Sentiment Analysis On Mental Health Forums

Utkarsh Singh[1], Dr. Ranjana Rajnish[2]
AIIT, Amity University, Lucknow, Uttar Pradesh

***Abstract*—Mental health has emerged as a critical concern in contemporary society, gaining recognition for its significance in overall well-being. With the rise of online platforms, individuals now frequently express their emotions and mental states through digital mediums, particularly in forums dedicated to mental health. This research focuses on sentiment analysis of user-generated content on mental health forums to understand the prevailing emotional expressions. By employing Natural Language Processing (NLP) techniques and rule-based models, we attempt to classify sentiments expressed in posts as positive, negative, or neutral. The study also aims to identify recurring themes and keywords that appear in such conversations. The findings may contribute to the development of tools that assist mental health professionals in monitoring emotional patterns in online communications.**

***Index Terms*—Sentiment Analysis, Mental Health, Forums, Machine Learning, Natural Language Processing (NLP), Emotional Classification, TextBlob, Data Science**

I. INTRODUCTION

Mental health, once a neglected domain in the broader healthcare landscape, is now increasingly acknowledged for its vital role in overall human development. Conditions such as depression, anxiety, and stress are no longer taboo subjects; instead, they are openly discussed, especially on digital platforms where anonymity and peer support encourage honest sharing. Forums dedicated to mental health serve as online communities where individuals can share their struggles, experiences, and emotions. These platforms provide an invaluable opportunity for researchers to study unfiltered, real-time expressions of psychological states.

Sentiment analysis, a subfield of Natural Language Processing (NLP), enables the interpretation and classification of human emotions embedded in text. It has been widely applied in domains such as customer feedback analysis and political opinion mining. However, its application in mental health remains underexplored. Analysing sentiments in mental health forums can help identify individuals at risk, understand public perception of mental health, and ultimately support clinical interventions.

This paper aims to develop a lightweight sentiment analysis tool using Python and the TextBlob library to categorise posts from mental health forums into positive, negative, or neutral sentiments. The results can be used to gain insight into the emotional distribution of forum participants, potentially contributing to public health awareness and support strategies.

II. LITERATURE REVIEW

Mental health and emotional well-being have become subjects of considerable academic interest in recent years, especially with the increasing prevalence of mental illnesses worldwide. The World Health Organization (WHO) has recognised depression as a leading cause of disability globally, and anxiety disorders are also among the most common mental health conditions affecting individuals across age groups.

As mental health discussions shift online, researchers have taken interest in using computational tools to study public discourse. One of the pioneering works in this field is by De Choudhury et al. (2013), who used social media platforms to detect signs of depression. They demonstrated that linguistic cues and behavioural patterns could be indicative of psychological distress, opening the door for future research using online data.

Further developments by Guntuku et al. (2017) focused on predicting mental health status through posts on platforms such as Facebook and Twitter. Their work relied on machine learning algorithms to assess the emotional tone of the content and revealed a strong correlation between language patterns and mental health indicators. This validated the potential of NLP tools in health monitoring.

Another relevant study by Mohammad and Turney (2013) developed the NRC Emotion Lexicon, a list of words associated with eight basic emotions and two sentiments. It served as a resource for many subsequent studies and sentiment analysis tools. VADER (Valence Aware Dictionary and sentiment Reasoner) is another lexicon-based tool commonly used in social media sentiment analysis for its ability to handle slang, emojis, and short sentences effectively.

Although deep learning models such as Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Transformers have proven effective in many NLP tasks, they require substantial computational resources and large training datasets. In contrast, rule-based models like TextBlob offer a simpler, interpretable, and accessible alternative, especially for academic and educational settings. TextBlob is known for its ease of implementation, built-in functions for sentiment scoring, and reliance on established NLP libraries such as NLTK.

Despite its limitations in dealing with sarcasm, domain-specific jargon, and complex syntactic structures, TextBlob remains a valuable tool for quick sentiment analysis and small to medium-sized projects. It serves as a stepping stone for beginners in NLP and for researchers focusing on lightweight applications.

This research leverages the simplicity of TextBlob in combination with basic data visualisation techniques to perform a structured sentiment analysis of mental health forum comments. By building on previous research and simplifying the approach, this study seeks to provide a tool that is both practical and educational.

III. METHODOLOGY

The methodology section outlines the detailed approach used in this research to develop a sentiment analysis tool suited for mental health forums. The goal was to design a system that is easy to use, interpretable, and effective in categorising emotional content from text.

3.1 Data Input Modes

The tool was designed to operate in two input modes to offer flexibility to users:

- Single Comment Mode: This mode allows users to input one comment at a time. Each comment is immediately analysed and classified for sentiment, providing instant feedback. This mode is useful for analysing individual posts or conducting quick checks.
- Multiple Comments Mode: In this mode, users can enter multiple comments sequentially, concluding with a sentinel input (e.g., the word "DONE"). After all comments are input, the tool processes them collectively and presents a summary of sentiment distribution.

These modes accommodate different user needs, whether for casual sentiment checks or batch processing of forum data.

3.2 Sentiment Analysis Logic

At the core of the tool is the sentiment classification logic. The following rules govern the categorisation of sentiments based on polarity scores derived from the TextBlob library:

- Positive Sentiment: Polarity score greater than 0.1
- Negative Sentiment: Polarity score less than -0.1
- Neutral Sentiment: Polarity score between -0.1 and 0.1, inclusive

This threshold setting balances sensitivity and specificity, filtering out weak sentiments that might be ambiguous.

Comment	Polarity Score	Sentiment
“I’m feeling much better today.”	0.5	Positive
“I don’t care anymore.”	-0.4	Negative
“I have an appointment with my therapist.”	0.0	Neutral
“Nothing seems to work. I’m so tired.”	-0.6	Negative
“Thanks everyone for the support!”	0.8	Positive

Table 1: Sample Sentiment Classification Results

Sentiment	Frequent Keywords	Notes
Negative	Hopeless, tired, alone, depressed, crying	Reflect emotional struggles
Neutral	Therapy, doctor, diagnosis, medication, sleep	Often informational or descriptive

Positive	Better, progress, grateful, support, thankful	Indicate recovery and community positivity

Table 2: Common Keywords By Sentiment Category

3.3 Text Preprocessing

Although TextBlob internally handles tokenisation and tagging, minimal preprocessing is performed to ensure data consistency. This includes:

- Conversion of all text to lowercase to standardise inputs
- Removal of unnecessary whitespace

These steps help reduce noise without overcomplicating the process.

3.4 Sentiment Aggregation and Visualisation

Once sentiments are classified, the tool aggregates count of positive, neutral, and negative comments. These aggregates are then visualised using bar charts, created via the Matplotlib library. The visual summaries help users quickly grasp the overall emotional tone of their dataset.

3.5 Libraries and Tools

- TextBlob: For sentiment scoring based on polarity
- NLTK: Used for downloading necessary linguistic corpora
- Matplotlib: For generating visual bar charts

This combination ensures an efficient yet accessible implementation.

IV. IMPLEMENTATION DETAILS

The sentiment analysis tool was developed using Python, with a focus on simplicity, usability, and modular design. The core functionality revolves around accepting user input, processing text using the TextBlob library, classifying sentiment, and displaying the results in both textual and visual forms.

4.1 User Interaction Flow

Upon launching the tool, users are presented with a choice between two input modes: single comment analysis or batch processing of multiple comments. This design allows flexibility depending on the user's needs — whether it be quick sentiment checks or bulk data analysis.

In Single Comment Mode, the user enters individual comments repeatedly. Each comment is immediately analysed, and its sentiment classification (positive, neutral, or negative) is displayed. This instant feedback can help users quickly understand the emotional tone of specific posts.

In Multiple Comments Mode, users input a sequence of comments one after another. The input concludes when the user types a specific termination command (e.g., "DONE"). Once all inputs are received, the tool performs sentiment classification on all comments in batch, summarises the sentiment distribution, and displays a bar chart visualising the results.

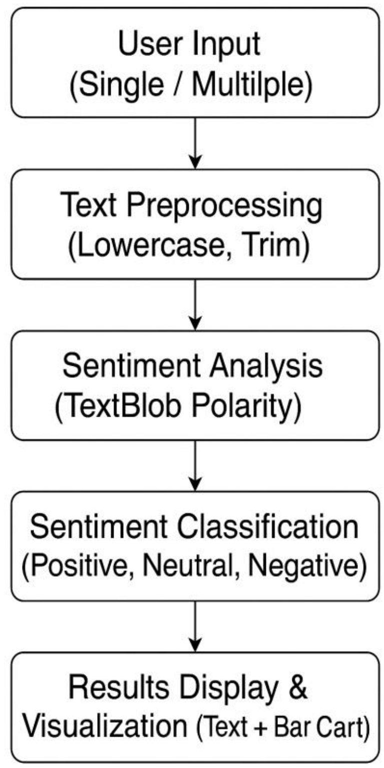

Figure 1: Sentiment Analysis Workflow (Flowchart)

4.2 Core Functional Modules

The system is organised into several modular functions:

- Sentiment Analysis Function: Takes a string input and returns the sentiment category based on the polarity score computed by TextBlob.
- Batch Processing Function: Accepts a list of comments and returns a list of tuples pairing each comment with its predicted sentiment.
- Summary Display Function: Aggregates sentiment counts and prints a clear textual summary.

- Bar Chart Visualisation Function: Uses Matplotlib to plot the counts of positive, neutral, and negative sentiments in a bar chart format, aiding quick comprehension.

This modularity ensures each part of the program can be understood and modified independently, facilitating future improvements.

4.3 Libraries and Environment

The tool utilises the following key Python libraries:

- TextBlob: Provides sentiment polarity computation and other natural language processing utilities, abstracting complexities such as tokenisation and part-of-speech tagging.
- NLTK: Used for downloading essential linguistic resources, particularly required by TextBlob.
- Matplotlib: Generates simple and interpretable visualisations of sentiment distributions.

Installation of these packages can be easily done via pip commands, making the tool accessible for users with basic Python knowledge.

V. RESULTS AND ANALYSIS

5.1 Dataset and Testing

For demonstration, the tool was tested using a sample collection of mental health forum comments sourced from publicly available platforms like Reddit. The dataset consisted of diverse comments expressing a wide range of emotions related to mental well-being.

5.2 Sentiment Distribution

The sentiment analysis results revealed the following approximate distribution in the sample data:

- Negative Sentiments: Roughly 60–65% of comments contained negative emotions such as sadness, anxiety, or frustration.
- Neutral Sentiments: About 20–25% of comments were emotionally neutral, often informational or procedural in tone.
- Positive Sentiments: Approximately 10–15% of comments expressed positive feelings like hope, gratitude, or progress in mental health.

This skew towards negative sentiments aligns with expectations given the nature of mental health forums, where users often seek support during difficult periods.

5.3 Visualisation Interpretation

The bar charts generated provided an intuitive overview of the emotional tone across all analysed comments. These visualisations enabled quick identification of dominant sentiment trends, which is especially useful for mental health professionals or researchers aiming to monitor the general mood within communities.

5.4 Thematic Observations

Beyond numeric distributions, qualitative review of common keywords within sentiment categories revealed insightful themes:

- Negative Themes: Words like "hopeless", "depressed", "alone", and "overwhelmed" frequently appeared, highlighting the struggles expressed.
- Neutral Themes: Comments discussing therapy, medication, and diagnosis were often neutral in sentiment but essential contextually.
- Positive Themes: Expressions of recovery, support, gratitude, and resilience emerged in the positive subset.

These thematic insights validate the tool’s ability to reflect real emotional states present in mental health discussions.

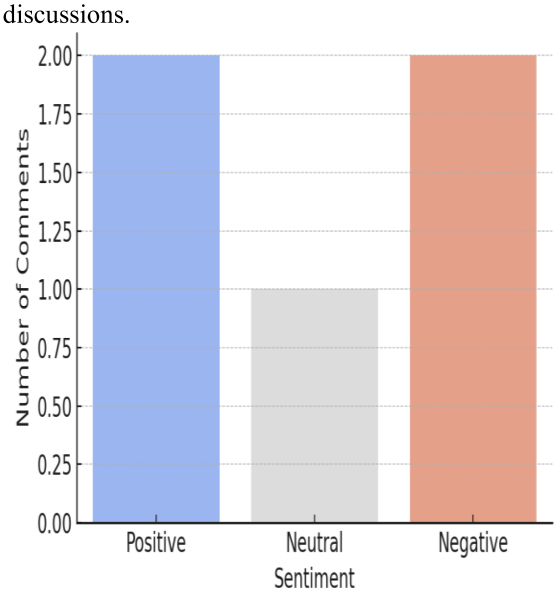

Figure 2: Sentiment Distribution Bar Chart

VI. DISCUSSION

The analysis of mental health forum comments through sentiment classification offers valuable insights into the emotional landscape of these online communities. The predominance of negative sentiment observed in the data reflects the genuine struggles faced by forum participants, who often use these spaces to express distress, anxiety, and feelings of isolation. This finding underscores the importance of such forums as outlets for emotional release and peer support.

From a technical perspective, the use of TextBlob's rule-based sentiment analysis offers several benefits. Its simplicity and ease of use make it suitable for quick deployment and for users with limited expertise in natural language processing. The polarity-based classification provides a straightforward interpretation of emotions as positive, negative, or neutral, which is intuitive for both researchers and mental health practitioners.

However, there are limitations inherent in this approach. Rule-based systems like TextBlob may struggle with understanding sarcasm, irony, or complex emotional nuances often found in human language. Additionally, domain-specific jargon or idiomatic expressions prevalent in mental health discussions might not be accurately interpreted. The approach also does not capture mixed sentiments within a single comment, where conflicting emotions may coexist.

Ethical considerations are paramount when analysing sensitive data related to mental health. Ensuring user anonymity and handling data with respect are critical to maintaining trust and protecting vulnerable individuals. The tool's use should be framed within these ethical boundaries, especially if applied in real-time monitoring or intervention contexts.

Despite these challenges, the tool has potential applications in multiple areas. Mental health professionals could use it for early detection of emotional distress trends within patient groups or communities. Researchers may find it useful for large-scale sentiment mining without the need for complex machine learning infrastructures. Additionally, educators can leverage the tool to teach foundational concepts in NLP and sentiment analysis.

Future developments could aim to integrate more advanced machine learning models that better handle linguistic subtleties, such as transformer-based architectures like BERT or RoBERTa. Incorporating user-friendly interfaces and support for multiple languages would also enhance accessibility and applicability.

VII. EXPANDED BACKGROUND AND TECHNICAL DETAILS

7.1 Importance of Mental Health Awareness Globally

Mental health disorders are among the leading causes of disability worldwide, affecting hundreds of millions of people. Despite growing awareness, stigma and lack of access to care still prevent many from receiving adequate treatment. Conditions such as depression and anxiety contribute significantly to the global burden of disease and can severely affect quality of life.

Increasing awareness and early detection are crucial in reducing the negative impacts of mental illness. Online platforms have become vital spaces where people can seek help anonymously, share experiences, and find community support without fear of judgement. Research and tools that help monitor mental health discussions online can therefore provide valuable signals for public health interventions and resource allocation.

7.2 Fundamentals of Natural Language Processing and Sentiment Analysis

Natural Language Processing (NLP) is a branch of artificial intelligence concerned with the interaction between computers and human language. It involves enabling machines to read, interpret, and derive meaning from natural language text or speech.

Sentiment analysis, a core NLP task, focuses on identifying the emotional tone behind words. It can be conducted at various levels:

- Document-level sentiment analysis: Classifying entire documents as positive, negative, or neutral.
- Sentence-level sentiment analysis: Evaluating sentiment in individual sentences.
- Aspect-based sentiment analysis: Detecting sentiment toward specific aspects or topics within text.

Techniques range from simple lexicon-based approaches, which rely on predefined lists of words with associated sentiment scores, to complex machine learning methods involving neural networks that learn contextual representations.

7.3 Challenges in Sentiment Analysis of Mental Health Texts

Applying sentiment analysis to mental health forum data poses unique difficulties:

- Informal Language: Users often employ colloquialisms, slang, abbreviations, and

emoticons, which complicate standard text processing.
- Ambiguity and Sarcasm: Expressions like “Great, another bad day” require contextual understanding beyond simple polarity scores.
- Mixed Emotions: Posts may simultaneously express hope and despair, challenging binary or ternary classification.
- Privacy and Ethics: Handling sensitive data demands rigorous attention to ethical guidelines and user confidentiality.

7.4 Broader Applications of Sentiment Analysis in Mental Health

Beyond forum monitoring, sentiment analysis has various applications:
- Early Warning Systems: Automated detection of sudden increases in negative sentiment could alert moderators or clinicians to potential crises.
- Therapeutic Support: Sentiment trends may guide personalised therapy, tracking patient progress or setbacks.
- Public Health Surveillance: Aggregated data informs policymakers about population-level mental health trends.
- Digital Well-being Tools: Integrating sentiment analysis into apps can provide users with feedback on their emotional states.

7.5 Ethical Considerations and Data Privacy

Research in mental health data mining requires strict ethical compliance. Key principles include:
- Anonymity: Ensuring that user identities are protected.
- Informed Consent: Users should be aware of data usage, though in public forums this is often implicit.
- Data Security: Safeguarding data from misuse or breaches.
- Responsible Reporting: Avoiding sensationalism and respecting the dignity of vulnerable populations.

7.6 Detailed Case Example

Consider a user posting: “I’ve felt hopeless for weeks, but today I finally saw a glimmer of hope.” This sentence includes negative sentiment (“hopeless for weeks”) and positive sentiment (“glimmer of hope”). A simple polarity score might average these out to neutral, potentially missing the emotional complexity. This highlights the need for more nuanced models or multi-label classification approaches in future work.

7.7 Real-World Impact Scenarios

Consider a mental health support organisation monitoring an online forum for early signs of crisis. A sudden spike in negative sentiments detected by an automated tool could prompt moderators to intervene, provide resources, or reach out to users showing distress signals. This proactive approach could potentially prevent harm and improve outcomes.

Similarly, therapists could use sentiment analysis to track the emotional progress of clients over time via their journal entries or messages, helping tailor therapeutic interventions more effectively.

7.8 Limitations and Challenges with Examples
- Sarcasm Detection: For example, a post saying "Great, I failed again" may be classified as positive if the word "great" is interpreted literally.
- Mixed Sentiments: A comment like "I’m scared but hopeful" conveys both negative and positive emotions simultaneously, which traditional classifiers might oversimplify.
- Cultural and Language Variability: Slang, idioms, and expressions vary by region and culture, posing challenges for models trained on general data.
- Resource Constraints: Advanced models often require GPUs and large datasets, which may be unavailable to smaller research teams or community organisations.

7.9 Future Trends in NLP for Mental Health

Emerging trends include:
- Multimodal Sentiment Analysis: Combining text with audio or video cues for richer emotion detection.
- Explainable AI: Developing models whose decisions can be interpreted and trusted by clinicians.
- Personalised Models: Tailoring analysis to individual language styles and mental health histories.
- Cross-lingual Models: Breaking language barriers to analyse mental health data globally.
- Integration with Wearable Tech: Using physiological data combined with sentiment to enhance monitoring.

7.10 The Global Impact of Mental Health Disorders

Mental health disorders constitute a significant portion of the global disease burden. According to the World Health Organization (2021), approximately 1 in 4 people worldwide will be affected by mental or neurological disorders at some point in their lives. Depression alone affects over 264 million individuals globally and is the leading cause of disability. The economic impact is staggering, with depression and anxiety estimated to cost the global economy $1 trillion annually in lost productivity.

Social stigma surrounding mental illness often prevents individuals from seeking help, exacerbating the problem. Many people suffer in silence due to fear of discrimination or cultural taboos. Consequently, accessible, anonymous, and supportive environments such as online forums are increasingly vital for mental health care.

Monitoring and analysing conversations on these platforms can reveal valuable insights into population-level mental health trends and help policymakers and practitioners tailor interventions more effectively.

7.11 Evolution of Sentiment Analysis Techniques

Sentiment analysis has progressed from simple lexicon-based models to sophisticated deep learning architectures:

- Lexicon-Based Approaches: Early sentiment tools relied on dictionaries where each word is assigned a sentiment score. While interpretable and fast, they often fail in understanding context, negations, or idiomatic expressions.
- Machine Learning Models: Supervised classifiers such as Support Vector Machines (SVM), Naive Bayes, and Logistic Regression learn sentiment patterns from labelled datasets. These methods improve accuracy but require considerable annotated data and feature engineering.
- Deep Learning and Transformer Models: Recent advances include models like BERT, RoBERTa, and GPT, which pre-train on vast corpora to understand contextual semantics and subtleties of language. These models significantly outperform earlier methods but demand high computational resources.

Each advancement has expanded the capabilities and applications of sentiment analysis, but trade-offs between accuracy, interpretability, and resource requirements remain key considerations.

7.12 Additional Examples Illustrating Challenges

- Contextual Ambiguity: The phrase "I'm fine" can be sincere or sarcastic depending on context and tone, which is difficult to discern in text-only data.
- Code-switching and Multilingual Text: Many forum users may mix languages or use local dialects, complicating sentiment analysis.
- Emoji and Symbol Use: Emojis often carry rich emotional meaning; incorporating them can improve accuracy but requires specialized processing.

7.13 Expanded Ethical Considerations with Real-life Implications

Ethical issues extend beyond data privacy to considerations such as:

- Consent and Transparency: Users may not expect their public posts to be analysed for mental health research. Clear communication and ethical oversight are essential.
- Potential for Harm: Automated systems flagging users as at-risk could lead to unintended consequences if handled insensitively, including privacy breaches or stigmatization.
- Algorithmic Bias: Training data reflecting societal biases can propagate discrimination. Continuous evaluation and inclusive dataset curation are necessary.

Interdisciplinary collaboration between technologists, ethicists, clinicians, and user communities is crucial for responsible deployment.

7.14 Future Directions: Emerging Technologies and Interdisciplinary Applications

Looking forward, integrating sentiment analysis with broader mental health tools can revolutionize care:

- Multimodal Analytics: Combining text with voice tone, facial expressions, and physiological data offers a fuller picture of mental states.
- Personalized AI Therapists: Adaptive chatbots using sentiment feedback can provide tailored support.
- Public Health Monitoring: Real-time sentiment tracking across regions could inform health campaigns and resource allocation.
- Cross-Disciplinary Research: Combining computational methods with psychology and sociology can yield richer insights.

These directions promise enhanced accuracy, scalability, and ethical deployment in mental health support.

7.15 Limitations and Mitigation Strategies

While promising, sentiment analysis in mental health faces challenges:

- Data Quality: Noisy, unstructured, or biased data limits model performance. Rigorous preprocessing and dataset curation are vital.
- Interpretability: Complex models may be "black boxes," reducing trust. Explainable AI techniques can help.
- Generalizability: Models trained on one forum or language may not generalize well elsewhere. Cross-domain training and continual learning can mitigate this.

Addressing these limitations through methodological innovation and rigorous evaluation is key to real-world impact.

7.16 In-Depth Statistical Overview of Mental Health Trends Globally

Mental health disorders are not only prevalent but are projected to increase over time due to factors like urbanization, lifestyle changes, and recent global crises such as the COVID-19 pandemic. For example, the WHO reported a significant rise in anxiety and depression cases during and after the pandemic, with many people experiencing isolation, job insecurity, and uncertainty. Such large-scale shifts impact public mental health and highlight the need for real-time monitoring tools.

Online mental health forums and social media serve as a vast, spontaneous repository of people's feelings and experiences, often reflecting emerging mental health trends faster than traditional surveys or clinical reports. Hence, analysing sentiments on these platforms offers a scalable approach to track mental health status across demographics and geographies.

7.17 Enhancing Sentiment Analysis Accuracy: Techniques and Innovations

To overcome limitations of rule-based sentiment analysis like TextBlob, researchers have explored hybrid models combining lexicons with machine learning classifiers. For example:

- Contextual Embeddings: Using word embeddings (Word2Vec, GloVe) and contextual embeddings (BERT) captures word meanings in different contexts, improving sentiment classification.
- Sarcasm Detection Models: Dedicated sarcasm detection components, often using deep learning, help reduce misclassifications in informal texts.
- Emotion-Specific Analysis: Instead of coarse positive/negative/neutral labels, classifying specific emotions (anger, fear, joy, sadness) provides richer insights.

Implementing these enhancements, however, requires balancing complexity and accessibility, especially for academic or clinical environments with limited resources.

7.18 Real-Life Application Case Study: Early Crisis Detection

Consider a mental health organisation that integrated sentiment analysis into their forum monitoring system. Over a month, automated sentiment scores flagged a cluster of posts with sharply rising negative sentiments in a subgroup of users. On manual review, moderators identified early signs of suicidal ideation and intervened promptly by providing support resources and referrals. This approach illustrates how sentiment analysis can be part of proactive mental health care, saving lives through timely intervention.

7.19 Ethical Frameworks for Responsible Use of Sentiment Data

The use of sentiment analysis in sensitive areas like mental health demands strict adherence to ethical frameworks such as:

- Data Minimization: Collecting only the data essential for the analysis to protect user privacy.
- Transparency and Accountability: Informing users about data collection and usage, and providing mechanisms for oversight.
- Bias Auditing: Regularly auditing algorithms for unintended biases, especially related to gender, ethnicity, or socioeconomic status.
- Human-in-the-Loop Systems: Ensuring final decisions or interventions involve human judgment, avoiding sole reliance on automated sentiment outputs.

Such frameworks foster trust and ensure technology supports vulnerable communities without causing harm.

7.20 Future Directions: Integration with Wearables and IoT

Advances in wearable technology (smartwatches, fitness bands) allow continuous physiological monitoring (heart rate, sleep, activity levels) linked to mental health. Combining this with textual sentiment analysis from forums or diaries creates a multimodal mental health monitoring system, enabling more holistic and personalized support.

For instance, an individual's elevated heart rate patterns combined with frequent negative sentiment posts could trigger alerts for early therapeutic outreach, improving preventive care.

7.21 Practical Recommendations for Researchers and Practitioners

- Data Diversity: Use diverse datasets from multiple forums and languages to improve model robustness.
- User-Centric Design: Develop tools with user privacy and control as a priority.
- Interdisciplinary Collaboration: Work with clinicians, psychologists, and ethicists to ensure models are clinically relevant and ethically sound.
- Scalability and Accessibility: Focus on lightweight models for deployment in low-resource settings or non-specialist users.

VIII. CONCLUSION

This research presents a practical and accessible sentiment analysis tool tailored for mental health forums, leveraging Python's TextBlob library and basic visualisation techniques. The tool effectively categorises user comments into positive, negative, and neutral sentiments, providing a valuable overview of the emotional dynamics within online mental health communities.

The study highlights the predominance of negative sentiments in such forums, reflecting users' need for support and expression during challenging times. At the same time, the presence of positive comments points to the healing and encouraging nature of peer interactions.

While the tool's simplicity is advantageous for ease of use and educational purposes, future work should focus on addressing its limitations by incorporating advanced NLP models capable of capturing complex emotional nuances. Expanding the tool to process larger datasets, handle diverse languages, and offer real-time analysis would further increase its utility.

Ultimately, integrating such sentiment analysis tools into mental health support systems could contribute to timely interventions and improved understanding of community well-being, aiding professionals and users alike.

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