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Survey of Detecting Mental Disorder in Social Media through Emotional Patterns- The Case of Anorexia and Depression

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Abstract: *Mental health disorders such as depression and anorexia nervosa have significantly increased in recent years, particularly among adolescents and young adults. With the widespread use of social media platforms such as Twitter and Reddit, users increasingly express their emotional states online, creating opportunities for early mental health detection. This survey reviews existing research on emotion-based detection of depression and anorexia using natural language processing (NLP), machine learning (ML), and deep learning (DL) techniques. Various approaches including sentiment analysis, lexicon-based methods, Support Vector Machines (SVM), Long Short-Term Memory (LSTM), and transformer-based models such as BERT are examined. Publicly available datasets, evaluation metrics, challenges, ethical concerns, and research gaps are discussed. The study highlights limitations in dataset imbalance, privacy issues, and generalization capability, and outlines future directions for developing robust and ethical mental health detection systems.*

Keywords*:* Mental Health Detection, Depression, Anorexia Nervosa, Emotional Pattern Analysis, Social Media Mining, Natural Language Processing, Deep Learning, Emotion Classification

I. INTRODUCTION

The rapid growth of social media platforms such as Twitter, Reddit, and Instagram has significantly transformed digital communication. Billions of users actively share personal experiences, emotions, and daily activities online, creating large volumes of user-generated textual data. These digital expressions often reflect users' psychological states, making social media a valuable resource for computational mental health research.

Simultaneously, mental health disorders such as depression and anorexia nervosa are rising globally, particularly among adolescents and young adults. Many individuals experiencing these conditions remain undiagnosed due to stigma, lack of awareness, or limited access to professional care. Early detection is crucial, as timely intervention can prevent severe psychological and physiological consequences.

Emotion-based analysis has emerged as a promising approach for detecting mental health conditions from textual content. Emotional patterns such as persistent sadness, hopelessness, guilt, anxiety, or body-image dissatisfaction are frequently reflected in online posts. Advances in Natural Language Processing (NLP), Machine Learning (ML), and Deep Learning (DL) enable automated extraction and classification of these emotional cues.

This survey paper reviews existing research on detecting depression and anorexia from social media using emotional pattern analysis. It categorizes approaches based on sentiment analysis, emotion detection, linguistic features, and advanced machine learning techniques. Furthermore, it compares datasets, evaluation strategies, research gaps, and ethical considerations to provide a comprehensive understanding of the field..

II. BACKGROUND

Depression

Depression is a common mental health disorder characterized by persistent feelings of sadness, loss of interest or pleasure in daily activities, fatigue, difficulty concentrating, and feelings of worthlessness or guilt. Individuals suffering from depression may also experience changes in sleep patterns, appetite, and energy levels, which can significantly affect their overall quality of life. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), depression is clinically diagnosed when these symptoms persist for at least two weeks and cause noticeable impairment in a person's social, occupational, or daily functioning. If left untreated, depression can lead to serious emotional, physical, and behavioral problems, highlighting the importance of early identification and intervention.

1. Online Behavioral Indicators

Research indicates that individuals with depression often exhibit:

- Increased use of first-person singular pronouns (I, me, myself)
- Frequent negative sentiment expressions
- Posts reflecting loneliness or hopelessness
- Reduced interaction and engagement
- Irregular posting time patterns

These linguistic and behavioral signals form the basis for computational detection models.

2. Anorexia Nervosa

Anorexia nervosa is an eating disorder characterized by restrictive food intake, distorted body image, and intense fear of weight gain. It can result in severe medical complications.

Behavioral Patterns

Online indicators include:

- Frequent discussion of dieting and calorie counting
- Obsession with body weight and appearance
- Sharing "thinspiration" content
- Self-critical or perfectionist language

3. Emotional Pattern Analysis in Social Media

Sentiment Analysis

Sentiment analysis classifies text into positive, negative, or neutral categories. Depression-related posts typically exhibit strong negative polarity. However, simple polarity classification may not capture nuanced psychological states.

Emotion Detection

Emotion detection extends beyond polarity by identifying specific emotional states such as:

- Sadness
- Fear
- Anger
- Disgust

Lexicon-based tools such as the NRC Emotion Lexicon and LIWC (Linguistic Inquiry and Word Count) quantify emotional expressions by mapping words to predefined emotional categories. Multi-class emotion classification has shown improved performance over binary sentiment analysis in mental health detection tasks.

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Linguistic Features

Several linguistic markers are correlated with mental health conditions:

- **Pronoun usage**: Increased first-person singular pronouns
- **Negation frequency**: Use of "not", "never", "no"
- **Temporal language**: References to past failures or hopeless future outlook

4. Machine Learning Techniques Reviewed

Traditional Machine Learning

Early studies applied:

Naïve Bayes – Probabilistic classifier effective for text

Support Vector Machine (SVM) – High-dimensional text classification

Random Forest – Ensemble method reducing overfitting

These methods rely heavily on feature engineering.

Deep Learning Approaches

CNN – Effective for local feature extraction

LSTM – Captures sequential dependencies in text

Bi-LSTM – Considers bidirectional context

Attention Mechanisms – Highlight emotionally significant words

Deep learning models reduce the need for manual feature extraction.

Transformer Models

Transformer-based architectures significantly improve contextual understanding:

BERT – Bidirectional contextual embeddings

RoBERTa – Optimized version of BERT

DistilBERT – Lightweight and efficient variant

Fine-tuned transformer models consistently outperform traditional ML in depression detection tasks.

III. OBJECTIVE OF SYSTEM

The objective is to identify patterns in the language of individuals with depression by comparing their vocabulary to that of healthy users. However, this approach faces limitations, particularly due to the substantial overlap in the vocabulary used by both groups, making precise differentiation challenging

- To collect and preprocess social media textual data for analysis.
- To identify linguistic and emotional features that may indicate depressive behavior.
- To apply Natural Language Processing (NLP) techniques to analyze user-generated text.
- To build and train machine learning models for detecting depression from textual data.

IV. PROPOSED SYSTEM

The process begins with users who interact on social media. These users provide Social Data, which includes information like User_ID, posts, profile information, and interactions on platforms like Twitter or Facebook.

Social Data (User_ID):

This is the raw data collected from the users' social media activities. It forms the foundation for the analysis and includes a variety of information such as profile details, tweets, social ties, and other relevant activities on social media.

Preprocessing Steps:

The selected features undergo preprocessing, which may involve cleaning the data, normalizing it, or converting it into a format suitable for machine learning models. This step is crucial for ensuring that the data is in the best possible shape for accurate prediction.

SYSTEM ARCHITECTURE

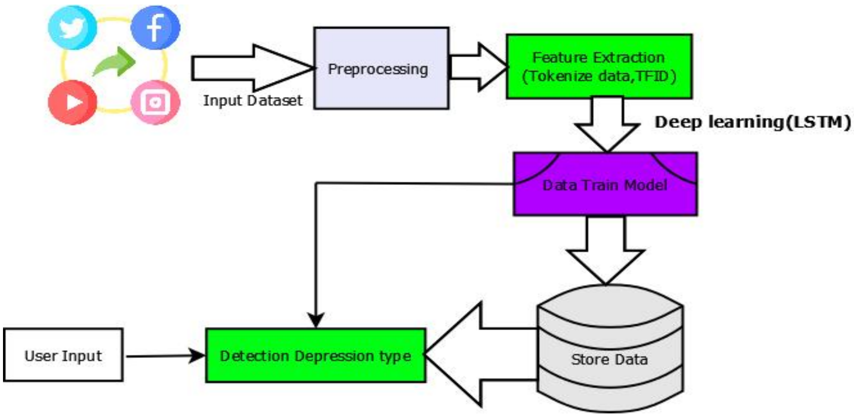

Fig 1. System Architecture

Feature Engineering:

Feature Extraction: The next step is feature extraction, where relevant information is extracted from the social data. This could involve pulling out specific patterns or elements such as frequency of posts, sentiment expressed in posts, or the nature of social interactions.

Feature Selection / Dimensionality Reduction: After extraction, the features are selected or reduced to remove irrelevant or redundant data. This step ensures that only the most important information is used for further processing, making the model more efficient.

Model Construction and Evaluation:

After preprocessing, the data is used to construct a predictive model. This involves training the model using historical data and then evaluating its performance to ensure it accurately predicts mental states based on the given features.

Prediction:

Once the model is developed and validated, it can be utilized to estimate the mental states of a new user based on their social media data.

Mental States:

The final output is the predicted mental state of the user, which can be used by healthcare providers, researchers, or even the users themselves to gain insights into their mental health.

V. METHODOLOGY

LSTM: LSTM is a type of convolution Neural Network (CNN) designed to handle sequential data and long-term dependencies. It finalizes the ending gradient problem in traditional CNNs.

CNNs are specialized neural networks for processing grid-like data, such as images, by automatically detecting spatial feature

System Description:

The system S can be described as:

S = {I, O, P, C},

Where:

I = Input (Social media text in the form of tweets).

O = Output (Detection of mental disorder such as depression or anorexia).

P = Processing (Tokenization of tweets, feature extraction, and classification using the LSTM algorithm).

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C = Constraints (Data quality, model limitations, ethical considerations).

Inputs (I):
I1: Social media text/tweets (**T**) = {T1, T2, T3, ... Tn}, where each tweet is a string.
I2: Emotional pattern dictionary or pretrained embeddings for feature extraction.

Outputs (O):
O1: Detect whether a mental disorder is present.
O2: Categorize the detected disorder (e.g., depression, anorexia).
O3: Generate a report/alert for intervention.

Processing (P):
P1: Preprocessing:
Tokenize the tweets (T) into individual words or phrases. Clean text by removing noise such as emojis, links, and stop words
Function:
Tprocessed=tokenize(T)

P2: Feature Extraction:
Convert tokens to numerical data using techniques like word embeddings (e.g., Word2Vec, GloVe) emotional sentiment scores.

Function:

$$features = embedding(Tprocessed)$$

P3: Classification:
Use an LSTM (Long Short-Term Memory) model to classify the emotional patterns and detect mental disorders.

Function:

$$disorder = LSTM(features)$$

To uphold the validity and minimize inherent biases this study review adheres to the established protocol, as in Figure 1. This framework, encompassing main components: planning, execution and analysis – provides an approach to the review process.
In the initial planning phase, a focused questions (RQs) were formulated to guide the investigation.
The subsequent execution phase involved a meticulous search strategy to identify relevant literature. This encompassed the development of comprehensive search strings, the identification of reputable databases, and the establishment of clear Criteria for study inclusion and exclusion for article selection. To ensure a consistent evaluation of among the identified studies, a standardized assessment matrix was developed.
Finally, in the analysis phase, data extraction was performed systematically, with key information extracted from the selected articles and meticulously recorded in a dedicated Study Characteristic Chart.
The extracted data was then subjected to rigorous analysis to synthesize findings and generate meaningful insights that address the initial RQs.

VI. CONCLUSION

This survey reviewed computational approaches for detecting depression and anorexia from social media using emotional pattern analysis. Traditional machine learning techniques provide baseline performance, while deep learning and transformer-based models achieve superior accuracy through contextual understanding. Emotion-aware models significantly enhance detection capability compared to keyword-based systems. However, dataset limitations, ethical concerns, cultural bias, and lack of explainability remain critical challenges. Future research should focus on privacy-preserving, interpretable, and multimodal systems to enable responsible and effective deployment of AI-based mental health detection tools. We demonstrated that representations based on fine-grained emotions can more effectively capture specific topics and issues expressed in social media by users Distress from depression or anorexia. The automatically extracted sub-emotions provide valuable information that aids in the detection of these mental disorders. The BoSE representation, in particular, outperformed the proposed baselines, including some deep learning models, and showed better results compared to using only broad emotions as features. Additionally, incorporating a dynamic analysis of these sub-emotions.

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