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Detecting Anorexia Nervosa through Emotional Dynamics in Social Media

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***Abstract*—Mental health conditions affect millions of people worldwide, often disrupting their thoughts and behaviours. Detecting these issues early is both challenging and essential, as timely intervention can prevent the situation from worsening. One promising approach is to observe how individuals communicate—particularly through what they write and the emotions they express on social media. This study explores two computational methods designed to capture emotional patterns and changes in social media posts. To evaluate these methods, focused on individuals with Depression and Anorexia. The results show that both the presence and fluctuation of expressed emotions can reveal meaningful insights about users affected by these conditions. Moreover, matching the best-known approach for detecting depression and coming very close (just 1% behind) to the top-performing method for anorexia. In addition to strong performance, these emotion-based representations offer the benefit of being trust the model's decisions..**

Keywords—Mental health, Emotion analysis, social media, Depression detection, Anorexia detection, Computational modelling, Emotion variability, Affective computing, Interpretability, Machine learning.

I. INTRODUCTION

Mental disorders disrupt an individual's thinking and behaviour, and their impact can range from mild to severe, often affecting the person's ability to manage everyday tasks. Conditions like depression and anorexia are among the most widespread mental health issues, potentially triggered by a single traumatic event or a series of stressful experiences. These disorders are even more prevalent in regions facing widespread violence or frequent natural disasters. For example, a 2018 study in Mexico found that 17% of the population lives with at least one mental disorder, and one in four individuals is expected to experience such a condition . In today's world, social interactions increasingly occur through online platforms. This shift presents both human communication. It aims the analysis of emotional patterns in social media content. Previous research has examined users' emotions on social media, often focusing on tone and contrast to infer attributes like age, gender, political views, sexual orientation, income, and personality traits. These studies highlight how emotional expression can reveal meaningful user information. Traditional approaches to detecting these disorders have primarily focused on linguistic cues and sentiment analysis, often using general sentiment polarities like positive or negative. These laid the groundwork for more advanced methods that use fine-grained emotional categories such as "anger," "joy," or "surprise." In earlier work, we introduced a novel way to represent emotional content by combining emotion lexicons with word embeddings. Using clustering techniques, we grouped similar emotional words into "sub-emotions," which offered a more nuanced and flexible representation. This method showed promising results, especially for depression detection, by identifying unique emotional distributions in affected users Building on this success, the current study expands that approach. We introduce a dynamic component that not only captures the presence of sub-emotions but also tracks how they change over time—acknowledging that individuals with mental disorders often show fluctuating emotional patterns. In recent years, social media platforms have emerged as powerful spaces for individuals to express their emotions, struggles, and experiences . This temporal analysis is integrated with the original static model to create a more comprehensive representation. When combined, these models—referred to as BOSE (Bag-of-Sub Emotions) and Δ-BOSE (Delta-BOSE)—demonstrate competitive performance, closely matching or exceeding current state-of-the-art methods. The static BOSE model is based on the premise that traditional emotion lexicons lack the granularity needed to capture subtle but important emotional cues. For instance, words like "furious," "angry," and "upset" are all tagged under "anger" but reflect different intensities and nuances. BOSE addresses this by clustering emotional words based on their embeddings, enabling a more precise emotional profile for each user. Meanwhile, Δ-BOSE is inspired by the idea that individuals with mental health disorders often exhibit greater emotional variability than healthy users. This dynamic model captures how sub emotions vary over time by extracting statistical features from the temporal sequences of users' posts.

I. LITERATURE REVIEW

R. Kessler.et.al., [1]. studied about depression is a mental health disorder characterized by a persistent lack of interest in routine activities, often leading to significant impairment in daily functioning. M. De Choudhury.et.al., [2]. explored the automatic detection of depression using data obtained through crowdsourcing, typically involving users who have self reported a clinical diagnosis. H. Schwartz.et.al., [3], A widely adopted technique in these studies involves extracting lexical features, such as individual words and word n-grams, and applying conventional machine learning classifiers. Y. Tausczik.et.al., [4] To identify linguistic patterns that differ between users with depression. M. Dredze.et.al., [5] Research employing LIWC-based features has demonstrated improved characterization of mental states, though the performance gain over basic lexical methods remains modest. M. Trotzek.et.al., [6], More recent approaches have utilized ensemble techniques, integrating both lexical and LIWC features with deep learning. For example, the combination of neural models with features like word frequency, user-level linguistic metadata, and word 2018 shared task for depression detection. Despite the progress, these methods often suffer from a lack of given that such systems are intended to assist mental health professionals rather than make autonomous clinical decisions. Some recent studies have attempted to mitigate this issue by developing techniques for user characterization and data visualization, aimed at providing actionable insights to psychologists.

II. METHODOLOGY

A. System Architecture

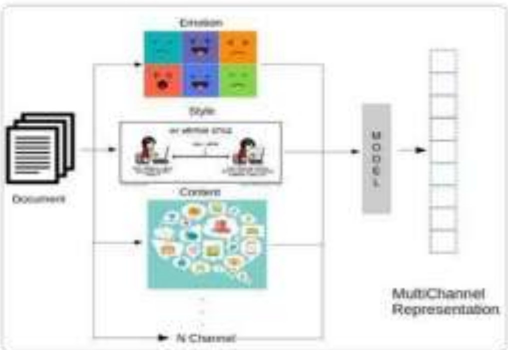

Figure 1: System Architecture

III. IMPLEMENTATION

1. Data Collection: Collect social media data using keywords (e.g., "thins po," "pro-ana") and user behaviour patterns.
2. Feature Extraction: Extract features like negative self- talk, body-image obsession, or food restriction mention using NLP and sentiment analysis.
3. Model Training: Train machine learning models on labelled datasets or behavioural trends. Model Validation: Validate the model with expert input to ensure accuracy and effectiveness.
4. Risk Scoring: Flag at-risk users with risk scores, balancing ethical concerns and privacy.
5. Ongoing Refinement: Continuously refine the approach to address challenges like linguistic ambiguity, cultural differences, and over generalization .

ALGORITHMS

1. NAIVE BAYES

Naïve Bayes is a supervised learning technique that operates under a strong independence assumption, where the presence or absence of one feature is considered unrelated to that of others within the same class. Despite this simplification, it has shown robust and efficient performance. Its effectiveness is often explained by its representation and learning bias. Although widely used in research due to its ease of implementation, fast learning speed, and reasonable accuracy on large datasets,

2. SUPPORT VECTOR MACHINE

In classification problems, a type of machine learning method called a discriminant approach focuses on learning a function that can accurately assign labels to new, unseen data. This is done using a training dataset where all data points are independently and identically distributed .

3. DECISION TREE

Decision tree classifiers are widely used in various fields due to their ability to extract clear and understandable decision-making rules from data.

4. LOGISTIC REGRESSION

Logistic regression is used to model the relationship between a categorical outcome (like Yes/No) and one or more input variables. When the outcome has only two categories, it's called binary logistic regression.

IV. RESULTS AND ANALYSIS

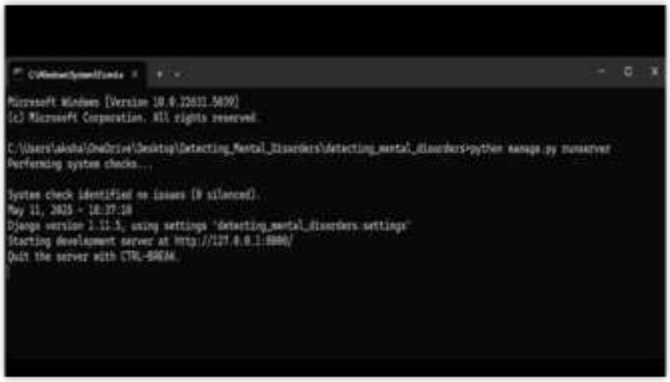

Fig. 2: Launching the Django

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Figure 3: Login Interface

Figure 4: Tweet type prediction based on emotional

Figure 5: Admin Login Interface

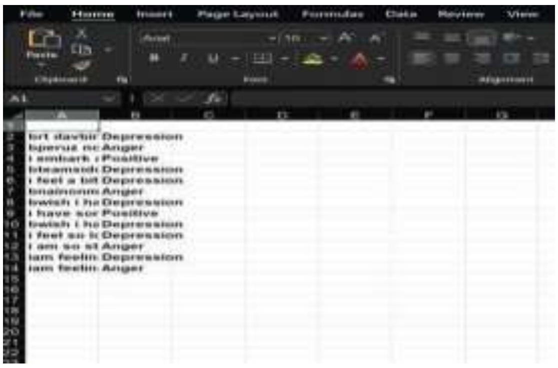

Figure 6: Labelled emotion dataset sample

Figure 7: Tweet emotion classification interface

Figure 8: Tweet emotion prediction result interface

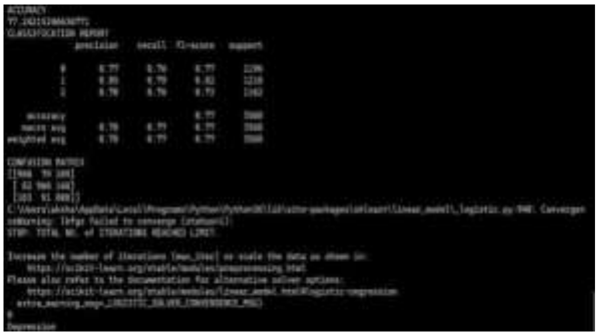

Figure 9: Classification report and confusion matrix of logistic regression model for tweet emotion detection

Figure 10:Distribution of Tweet types related to Mental Health Condition

Figure11: Comparison of classification model

V. CONCLUSION

We found that using detailed emotions (sub-emotions) from social media posts helps detect signs of depression and anorexia better than just using broad emotions. Our method, called BOSE, worked better than other models, and a version that tracks emotion changes over time (_-BOSE) improved results even more. support mental health while respecting user privacy. It involves sensitive personal information. Our work is for research only, and misuse of the data is not allowed.

VI. FUTURE SCOPE:

Future research can enhance the detection of anorexia nervosa by leveraging advanced natural language processing models to identify subtle emotional cues across diverse social media platforms. Integrating temporal analysis may enable the tracking of emotional shifts over time, supporting early detection. Additionally, personalized models tailored to individual language patterns and culturally adapted systems for multilingual users can improve accuracy. Ethical deployment, with strong privacy safeguards, and integration with clinical or digital support systems will be crucial for real-world applications.

VII. REFERENCES

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