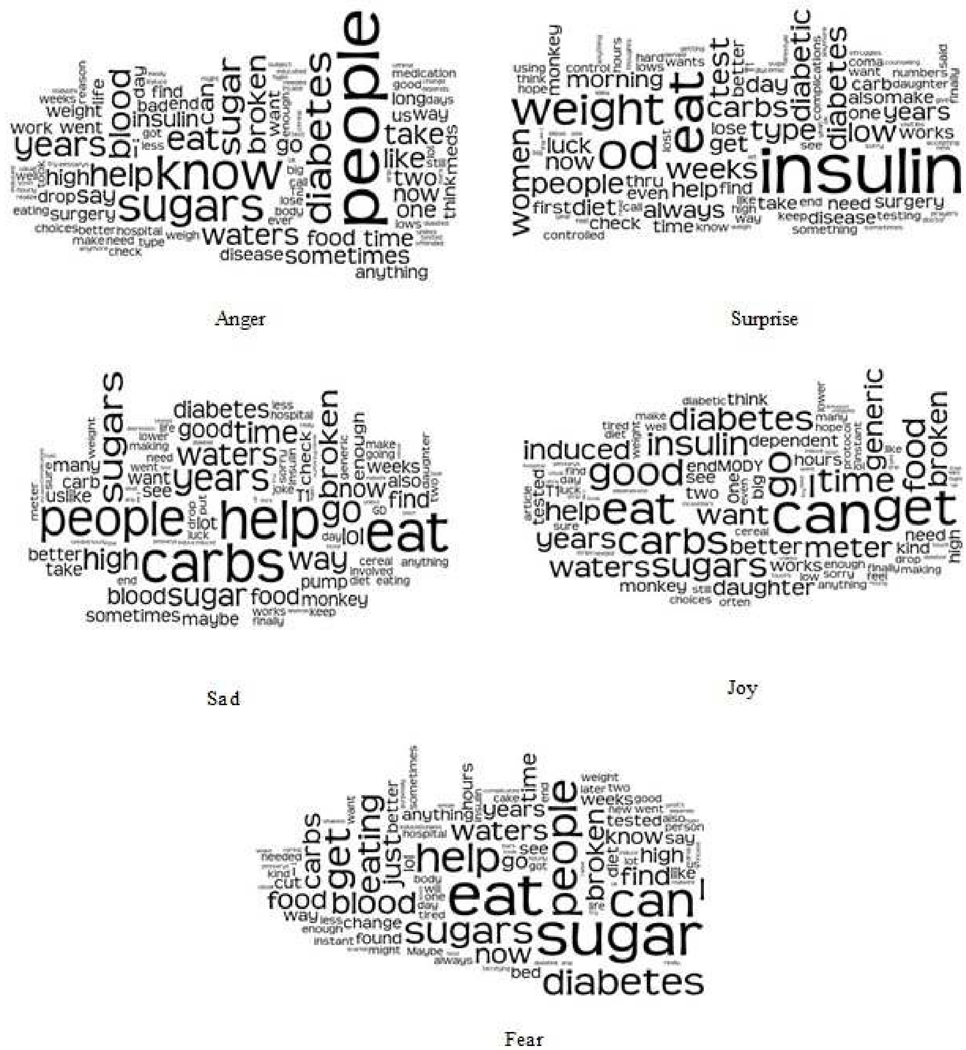

Figure 2. Top topics for each emotion

Table 1. Top Ten Topics For Each Emotion

Sad		Surprise		Joy		Fear		Anger	
Words	***N***	***Words***	***N***	***Words***	***N***	***Words***	***N***	***Words***	***N***
Eat	117	OD	76	Can	136	Eat	130	Diabetes	57
Time	83	Eat	61	Eat	136	Can	121	Sugar	55
Sugar	80	Insulin	43	Diabetes	86	Diabetes	87	Help	45
Year	76	Diabetes	41	Insulin	87	Help	65	People	41
Help	69	Type	32	Carbs	77	People	53	Know	41
Carb	68	Carb	32	Good	77	Sugar	35	Years	39
People	49	Weight	31	Food	40	Blood	39	High	32
Blood	44	Diabetic	23	Sugars	32	Carbs	29	Blood	28
Water	17	Women	16	Water	13	Eating	29	Broken	16
Broken	16	Test	17	Meter	14	Food	25	Water	12

Looking at the topics, words such as *eat, diabetes, sugar, insulin* and *help* seemed to appear across all emotions. For example, the sample posts below were extracted for the topic "*eat*":

Feeling guilty about your food choices could actually have a bigger impact on your metabolism than the food you're ***eat****ing!* **- Surprise**

I completely sympathize! I like eggs but not enough to ***eat*** *them everyday! I also spike in the morning even with one piece of whole wheat toast* **- Sad**

Sugar free pudding, I used to ***eat*** *sugar chocolate pudding & mix some peanut butter with it and have a sliced apple to dip it in for a snack.* **- Joy**

Way toooo many carbs and sugars for someone with diabetes to ***eat*** *. . .* ***eat*** *this you'll have a major sugar spike . . . weigh the pros and cons is* ***eat****ing a piece of this cake worth losing a toe or your eyesight?* **- Fear**

Topics for joy were mostly related to a good diet, carbs, etc. suggesting that the majority of those emoting joy are probably sharing their successful recipes or lifestyle changes, and providing mental and emotional support to one another. This is very much in line with studies that found Facebook groups to serve as effective avenues to connect, share knowledge and provide peer support to each other [11, 23]. Sample posts below provide support to this finding:

How ***can*** *I help support a friend who is newly diagnosed with Type 2 diabetes?*

Only 6g of ***carbs*** *in this yummy dish! Enjoy it with some leftover Thanksgiving turkey instead of the sausage!*

Finally, Table 2 shows the comparative performance for all three mechanisms based on their accuracies and F-measures. MNB-string outperformed all the other mechanisms, regardless of the emotions detected. This is probably due to the reduced dimensionality that helps to match attributes within the text by removing attributes that are otherwise considered useless. For example, in this study, the focus was on words that can be associated with emotions, hence attributes like “appear, pharmaceuticals etc.” were dropped by the algorithm in order to reduce over fitting and produce more accurate results. Indico API had the poorest classification performance.

Table 2. Emotion Detection Effectiveness

Emotion	**Emolex**		**MNB-string**		**Indico API**	
	Accuracy	***F-measure***	***Accuracy***	***F-measure***	***Accuracy***	***F-measure***
Surprise	0.520	0.684	0.752	0.854	0.429	0.431
Sadness	0.572	0.728	0.605	0.744	0.448	0.440
Joy	0.748	0.856	0.820	0.870	0.478	0.492
Fear	0.827	0.905	0.891	0.870	0.590	0.628
Anger	0.558	0.716	0.656	0.771	0.483	0.501
Average	***0.65***	***0.78***	***0.75***	***0.82***	***0.49***	***0.50***

5. Conclusion

The study analysed human emotions based on online communication among diabetes community using three different mechanisms, namely, a string-vector based MNB, Emolex and also Indico API.

Generally, findings indicate the machine-learning technique to have outperformed both Emolex and the API, with an average accuracy of 75% and F-score of 82%. Moreover, the majority of the posts were found to be joyful, followed by anger and sadness, probably further attesting to the severity of the disease studied, that is, diabetes. This is also supported by the top topics identified that were mostly related to the disease and its implications, and also the support one provides to each other in the community

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