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Analyzing Sentiment in Social Media Communication and Its Effect on Mental Health

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Abstract - *This paper investigates the psychology of sentiment analysis & its effects on the mental well-being of communication through social media. Through analyzing the responses gathered by a Google Form survey, tweets from Sentiment 140 data-set from Kaggle and real time tweets retrieved via API's applying NLP and logistic regression for classification. User sentiments are classified as positive, neutral and negative, and evaluate their correlation to mental health indicators. This research focuses on analyzing sentiment to provide a qualitative assessment of sentiment accuracy.*

***Key Words*: Sentiment Analysis, Social Media, Mental Health, Emotion Detection, Online Communication**

1. INTRODUCTION

1.1 Internet:

The internet is a vast system of interconnected networks that enables users to access and exchange data, websites, services, and content from anywhere in the world. The internet has profoundly shaped modern life, becoming an essential source of news, entertainment, and education for people worldwide for over two decades. The internet has become an essential part of modern life, connecting people globally and enabling access to a wealth of resources.

fig.1: communication in the age of social media using Internet

1.2 Social media

Social media refers to digital platforms that allow users to create and share content with their networks online. Popular platforms like Facebook, Twitter, Instagram, Snapchat, WhatsApp and LinkedIn provide an easy way for users to quickly share images, links, ideas and messages. However, the rise of social media has both positive and negative impacts on mental health.

- On the positive side, social media can foster a sense of belonging and support through meaningful interactions.
- On the other hand, negative experiences such as cyberbullying, social comparison, and online harassment can contribute to mental health issues like depression and anxiety.

1.3 Sentiment Analysis

Sentiment Analysis also known as opinion mining, is the systematic methodology of using natural language processing, machine learning and computational techniques to identify and extract the emotional tone or sentiment expressed in a piece of text. The objective is to identify whether the sentiment expressed in the text is positive, negative, or neutral.

2. Literature Review

A significant amount of research has been conducted in sentiment analysis, particularly within the fields of product reviews, movie reviews, and blogs. Several studies highlight the impact of social media sentiment on mental health. Research suggests that excessive exposure to negative content can increase psychological distress, while positive content enhances well-being. Sentiment analysis has been widely applied in fields such as marketing, politics, and health, making it a valuable tool for understanding emotional trends in social media interactions. This study builds upon existing research by examining real-world responses and their mental health implications.

3. Methods & Materials

By analysing the responses collected from a Google Form survey, tweets from the Sentiment 140 dataset on Kaggle and real-time tweets retrieved via APIs, this study applies Natural Language Processing and logistic regression for sentiment classification. User sentiments are categorized as positive, neutral, or negative, and their correlation with mental health indicators is evaluated. The research aims to assess sentiment accuracy qualitatively through sentiment analysis.

It includes the following six fields:

1. target: The sentiment polarity of the tweet (0 : negative, 2 : neutral, 4 : positive)
2. ids: The unique identifier for the tweet
3. date: The date when the tweet was posted
4. flag: The query associated with the tweet
5. user: The user who posted the tweet
6. text: The content of the tweet

To analyze sentiment in tweets related to mental health, three main steps were employed using Python scripts to automate and optimize the analysis process:

1. data collection
2. text preprocessing
3. model training/evaluation.

3.1 Data Collection

We used the tweepy library to interact with the Twitter API. The script (twitter_fetch.py) was configured with authentication credentials and a search query targeting mental health-related keywords (e.g., depression, anxiety, stress). The collected dataset consisted of 100 tweets, which were then used for sentiment analysis.

3.2 Text Preprocessing and Cleaning

In the sentiment_analysis.py and twitter_analysis.py scripts, the following steps were performed:

a) Removal of URLs, mentions, hashtags, and special characters.
b) Conversion of text to lowercase to standardize the data.
c) Removal of stopwords (commonly occurring words such as the, and, is).

The text cleaning ensured that only meaningful words remained, improving the accuracy of sentiment analysis.

3.3 Sentiment Classification Model

We used two different machine learning models:

- Logistic Regression was implemented in sentiment_analysis.py, where the cleaned tweets were vectorized using TF-IDF (Term Frequency-Inverse Document Frequency). The vectorized data was split into training and validation sets, and the logistic regression model was trained on the training data. The model was evaluated using accuracy scores and a classification report.
- Naive Bayes was used in twitter_analysis.py, where the text was similarly preprocessed, and the features were extracted using TF-IDF. A Multinomial Naive Bayes model was trained and evaluated on the sentiment data, and the trained model was saved for future use using joblib.

3.4 Evaluation

To evaluate the performance of the sentiment classification metrics were used as accuracy and the classification report.

4. Results And Discussion

A Sentiment Distribution Bar Graph that displayed the distribution of different sentiment labels (positive, neutral, negative) within the dataset, providing insights into sentiment trends.

4.1 Sentiment Distribution

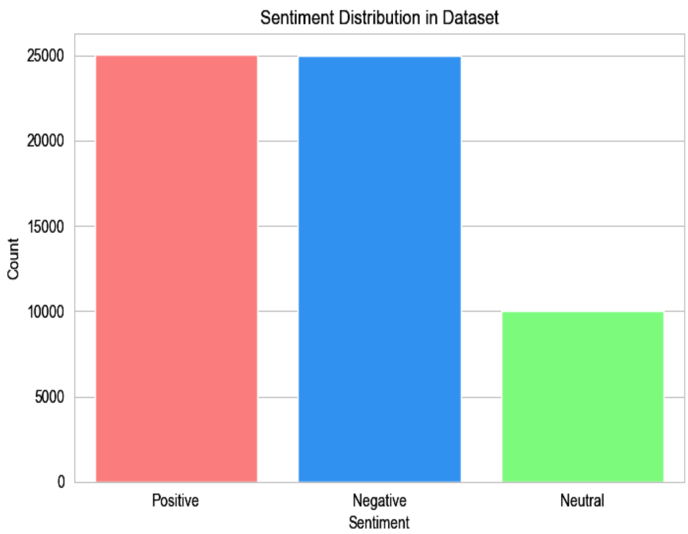

fig.1 Bar graph of sentiment distribution

a) Positive sentiment interactions were associated with increased feelings of happiness and social support.
b) Negative with increased sadness, anxiety etc.
c) Neutral sentiments suggested indifference or limited emotional impact.

```
sentiment
Positive     25014
Negative     24986
Neutral      10000
Name: count, dtype: int64
```

fig.2 Distribution of 60,000 tweets

```
Validation Accuracy: 0.6213333333333333
              precision    recall  f1-score   support

    Negative       0.64      0.73      0.68      5058
     Neutral       0.07      0.00      0.01      2024
    Positive       0.61      0.76      0.68      4918

    accuracy                           0.62     12000
   macro avg       0.44      0.50      0.46     12000
weighted avg       0.53      0.62      0.57     12000
```

fig.3 Model Evaluation

4.2 Correlation with Mental Health

For this study, data was collected through an online survey created using Google Forms. The questions were structured to collect both quantitative and qualitative data, with the majority being multiple-choice, Likert scale and yes/no questions.

The questions included:

1. **Demographic Information:**
   a) What is your age group?
   b) What is your gender?
   c) What is your primary occupation?
2. **Social Media Usage:**
   a) How frequently do you use social media?
   b) How often do you encounter emotionally charged content (e.g., positive or negative)?
3. **Impact of Social Media on Emotions:**
   a) Does social media content affect your mood or emotions?
   b) Have you ever felt overwhelmed or stressed after engaging with social media?
   c) Have you ever come across mental health-related campaigns on social media?
   d) Do you think social media platforms provide adequate support/resources for mental health?
4. **Personal Experiences:**
   a) How likely are you to share personal mental health experiences on social media?
   b) How do you usually express emotions in your posts or comments?
   c) Have you ever felt judged or negatively impacted by others' comments or sentiments online?
   d) In your opinion, how can social media better support mental health awareness?
   e) Share a personal experience (optional) where social media significantly impacted your mental health.
5. **Consent:**
   a) Do you consent to your responses being used for academic research purposes?

4.3 Key Findings

a) Social media influences mental health significantly, with both positive and negative effects.
b) Online interactions shape emotional well-being and can act as both a support system and a stressor.
c) Respondents who reported frequent exposure to negative sentiment were more likely to experience stress and anxiety.
d) Awareness campaigns and digital well-being initiatives are essential for promoting healthy social media usage.

4.4 Google Form Figures

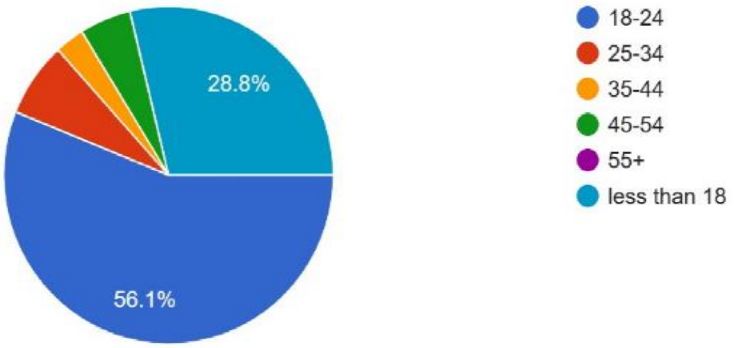

fig.4 Age Group Representation

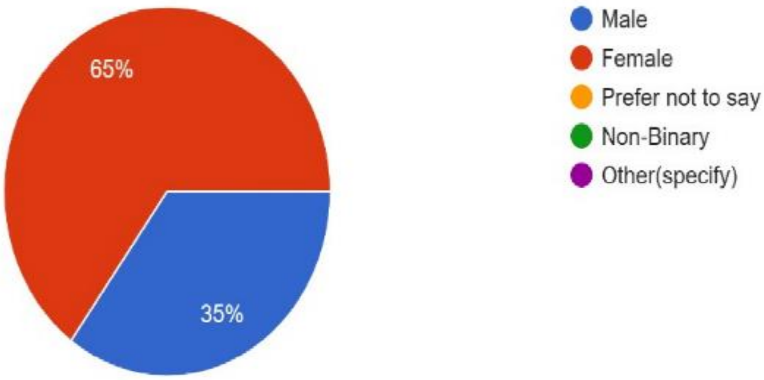

fig.5 Gender Representation

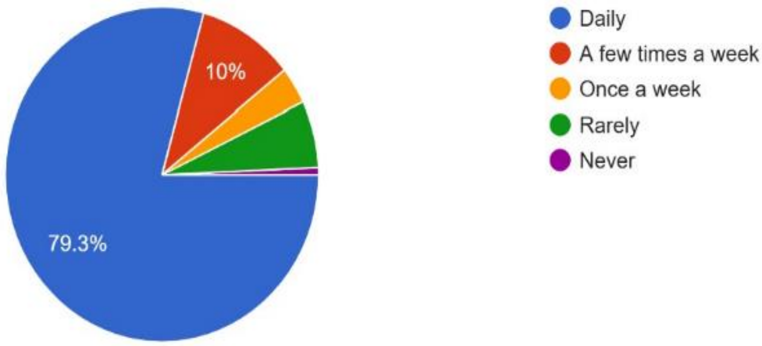

fig.6 Usage of Social Media

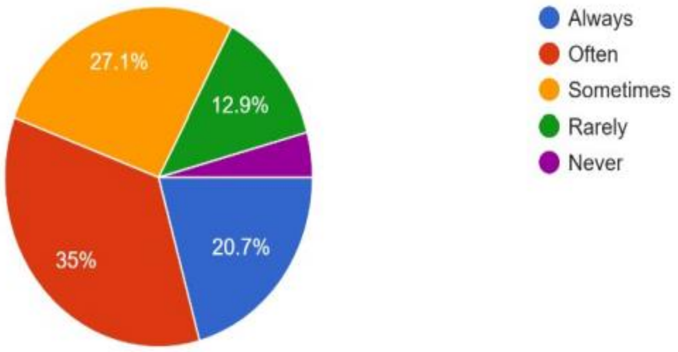

fig.7 Encounter emotionally charged

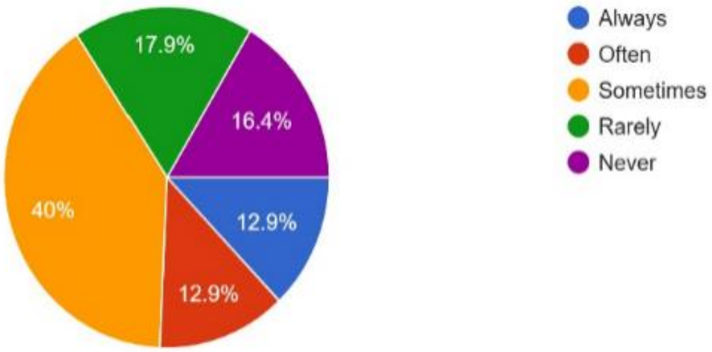

fig.8 Affect on mood or emotions

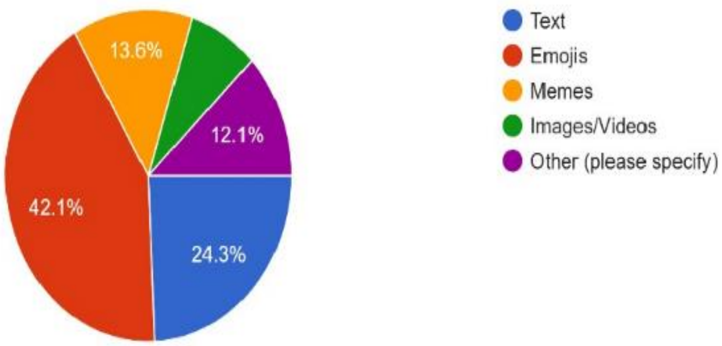

fig.9 Expression of emotions in posts or comments

This organizes the data clearly and presents the key findings about social media usage and emotional engagement.

- According to data collected, 56.1% of individuals aged 18-24 use social media sites and applications,
- 28.8% of children under 18 are also active on these platforms.
- The gender distribution reveals that 65% of social media users are female, while 35% are male.
- 79.3% of people engage with social media on a daily basis.
- In terms of emotional engagement, 20.7% of users frequently encounter emotions while interacting on social media,
- while 35% experience such emotions often, and
- 27.1% encounter them occasionally.
- When it comes to the expression of emotions in posts or comments, 42.1% of users are influenced by emojis, 24.3% by text, 13.6% by memes and 7% by images/video content.

5. CONCLUSIONS

This study highlights how sentiment analysis can help understand the psychological effects of social media. It emphasizes the importance of platforms taking responsibility for reducing harmful content and fostering positive interactions, which can lead to a healthier online environment. With social media being such a powerful tool for reaching diverse audiences, it's crucial for businesses, influencers, and organizations to carefully consider their target audience, the messages they wish to convey, and the platform that best suits their objectives. By aligning content strategies with platform-specific dynamics and audience preferences, users can create more impactful and engaging interactions, ultimately promoting a more supportive digital space.

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