International Journal of Engineering Science and Advanced Technology (IJESAT)
Vol 25 Issue 04, APR, 2025

Detecting Mental Disorders in social media Through Emotional Patterns - The case of Anorexia and Depression

[1]Rajana Balavamsi,Shaik [2]Arshad Ahammad, [3]Sarampati Pavan Sai,[4]Dr. B. Varaprasad Rao

[1,2,3]B. Tech Student, Dept. of Computer Science and Engineering, R.V.R. & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India
[4]Professor, Dept.of Computer Science and Engineering, R.V.R & J.C College of Engineering, Chowdavaram, Guntur, Andhra Pradesh, India

ABSTRACT: Millions of people around the world are affected by one or more mental disorders that interfere in their thinking and in their behavior. A timely detection of these issues is challenging but crucial, since it could open the possibility to offer help to people before the illness gets worse. One alternative to accomplish this is to monitor how people express themselves, i.e., for example what and how they write, or even a step further, what emotions they express in their social media communications. In this study, we analyse two computational representations that aim to model the presence and changes of the emotions expressed by social media users. In our evaluation we use two recent public datasets for two important mental disorders: Depression & Anorexia. The obtained results suggest that the presence and variability of emotions, captured by the proposed representations, allow to highlight important information about social media users suffering from depression or anorexia. Furthermore, the fusion of both representations can boost the performance, equalling the best reported approach for depression and barely behind the top performer for anorexia by only 1 percent. Moreover, these representations open the possibility to add some interpretability to the results.

1. INTRODUCTION

The introduction section provides a contextual view of detection of mental disorders in social media through emotional patterns, emphasizing the significance of mental health awareness and the impact of social media on individuals' expressions and behaviours. Motivated by the need for early intervention, the research utilizes computational representations like Bag-of-Emotions (BoE) and Bag-of-Sentiments (BoSE) to capture emotional patterns in social media data. The experimental setup involves data collection, feature extraction, and classification using machine learning algorithms. The findings indicate promising results in detecting Depression and Anorexia, with BoE and BoSE outperforming traditional approaches. This study highlights the potential of leveraging social media data for proactive mental health support and suggests future research directions focusing on scalability and ethical considerations.

1.1 Background

The study focuses on detecting mental disorders through emotional patterns in social media data. It highlights the importance of mental health awareness and the role of social media in shaping individuals' expressions and behaviors related to mental health. Motivated by the need for early detection and intervention, the research utilizes computational representations like Bag-of-Emotions (BoE), Bag-of-Sentiments (BoSE), and Bag-of-Words (BoW) to capture emotional content in social media posts.

The experimental setup involves data collection, feature extraction, and classification using machine learning algorithms. Results show promising outcomes in detecting Depression and Anorexia using emotional patterns, with BoE and BoSE representations outperforming traditional approaches. The study's findings have implications for early prediction and intervention in mental health issues, leveraging social media data for proactive screening. Future research directions include addressing scalability and ethical concerns, as well as exploring multimodal data sources for enhanced predictive capabilities.

1.2. Problem Statement

The study investigates the detection of mental disorders in social media through emotional patterns, acknowledging the critical role of mental health awareness and social media in shaping individuals' expressions and behaviours. Motivated by the importance of early intervention, the research employs computational representations like Bag-of-Emotions (BoE) and Bag-of-Sentiments (BoSE) to capture emotional patterns in social media data. The experimental setup includes data collection, feature extraction, and classification using machine learning algorithms. Promising results are found in detecting Depression and Anorexia, with BoE and BoSE outperforming traditional methods. The study underscores the potential of social media for proactive mental health support and suggests future research directions addressing scalability and ethical concerns.

1.3 Objectives

The study aims to assess the effectiveness of computational representations of emotional patterns in social media data for detecting signs of Depression and Anorexia. Specific objectives include analyzing emotional patterns, evaluating computational representations, comparing detection accuracy with traditional methods, exploring fusion strategies, and assessing transferability between disorders. Methodological goals involve data collection, algorithm implementation, and rigorous experimentation. Practical implications include potential use for early detection and intervention in mental health, offering recommendations for healthcare professionals and policymakers.

1.4 Limitations for the Existing Techniques

Interpretability: Existing techniques, such as deep learning models and ensemble approaches, may lack interpretability, making it challenging to understand how specific emotional patterns contribute to the detection of mental disorders.

External Validity: Some approaches, when tested on mental health patients, may demonstrate limited external validity, highlighting the need for more robust validation and generalizability across diverse populations.

Complexity: The complex designs and training frameworks of certain models can hinder their practical application in real-world settings, especially for healthcare professionals seeking straightforward and interpretable diagnostic tools.

Limited Emotional Nuances: Traditional linguistic and sentiment analysis approaches may overlook fine-grained emotional nuances that are crucial for detecting subtle signs of Depression and Anorexia in social media communications.

Data Collection Bias: Techniques relying on crowdsourced data or specific social media platforms may introduce bias in the training data, potentially affecting the model's performance and generalizability.

Privacy Concerns: Analysing social media data for mental health screening raises ethical concerns related to user privacy and data protection, necessitating careful consideration of data anonymization and consent issues.

Disorder Severity Prediction (Mild, Moderate, Severe)

Predicting not just the presence but also the severity of mental disorders such as Depression and Anorexia (categorized as mild, moderate, and severe) enhances the practical utility of mental health detection systems. Severity prediction involves a deeper emotional analysis, where fine-grained emotional patterns, sentiment intensity, and linguistic cues are analyzed. Machine learning models such as Support Vector Machines (SVM), Random Forests, and deep neural networks are commonly used for this multi-class classification task. Features like emotional variability, word embeddings, and posting behaviors are critical in distinguishing between different severity levels, with datasets like eRisk often labeled with severity annotations based on clinical assessments and user histories.

The severity levels are identified by capturing and analyzing the intensity and variability of emotional expressions across users' posts. For instance, mild cases show slight emotional deviations and subtle negative expressions, moderate cases reveal stronger signs of emotional distress and mood instability, while severe cases exhibit extreme fluctuations, persistent negative emotions, and language reflecting hopelessness or risk behaviors. Representations such as BoSE and D-BoSE significantly aid this process, with the dynamic analysis of sub-emotions (like standard deviation and variance) strongly correlating with the degree of severity. Evaluation metrics like Precision, Recall, F1-score, and confusion matrices for each class help measure the performance and reliability of these models.

Integrating severity prediction into mental health monitoring systems allows early intervention strategies to be more precisely targeted. Cases flagged as severe can be prioritized for immediate attention by mental health professionals, while mild or moderate cases can receive timely preventive care. This approach not only improves healthcare outcomes but also optimizes resource allocation in mental health services. Future enhancements could involve the use of personalized models that take into account demographic, temporal, and behavioral data, offering a holistic, dynamic, and ethical framework for mental health severity analysis on social media platforms.

2. LITERATURE REVIEW

R. C. Kessler, E. J. Bromet, P. de Jonge, V. Shahly and M. Wilcox ,“ The burden of depressive illness,” Public Health Perspectives Depressive Disorders, in N. L. Cohen Ed., Johns Hopkins Univ. Press, 2017, pp. 40–66.

Even when these indirect effects of major depressive disorder (MDD) on early mortality are taken into consideration, a good case could be made that the overall human costs of depression are substantially underestimated by Global Burden of Disease (GBD) due to the fact that the GBD methodology focused on the effects of current disorders on productive functioning and mortality risk. Three other important types of burdens were excluded. The first are the burdens associated with the fact that early onset depression has adverse effects on life course role incumbency. The second are the burdens associated with the fact that both lifetime and current depressive illness influence role functioning in ways that go well beyond the effects on productive functioning that were the focus of GBD. The third are the burdens associated with the fact that lifetime history of depression influences risk of onset, persistence, and severity of a wide range of other disorders not captured in the GBD analysis of indirect effects through suicide and ischemic heart disease. We present an overview of the literature on all three of these additional burdens of depressive illness in this chapter.

In addition, we explore the argument that at least some of the putative burden of depression is actually due to comorbid disorders, especially comorbid anxiety disorders. But before turning to any of these topics, we present a brief overview of the basic descriptive epidemiology of depressive illness, as a background in this literature is important for understanding the processes underlying the burden of depressive illness. (PsycInfo Database Record (c) 2023 APA, all rights reserved)

[1] M. Trotzek, S. Koitka, and C. Friedrich, “Linguistic metadata augmented classifiers at the CLEF 2017 task for early detection of depression,” in Proc. 8th Int. Conf. CLEF Assoc., 2017.

Methods for automatic early detection of depressed individuals based on written texts can help in research of this disorder and especially offer better assistance to those affected. FHDO Biomedical Computer Science Group (BCSG) has submitted results obtained from five models for the CLEF 2017 eRisk task for early detection of depression that are described in this paper.

All models utilize linguistic metainformation extracted from the texts of each evaluated user and combine them with classifiers based on Bag of Words (BoW) models, Paragraph Vector, Latent Semantic Analysis (LSA), and Recurrent Neural Networks(RNN) using Long Short-Term Memory (LSTM). BCSG has achieved top performance according to ERDE5 and F1 score for this task.

[2] Juan S. Lara, Mario Ezra Aragon, Fabio A. Gonz ´ alez, Manuel Montes-y-G ´omez This paper presents the Deep Bag-of-Sub-Emotions (DeepBoSE), a novel deep learning model for depression detection in social media. The model is formulated such that it internally computes differentiable Bag-of-Features (BoF) representation that incorporates emotional information. This is achieved by a reinterpretation of classical weighting schemes like term frequency-inverse document frequency into probabilistic deep learning operations.

An important advantage of the proposed method is that it can be trained under the transfer learning paradigm, which is useful to enhance conventional BoF models that cannot be directly integrated into deep learning architectures. Experiments were performed in the eRisk17 and eRisk18 datasets for the depression detection task; results show that DeepBoSE outperforms conventional BoF representations and it is competitive with the state of the art, achieving a F1-score over the positive class of 0.64 ineRisk17 and 0.65 in eRisk18.

[3] Y. Tausczik and J. Pennebaker, “The psychological meaning of words: LIWC and computerized text analysis methods,” J. Lang.Soc. Psychol., vol. 29, pp. 24–54, 2010.

We are in the midst of a technological revolution whereby, for the first time, researchers can link daily word use to a broad array of real-world behaviours. This article reviews several computerized text analysis methods and describes how Linguistic Inquiry and Word Count (LIWC) was created and validated. LIWC is a transparent text analysis program that counts words in psychologically meaningful categories. Empirical results using LIWC demonstrate its ability to detect meaning in a wide variety of experimental settings, including to show attentional focus, emotionality, social relationships, thinking styles, and individual differences.

[4] M. Trotzek, S. Koitka, and C. Friedrich, “Word embeddings and linguistic metadata at the CLEF 2018 tasks for early detection of depression and anorexia,” in Proc. 9th Int. Conf. CLEF Assoc., 2018.

Developing methods for the early detection of mental disorders like depression and anorexia based on written text has become an important aspect with the rise of social media platforms. The CLEF2018 eRisk shared task consists of two subtasks focused on the detection of these two disorders and FHDO Biomedical Computer Science Group (BCSG) has submitted results obtained from four machine learning models as well as from a final late fusion ensemble. This paper describes these models based on user-level linguistic metadata, Bags of Words (BoW), neural word embeddings, and Convolutional Neural Networks (CNN). BCSG has achieved top performance according to ERDE50 and F1 scorein both subtasks.

[5] D. E. Losada, F. Crestani, and J. Parapar, "eRISK 2017: CLEF lab onearly risk prediction on the internet: Experimental foundations," inProc. 8th Int. Conf. CLEF Assoc., 2017, pp. 346–360

Depression is a common and very important health issue with serious effects in the daily life of people. Recently, several researchers have explored the analysis of user-generated data in social media to detect and diagnose signs of this mental disorder in individuals. In this regard, we tackled the depression detection task in social media considering the idea that terms located in phrases exposing personal statements (i.e., phrases characterized using singular first person pronouns) have a special value for revealing signs of depression. First, we assessed the value of the personal statements for depression detection in social media. Second, we adapted an automatic approach that emphasizes the personal statements by means of a feature selection method and a term weighting scheme. Finally, we addressed the task in hand as an early detection problem, where the aim is to detect traces of depression with as much anticipation as possible. For evaluating these ideas, benchmark Reddit data for depression detection was used. The obtained results indicate that personal statements have high relevance for revealing traces of depression. Furthermore, the results on early scenarios demonstrated that the proposed approach achieves high competitiveness compared with state-of-the-art methods, while maintaining its simplicity and interpretability.

[6] H. Schwartz et al."Towards assessing changes in degree of depression through Facebook," in Proc. Workshop Comput. Linguistics Clin. Psychol.: From Linguistic Signal Clin. Reality, 2014, pp. 118–125.

Depression is typically diagnosed as being present or absent. However, depression severity is believed to be continuously distributed rather than dichotomous. Severity may vary for a given patient daily and seasonally as a function of many variables ranging from life events to environmental factors. Repeated population-scale assessment of depression through questionnaires is expensive. In this paper we use survey responses and status updates from 28,749 Facebook users to develop a regression model that predicts users' degree of depression based on their Face-book status updates.

Our user-level predictive accuracy is modest, significantly outperforming a baseline of average user sentiment. We use our model to estimate user changes in depression across seasons, and find, consistent with literature, users' degree of depression most often increases from summer to winter. We then show the potential to study factors driving individuals' level of depression by looking at its most highly correlated language feature Repeated population-scale assessment of depression through questionnaires is expensive. In this paper we use survey responses and status updates from 28,749 Facebook users to develop a regression model that predicts users' degree of depression based on their Face-book status updates.

[7] D. Preo tiuc-Pietro, S. Volkova, V. Lampos, Y. Bachrach, and ¸N. Aletras, "Studying user income through language, behaviour and affect in social media," PloS One, vol. 10, no. 9, 2015, Art.no. e0138717.

Automatically inferring user demographics from social media posts is useful for both social science research and a range of downstream applications in marketing and politics. We present the first extensive study where user behaviour on Twitter is used to build a predictive model of income. We apply non-linear methods for regression, i.e. Gaussian Processes, achieving strong correlation between predicted and actual user income. This allows us to shed light on the factors that characterize income on Twitter and analyses their interplay with user emotions and sentiment, perceived psycho-demographics and language use expressed through the topics of their posts. Our analysis uncovers correlations between different feature categories and income, some of which reflect common belief e.g. higher perceived education and intelligence indicates higher earnings, known differences e.g. gender and age differences, however, others show novel findings e.g. higher income users express more fear and anger, whereas lower income users express more of the time emotion and opinions.

[8] d. funez et al., "unsl's participation at erisk 2018 lab," in proc. 9th int. conf. clef assoc., 2018.

Mental state assessment by analysing user-generated content is a field that has recently attracted considerable attention. Today, many people are increasingly utilizing online social media platforms to share their feelings and moods. This provides a unique opportunity for researchers and health practitioners to proactively identify linguistic markers or patterns that correlate with mental disorders such as depression, schizophrenia, or suicide behaviour.

This survey describes and reviews the approaches that have been proposed for mental state assessment and identification of disorders using online digital records. The presented studies are organized according to the assessment technology and the feature extraction process conducted. We also present a series of studies which explore different aspects of the language and behaviour of individuals suffering from mental disorders, and discuss various aspects related to the development of experimental frameworks. Furthermore, ethical considerations regarding the treatment of individuals' data are outlined. The main contributions of this survey are a comprehensive analysis of the proposed approaches for online mental state assessment on social media, a structured categorization of the methods according to their design principles, lessons learnt over the years and a discussion on possible avenues for future research.

[9] J. Pennington, R. Socher, and C. Manning, "GloVe: Global vectorsfor wordrepresentation," in Proc. Conf. Empir. Methods Natural Lang. Process., 2014, pp. 1532– 1543.

Recent methods for learning vector space representations of words have succeeded in capturing fine-grained semantic and syntactic regularities using vector arithmetic, but the origin of these regularities has remained opaque. We analyze and make explicit the model properties needed for such regularities to emerge in word vectors. The result is a new global log-bilinear regression model that combines the advantages of the two major model families in the literature: global matrix factorization and local context window methods.

Our model efficiently leverages statistical information by training only on the nonzero elements in a word-word co-occurrence matrix, rather than on the entire sparse matrix or on individual context windows in a large corpus. The model produces a vector space with meaningful substructure, as evidenced by its performance of 75% on a recent work analogy task. It also outperforms related models on similarity tasks and named entity recognition.

[10] D. Preotiuc -Pietro et al., "The role of personality, age and gender in tweeting about mental illnesses," in Proc. 2nd Workshop Comput. Linguistics Clin. Psychol., 2015, pp. 21–30

Mental illnesses, such as depression and posttraumatic stress disorder (PTSD), are highly underdiagnosed globally. Populations sharing similar demographics and personality traits are known to be more at risk than others. In this study, we characterize the language use of users disclosing their mental illness on Twit-ter. Language-derived personality and demo-graphic estimates show surprisingly strong performance in distinguishing users that tweet a diagnosis of depression or PTSD from random controls, reaching an area under the receiver-operating characteristic curve – AUC – of around .8 in all our binary classification tasks. In fact, when distinguishing users disclosing depression from those disclosing PTSD, the single feature of estimated age shows nearly as strong performance (AUC = .806) as using thousands of topics (AUC = .819) or tens of thousands of n-grams (AUC = .812). We also find that differential language analyses, controlled for demographics, recover many symptoms associated with the mental illnesses.

3. METHODOLOGIES USED

3.1 Architecture

Data Collection:

Describe the process of collecting social media data related to Depression and Anorexia, including the selection of appropriate datasets and the ethical considerations involved in data acquisition.

Emotional Pattern Analysis:

Explain the methodology for analyzing emotional patterns in social media content, focusing on the extraction of fine-grained emotions from text using lexicons like EmoLEX and sentiment analysis techniques.

Computational Representations:

Detail the creation of computational representations based on emotional patterns, such as Bag-ofEmotions (BoE) and Bag-of-Sentiments (BoSE), to capture the emotional content of social media communications.

Machine Learning Models:
Discuss the machine learning algorithms employed for classifying emotional patterns associated with Depression and Anorexia, including the use of neural networks, convolutional neural networks, and deep learning classifiers.

Fusion Strategies:
Explain the fusion strategies used to combine static and dynamic representations, such as early and late fusion techniques, to enhance the detection of mental health disorders through emotional patterns.

Evaluation Metrics:
Define the performance metrics used to evaluate the effectiveness of the proposed methodologies, including accuracy, precision, recall, F1 score, and area under the curve (AUC).

Experimental Setup:
Outline the experimental design, including the division of datasets into training and testing sets, cross-validation procedures, and parameter tuning for machine learning models.

Results Analysis:
Present and analyses the results of detecting emotional patterns related to Depression and Anorexia, discussing the performance of the computational representations and the impact of fusion strategies on detection accuracy.

Interpretability:
Interpret the findings in the context of mental health screening, highlighting the significance of emotional patterns in identifying early signs of mental disorders and the potential implications of the healthcare.

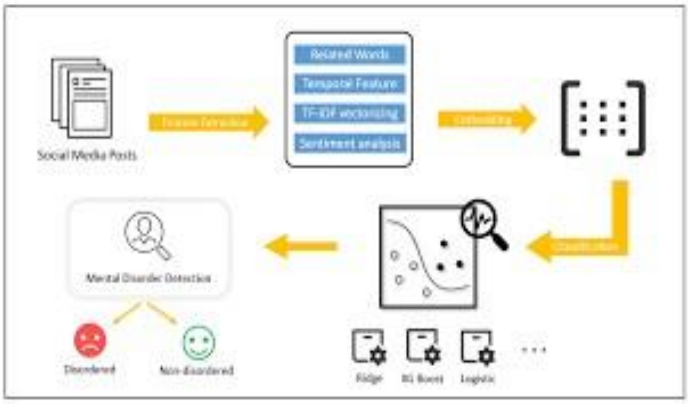


Fig.3.1.1Architecture

3.2 Datasets to be used:

eRisk 2018 Evaluation Task:
Utilize the datasets from the eRisk 2018 evaluation task, which contain posts from users on the Reddit platform. Include two categories of users: positive users affected by either Anorexia or Depression and a control group of users without any mental disorder.

Sample Dataset from reddit platform

```
INDIVIDUAL>
ID>test_subject25&lt;/ID&gt;
WRITING>
    &lt;TITLE&gt;  &lt;/TITLE&gt;
    &lt;DATE&gt; 2015-03-15 23:52:36 &lt;/DATE&gt;
    &lt;INFO&gt; reddit post &lt;/INFO&gt;
    &lt;TEXT&gt; Malcom In the middle.Will take away your social life and has seven seasons so plenty of quantity &lt;/TEXT&gt;
/WRITING>
WRITING>
    &lt;TITLE&gt;  &lt;/TITLE&gt;
    &lt;DATE&gt; 2014-05-11 22:08:32 &lt;/DATE&gt;
    &lt;INFO&gt; reddit post &lt;/INFO&gt;
    &lt;TEXT&gt; Maybe the new Need For speed Game &lt;/TEXT&gt;
/WRITING>
WRITING>
    &lt;TITLE&gt;  &lt;/TITLE&gt;
    &lt;DATE&gt; 2014-05-09 05:06:32 &lt;/DATE&gt;
    &lt;INFO&gt; reddit post &lt;/INFO&gt;
    &lt;TEXT&gt; Best play through of prison architect I have probably ever seen
idn't get to watch the whole factorio episode cuz I was in Math class but it seems to have potential maybe go to like an episode 3 or something
 remain &lt;/TEXT&gt;
/WRITING>
WRITING>
    &lt;TITLE&gt;  &lt;/TITLE&gt;
    &lt;DATE&gt; 2014-04-14 01:58:41 &lt;/DATE&gt;
    &lt;INFO&gt; reddit post &lt;/INFO&gt;
    &lt;TEXT&gt; Need for speed Rivals &lt;/TEXT&gt;
/WRITING>
/INDIVIDUAL>
```

1. **Data Collection Process**:
Collect social media posts from individuals who explicitly mention being diagnosed with clinical Depression or Anorexia by a medical specialist. Ensure that the data collection process adheres to ethical guidelines and respects user privacy and confidentiality.
2. **Dataset Characteristics**:
Include posts that reflect a range of emotions, sentiments, and linguistic features associated with Depression and Anorexia. Ensure that the dataset is diverse and representative of the target population to enhance the generalizability of the findings.
3. **Annotation and Labelling:**
Annotate the dataset with labels indicating whether a post is from a positive user (with Depression or Anorexia) or a control user (without any mental disorder). Ensure that the labelling process is consistent and reliable to support the training and evaluation of machine learning models.
4. **Dataset Split**:
Divide the dataset into training and testing sets to train the detection models and evaluate their performance. Consider using cross-validation techniques to assess the robustness of the models and prevent overfitting.

Mental Dissorders Data Sets Used for Experimentation

Data set	Training		Test	
	P	C	P	C
Users dep eRisk'18	135	752	79	741
avg. num. posts	367.1	640.7	514.7	680.9
avg num. words per post	27.4	21.8	27.6	23.7
avg. activity period (days)	586.43	625.0	786.9	702.5
Users anor eRisk'18	20	132	41	279
avg. num. posts	372.6	587.2	424.9	542.5
avg num. words per post	41.2	20.9	35.7	20.9
avg. activity period (days)	803.3	641.5	798.9	670.6

(P = Positive, C = Control).

5. **Data Preprocessing:**
Preprocess the text data by removing noise, tokenizing the text, and converting it into suitable input formats for the machine learning algorithms. Apply techniques such as text normalization, stop-word removal, and vectorization to prepare the data for analysis.

4. PROPOSED MODEL

EMOTION-BASED REPRESENTATION:

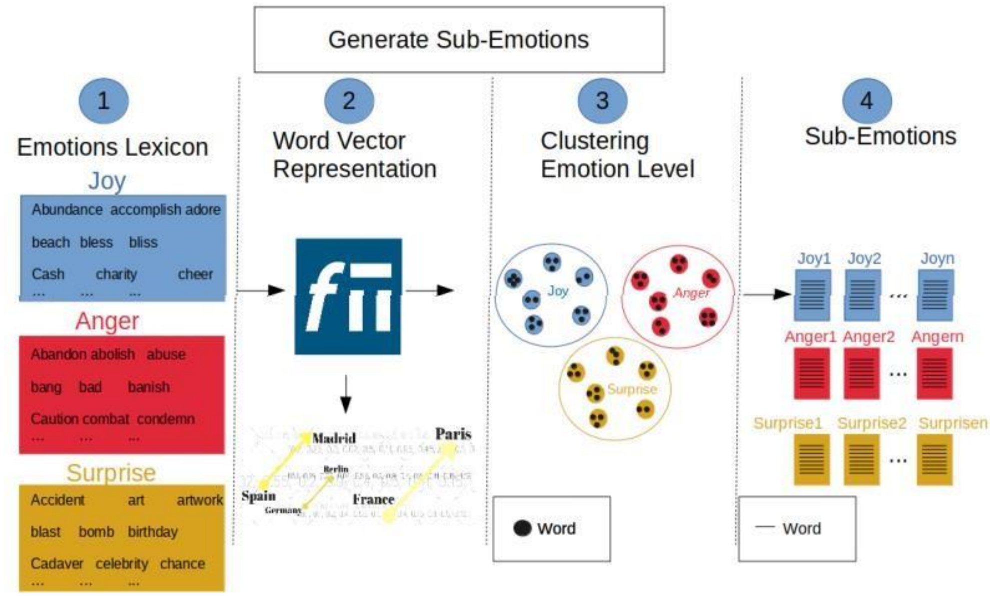


Fig. 4.1. Procedure to generate the sub-emotions for each emotion from the given lexical resource.

Methodology:

- We represent set of emotions as E= {E1, E2…..En} .
- Each emotion is represented as Ei= {w1, w2….w_n}.
- For each word we create a vector by using fast text (pre-trained sub-word embedding.
- After concluding vector for every word, we apply AP (Affinity Propagation).
- After applying this algorithm, clusters different sub-emotions. So, each emotion is modelled as a set of sub-emotions. i.e., Ei= {s1, s2….,s_n}.

Conversion of text to sub-emotions:

Basically , each document d is represented as a vector of weights associated to sub-emotions, d=<w1,w2,....,wm> where m is the total number of generated sub-emotions and 0<=wi<=1 represents the relevance of sub-emotion Si to the document d.This weight is computed in a tf-idf fashion as,

$$wi = freq(si,d).log(|D|/\#D(Si))$$

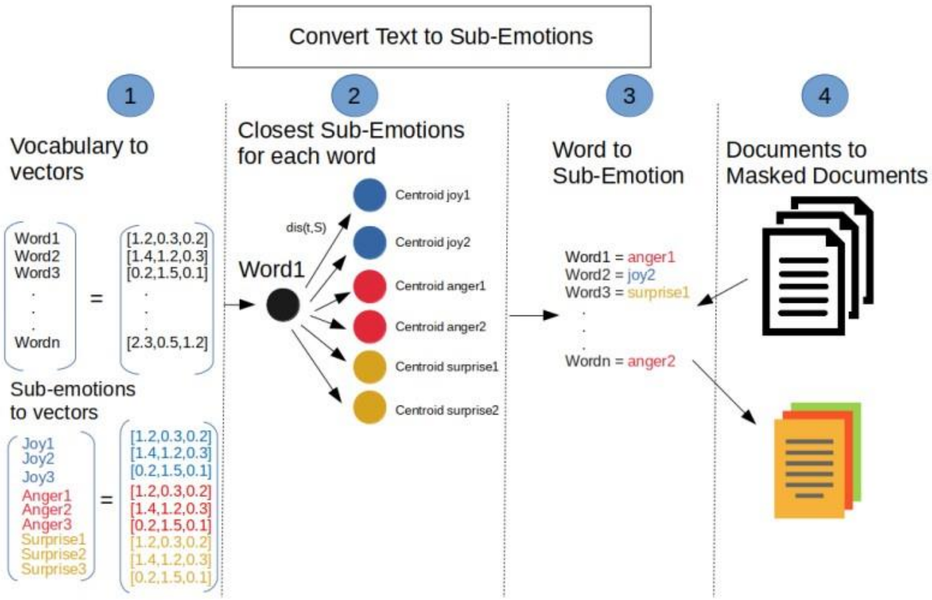


Fig. 4.2. Procedure to transform the texts to sub-emotions sequences.

Delta Bose:

- We first divide the post history of each user in n-parts or chunks.
- Then for each chunk we calculate its BoSE representation.
- Our purpose is to model the temporal variability of the emotions, so we represent each subemotion by eight statistical values, they are (mean, sum, max, min, standard deviation, variance, average, median)

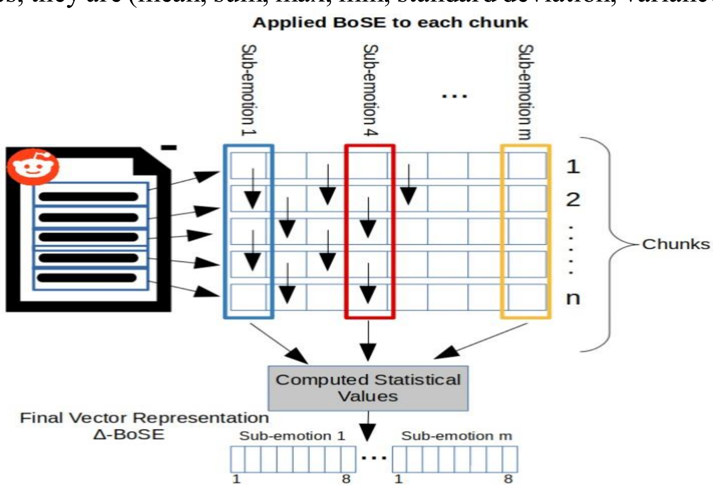


Fig. 4.3. Construction of the D-BoSE representation. First, BoSE is obtained for each part of the document; then, statistical values are calculated for each sub-emotion creating a new vector representation.

5. RESULTS

Comparison Against eRisk Participants:

The study compared the performance of the proposed approach with participants in the eRisk-2018 shared task for Anorexia and Depression detection. The results demonstrated competitive performance, with the fusion of emotional representations enhancing the classification accuracy.

Present and analyze the results of detecting emotional patterns related to Depression and Anorexia, discussing the performance of the computational representations and the impact of fusion strategies on detection accuracy. Interpret the findings in the context of mental health screening, highlighting the significance of emotional patterns in identifying early signs of mental disorders and the potential implications for healthcare interventions.

F1 Score:

The F1 score over the positive class is presented in this table for the initial evaluation. It shows that the BoSE representation outperforms all baseline results, including deep learning models, indicating the effectiveness of the approach.

F_1-Scores for BoSE, Δ-BoSE and Their Combinations

	Depression'18	Anorexia'18
BoSE	0.63	0.82
Δ-BoSE	0.53	0.79
Early Fusion	0.62	0.77
Late Fusion	**0.64**	**0.84**

This table compares the F1-scores for BoSE, D-BoSE, and their combinations for depression and anorexia. It shows that the fusion of BoSE and D-BoSE achieves competitive results in both tasks, highlighting the effectiveness of the combined approach.

F_1-Scores for BoSE, Δ-BoSE and Their Combinations

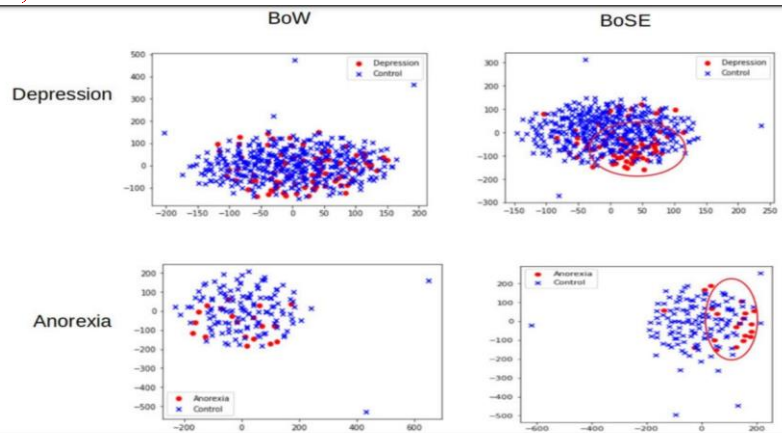
	Depression'18	Anorexia'18
BoSE	0.63	0.82
Δ-BoSE	0.53	0.79
Early Fusion	0.62	0.77
Late Fusion	**0.64**	**0.84**

The table compares the approach of fusing BoSE and D-BoSE against other participants in the eRisk 2018 evaluation tasks. It demonstrates that the approach achieves competitive results in -both tasks, focusing on accurate classifications.

F_1, $Precision$ and $Recall$ Results Over the Positive Class: BoSE Fusion Approach and the Top Performers at eRisk

Task	Depression 2018			Anorexia 2018		
Metric	F1	P	R	F1	P	R
first place	**0.64**	0.64	0.65	**0.85**	0.87	**0.83**
second place	0.60	0.53	**0.70**	0.79	**0.91**	0.71
third place	0.58	0.60	0.56	0.76	0.79	0.73
Late Fusion	**0.64**	**0.67**	0.61	0.84	0.87	0.80

This figure illustrates the advantage of using BoSE over Bag of Words (BoW) in building a better classification function. It shows that BoSE allows the classifier to capture more specific topics and emotions, leading to improved classification performance.



The results by chunk in the data sets are presented in this figure. It shows the F1 results over time, indicating how the classification performance evolves as more data is accumulated.

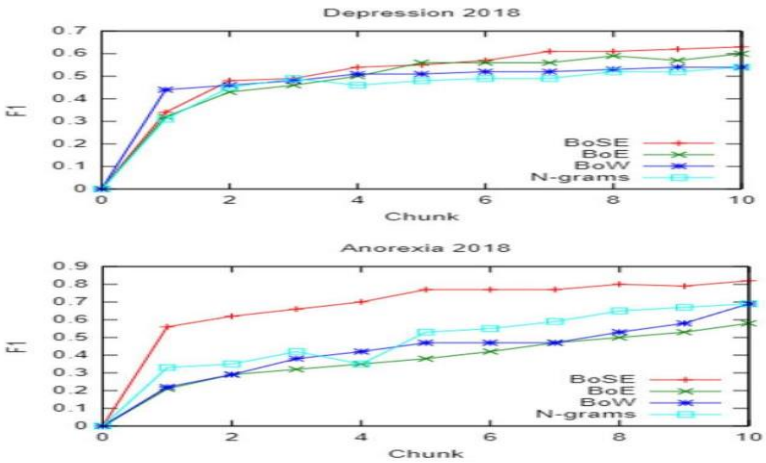


Fig. 5.2. Results by chunk in the data sets. X-axis represent the chunks and Y -axis the F1 result.

A comparison of emotional signals between the control and mental disorder groups is shown in this figure. It highlights the emotional variability and differences in emotional expressions between the two groups over time.

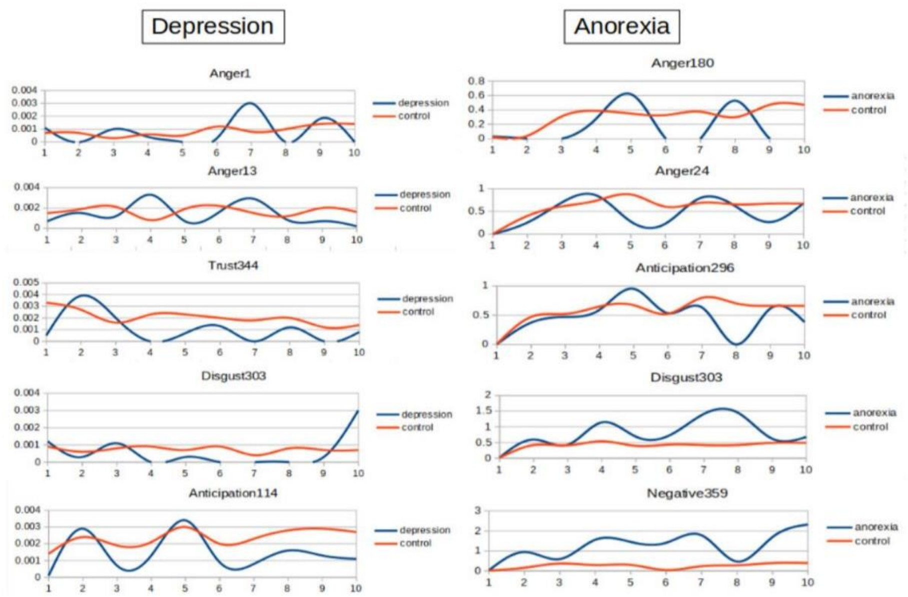


Fig. 5.3. Comparison of the emotional signals between control and mental-disorder groups. Xaxis represents the chunks (time span) and Y -axis represents the average value of the sub emotion at each chunk.

6. CONCLUSION AND FUTURE WORK

Conclusion:

The automatically extracted sub-emotions present useful information that helps the detection of these two mental disorders. On the one hand, the BoSE representation obtained better results than the proposed baselines, including some deep learning approaches and also improved the results of only using broad emotions as features. On the other hand, the inclusion of a dynamic analysis over the sub-emotions, called Delta BoSE improved the detection of users that presents signs of anorexia and depression, showing the usefulness of considering the changes of sub-emotions over time.

Future Work:

Exploring Additional Mental Disorders: Consider expanding the study to include other mental health conditions beyond depression and anorexia. Analyzing emotional patterns for a broader range of disorders could provide valuable insights into early detection and intervention strategies. Enhancing Emotional Representations: Investigate further refinements to the emotional representations used in the study. Exploring different sub-emotions or incorporating additional emotional features could improve the accuracy of detecting mental disorders in social media content. Collaboration with Mental Health Professionals: Collaborate with mental health professionals and researchers to validate the findings and explore practical applications of the research outcomes. Engaging experts in the field can provide valuable insights and ensure the relevance of the study in clinical settings.

7. REFERENCES

[1] R. C. Kessler, E. J. Bromet, P. de Jonge, V. Shahly, and M. Wilcox, “The burden of depressive illness,” Public Health Perspectives Depressive Disorders, in N. L. Cohen Ed., Johns Hopkins Univ. Press, 2017, pp. 40–66.

[2] W. H. Organisation, “Mental health: Fact sheet,” 2019. [Online]. Available: https://www.euro.who.int/en/health-topics/ noncommunicable-diseases/mental-health

[3] M. Renteria-Rodriguez, “Salud mental en mexico,” 2018. [Online]. Available: https://foroconsultivo.org.mx/INCyTU/index.php/ notas/sociedad/91-7-salud-mental-en-mexicon- [4] S. Guntuku, D. Yaden, M. Kern, L. Ungar, and J. Eichstaedt, “Detecting depression and mental illness on social media: An integrative review,” Curr. Opin. Behav. Sci., vol. 18, pp. 43–49, 2017. [5] J. Pestian, H. Nasrallah, P. Matykiewicz, A. Bennett, and A. Leenaars, “Suicide note classification using natural language processing: A content analysislin heidelberg,” Biomed. Informat. Insights, vol. 3, 2010, Art. no. BII.

[6] P. Chikersal et al., “Understanding client support strategies to improve clinical outcomes in an online mental health intervention,” in Proc. CHI Conf. Hum. Factors Comput. Syst., 2020, pp. 1–16.

[7] M. Kosinski, D. Stillwell, and T. Graepel, “Private traits and attributes are predictable from digital records of human behavior,” Proc. Nat. Acad. Sci. USA, vol. 110, pp. 5802–5805, 2013.

[8] M. Kosinski, Y. Bachrach, P. Kohli, D. Stillwell, and T. Graepel, “Manifestations of user personality in website choice and behaviour on online social networks,” Mach. Learn., vol. 95, pp. 357–380, 2014.

D. Preo tiuc-Pietro, S. Volkova, V. Lampos, Y. Bachrach, and ¸ N. Aletras, “Studying user income through language, behaviour and affect in social media,” PloS One, vol. 10, no. 9, 2015, Art. no. e0138717.

[10] T. Correa, A. Willard Hinsley, and H. G. De Zuniga, “Who interacts on the web?: The intersection of users’ personality and social media use,” Comput. Hum. Behav., vol. 26, no. 2, pp. 247–253, 2010.

[11] S. Volkova and Y. Bachrach, “Inferring perceived demographics from user emotional tone and user-environment emotional contrast,” in Proc. 54th Annu. Meeting Assoc. Comput. Linguistics, 2016, pp. 1567–1578

[12] D. Ram ırez-Cifuentes and A. Freire, “UPF’s participation at the CLEF eRisk 2018: Early risk prediction on the Internet,” in Proc. 9th Int. Conf. CLEF Assoc., 2018, pp. 1–12.

[13] H. Schwartz et al.“Towards assessing changes in degree of depression through Facebook,” in Proc. Workshop Comput. Linguistics Clin. Psychol.: From Linguistic Signal Clin. Reality, 2014, pp. 118–125.

[14] G. Coopersmith, M. Dredze, and C. Harman, "Quantifying mental health signals in Twitter," in Proc. Workshop Comput. Linguistics Clin. Psychol., 2014, pp. 51–60.
[15] C. Xuetong, D. Martin, W. Thomas, and E. Suzanne, "What about mood swings? Identifying depression on Twitter with temporal measures of emotions," in Companion Proc. Web Conf. Int. World Wide Web Conf. Steering Committee, 2018, pp. 1653–1660.
[16] M. Aragon, A. L opez-Monroy, L. Gonz alez-Gurrola, and M. Montes-y G omez, "Detecting depression in social media using fine-grained emotions," in Proc. Conf. North Amer. Chapter Assoc. Comput. Linguistics: Hum. Lang. Technol., 2019, pp. 1481–1486.
[17] C. Mathers and D. Loncar, "Projections of global mortality and burden of disease from 2002 to 2030, " PLoS Med., vol. 3, 2006, Art. no. e442.
[18] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, "Predicting depression via social media," in Proc. 7th Int. AAAI Conf. Weblogs Soc. Media, 2013. [Online]. Available: https://www.microsoft.com/en-us/research/publication/predicting-depressionvia-social-media
[19] M. De Choudhury, S. Counts, and E. Horvitz, "Social media as a measurement tool of depression in populations," in Proc. 5th Annu. ACM Web Sci. Conf., 2013, pp. 47–56.
[20] S. Tsugawa, Y. Kikuchi, F. Kishino, K. Nakajima, Y. Itoh, and H. Ohsaki, "Recognizing depression from Twitter activity," in Proc. 33rd Annu. ACM Conf. Hum. Factors Comput. Syst., 2015, pp. 3187–3196.
[21] G. Coppersmith, C. Harman, and M. Dredze, "Measuring post traumatic stress disorder in Twitter," in Proc. 8th Int. AAAI Conf. Weblogs Soc. Media, 2014, pp. 579–582.
[22] Y. Tausczik and J. Pennebaker, "The psychological meaning of words: LIWC and computerized text analysis methods," J. Lang. Soc. Psychol., vol. 29, pp. 24–54, 2010.
[23] G. Coppersmith, M. Dredze, C. Harman, and K. Hollingshead, "From ADHD to SAD: Analyzing the language of mental health on Twitter through self-reported diagnoses," in Proc. 2nd Workshop Comput. Linguistics Clin. Psychol., 2015, pp. 1–10.
[24] M. Trotzek, S. Koitka, and C. Friedrich, "Linguistic metadata augmented classifiers at the CLEF 2017 task for early detection of depression," in Proc. 8th Int. Conf. CLEF Assoc., 2017.