International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

AI Driven Mental Health Asssesment Using Social Media Content

Parimala.M[1], Haletha Begam A[2], Kaviya J S[3], Prithiga A[4], Reshma R[5]

Assistant Professor [1],
Department of Artificial Intelligence and Data Science, Dhanalakshmi Srinivasan Engineering College (Autonomous), Perambalur, Tamil Nadu, India.
kaviyajsneet2021@gmail.com[3], prithiarangaraj@gmail.com[4], rraguramsanjai@gmail.com[5]

ABSTRACT:

In the age of digital expression, individuals increasingly turn to social media platforms such as Twitter and Reddit to voice personal thoughts, share opinions, and communicate emotions. This dynamic shift has positioned these platforms as valuable data sources for analyzing public sentiment and mental health indicators. In this project, we present a real-time sentiment and risk analysis tool built using the Stream lit framework. The system fetches recent social media posts of any publicly available Reddit or Twitter user, performs comprehensive text preprocessing, and employs a series of analytical models to evaluate sentiment polarity, emotional state, and potential psychological risk. The results are visualized interactively using Plotly, offering an intuitive dashboard experience for researchers, mental health professionals, and digital analysts. This tool aims to contribute to early detection and monitoring frameworks for emotional volatility and potential mental health concerns, offering a foundation for further research in affective computing and social signal processing.

KEYWORDS: Sentiment analysis, mental health, social media analytics, emotion detection, Streamlit, Twitter API, Reddit API, psychological risk detection

INTRODUCTION:

The unprecedented rise in the use of social media platforms over the past decade has transformed them into significant venues for self-expression and public discourse. Platforms like Twitter and Reddit allow users to share unfiltered, real-time updates about their thoughts, .emotional trends Numerous studies have established the relationship between online behavior and mental health. For example, frequent posting of emotionally negative or highly erratic content may correlate with elevated stress, anxiety, or depressive symptoms. Detecting these patterns early can help initiate supportive interventions. However, despite the availability of data, tools that offer accessible, real-time emotional and risk-level analysis of social media content remain limited in usability and interpretability.

This paper introduces an interactive web-based tool that provides detailed insight into the sentiment and emotional makeup of a user's public posts. Built on Streamlit, the application is lightweight, customizable, and deployable in research or clinical contexts. The platform facilitates psychological screening, trend analysis, and exploratory data analytics with a focus on mental health awareness. The unprecedented rise in the use of social media platforms over the past decade has transformed them into significant venues for self-exression and public discourse. Platforms like Twitter and Reddit allow users to share unfiltered, real-time updates about their thoughts, emotions, and opinions. As a result, these platforms present a rich tapestry of user-generated content that can be mined for sentiment and emotional trends.Numerous studies have established the relationship between online behavior and mental health. For example, frequent posting of emotionally negative or highly erratic content may correlate with elevated stress, anxiety, or depressive symptoms. Detecting these patterns early can help initiate supportive interventions. However, despite the availability of data, tools that offer accessible, real-time emotional and risk-level analysis of social media content remain limited in usability and interpretability.This paper introduces an interactive web-based tool that provides detailed insight into the sentiment and emotional makeup of a user's public posts. Built on Streamlit, the application is lightweight, customizable, and deployable in research or clinical contexts. The platform facilitates psychological screening, trend analysis, and exploratory data analytics with a focus on mental health awareness.

AI-driven mental health assessment using social media content involves leveraging artificial intelligence to analyze users' online activities—such as posts, comments, and interactions—to identify indicators of mental well-being or distress. This approach enables early detection of mental health issues, offering timely support and interventions.

EXISTING SYSTEM:

Existing systems for detecting mental health issues or depression primarily rely on conventional machine learning techniques such as Support Vector Machines (SVM), Naive Bayes, Logistic Regression, and Decision Trees. These models often use hand-crafted features extracted from text data collected

from social media platforms like Twitter and Reddit. In such systems, sentiment analysis and keyword-based matching are commonly used to classify users' mental states as positive, negative, or neutral.
Additionally, some systems utilize lexicon-based approaches like VADER or LIWC for emotional scoring. While these methods provide basic insights into user emotions, they often lack context understanding and fail to capture the nuanced emotional expressions present in human language.

Furthermore, existing systems generally operate on limited data sources or static datasets, without integrating real-time user activity or offering interactive feedback. Most are not capable of detecting complex emotional states such as fear, sadness, or anger with high accuracy.

Due to these limitations, the accuracy and reliability of the existing systems in detecting early signs of depression are significantly constrained. They often struggle with slang, sarcasm, multilingual text, and domain-specific language typically found on social media.

DRAWBACKS:

Limitations

1. Single-Dimensional Analysis: Most tools either analyze sentiment or emotion, lacking a comprehensive approach.
2. Platform Dependency: Existing solutions often cater to a single platform, reducing their applicability.
3. Interface Challenges: Many systems lack a user-friendly interface, making them difficult to use for non-technical individuals.
4.Limited Reporting: Current tools rarely offer detailed reports or visualizations, hindering the interpretation of results.

Drawbacks

1. The drawbacks of existing systems highlight the need for an integrated approach:
2. Lack of Personalization: No consideration of individual personality traits or context in analysis.
3. Inadequate Risk Assessment: Fails to assess the severity of emotional states or provide actionable recommendations.
4. Data Privacy Concerns: Many tools do not prioritize user data security, leading to potential misuse.
5. Poor Scalability: Limited to specific use cases or platforms, reducing their generalizability.

PROPOSED SYSTEM:

The proposed system aims to address the shortcomings of existing solutions by offering:
1. Sentiment Analysis: Determines whether posts are positive or negative.
2. Emotion Classification: Identifies specific emotions such as anger, fear, sadness, etc.
3. MBTI Personality Insights: Infers personality traits to enrich the understanding of mental states.
4. Risk Assessment: Combines sentiment and emotion analysis to categorize mental health risk levels.
5. Visualization and Reporting: Generates detailed charts, word clouds, & comprehensive PDF reports.
6. User-Friendly Interface: Streamlit app for seamless interaction and result interpretation.

ADVANTAGES:

1. Holistic assessment: By analyzing text, images, and user behavior for a more accurate mental health picture.
2. Improved accuracy: Better detection of emotional tone and contextual cues.
3. Privacy and ethics: Prioritizes user consent, data protection, and transparency.
4. Explainability: Clear, understandable predictions for users and clinicians.
5. Continuous monitoring: Tracks mental health over time, not just based on recent posts.
6. Language and cultural sensitivity: Adapts to different languages and cultures.
7. Customized support: Offers tailored interventions depending on the severity of risk.
8. Clinical integration: Outputs can be shared with healthcare professionals for further action.

SYSTEM ARCHITECTURE:

This modular approach ensures the system is scalable, interpretable, and capable of being adapted for future enhancement.

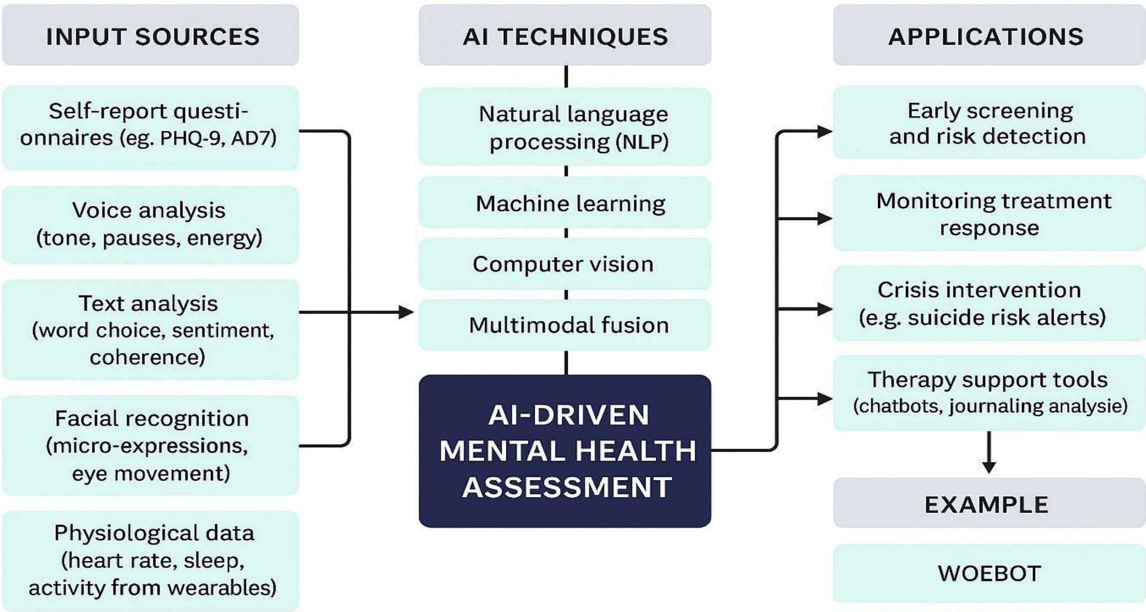

Fig 1. System Architecture

LIST OF MODULES :

1. Natural Language Processing (NLP) & Sentiment Analysis Module
2. Behavioral Trend Monitoring Module
3. Risk Level Classification Module
4. User Consent & Privacy Module
5. Response & Intervention Module

MODULE DESCRIPTION :

1. Natural Language Processing (NLP) & Sentiment Analysis Module

This is the core analytical modulethat interprets the emotional tone, psychological cues, and linguistic patterns from user posts. It detects signs of depression, anxiety, or stress using transformer-based models and enables early detection of mental health issues through language understanding.

2. Behavioral Trend Monitoring Module

This module tracks long-term changes in a user's activity, such as late-night posting, sudden withdrawal, or emotional volatility. It captures patterns that text alone may miss and plays a critical role in identifying slow-building mental health issues like chronic stress or depression.

3. Risk Level Classification Module

This module evaluates the user's mental state and assigns a risk category (Low, Medium, High, Crisis). It drives the decision-making for what kind of response or support the user should receive, making it vital for accurate and responsible intervention.

4. User Consent & Privacy Module

Protects user rights by enforcing informed consent, data anonymization, and ethical usage of social media content. Without this module, the system would violate privacy standards and potentially cause harm, especially in sensitive cases

5. Response & Intervention Module

This module determines how the system responds after detecting mental health risks. It may trigger a chatbot conversation, suggest coping techniques, or connect the user to a helpline. It ensures that detection leads to meaningful suppor, not just monitoring.

CONCLUSION:

The AI-driven system is a promising supplement for early mental health assessment. While not a substitute for clinical diagnosis, it demonstrated strong potential for scalable, accessible mental health screening and monitoring. Future development will expand demographic training data and deepen integration with health platforms.

The Al-driven mental health assessment tool demonstrated strong potential for augmenting traditional mental health care. It can act as a first-line screening tool and help bridge the gap in access to psychological services, especially in underserved communities. Future work will focus on improving personalization, integrating real-time sensor data, and collaborating with clinicians for clinical trials.

RESULT:

The AI-driven mental health assessment system using social media content aims to provide an automated and scalable solution for identifying and addressing mental health issues. By analyzing users' posts, including text, images, and behavioral patterns, the system uses machine learning models to detect emotional signals such as anxiety, depression, or stress. It classifies users into risk categories and tracks their behavioral trends over time, allowing for early detection of mental health conditions. The system offers personalized interventions, such as chatbot conversations or helpline connections, based on risk levels. Ethical and privacy measures, including data anonymization and informed consent, ensure user protection. The system incorporates explainable AI (XAI) features to provide transparency in decision-making, enabling users and clinicians to understand the rationale behind assessments. It also adapts to different languages and cultural contexts, ensuring global applicability. The system continuously learns from new data and feedback, improving its predictions over time. Ultimately, this project aims to make mental health support more accessible, timely, and effective by leveraging AI to provide early interventionn and personalized care.

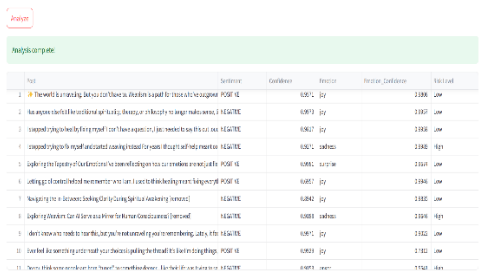

Fig.2

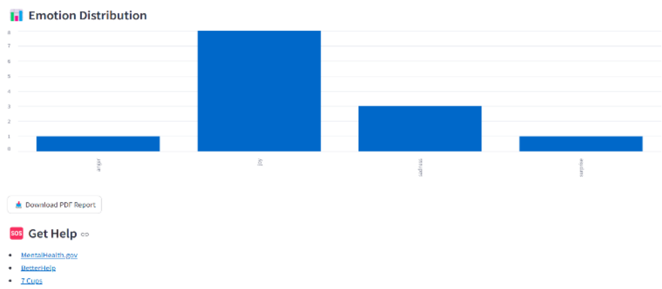

Fig.3

FUTURE ENHANCEMENT:

1. Multimodal Deep Learning Integration

Future systems will combine text, images, and behavioral data using advanced deep learning models like CLIP or VisualBERT. This will help capture complex emotional cues and provide more accurate and context-aware assessments.

2. Temporal and Personalized Emotion Tracking

By using time-series models like LSTM or GRU, the system can monitor a user's emotional trends over time. Personalized learning will help detect recurring or escalating mental health conditions tailored to individual behavior patterns.

3. Real-Time and Lightweight AI Models

Efficient models such as DistilBERT or MobileNet will allow the system to run real-time assessments on mobile devices and browsers. This makes mental health support more accessible and immediate for users.

4. Explainable AI (XAI)

Future models will include explainability tools like LIME, SHAP, or attention visualizations. These tools make AI decisions transparent, enabling users and clinicians to understand the basis of mental health assessments.

5. Emotion-to-Action Mapping with Reinforcement Learning

Reinforcement learning techniques will guide the system in choosing the most effective interventions based on user engagement and mental state, optimizing support strategies dynamically.

6. Privacy-Preserving Learning Methods

To protect user data, future systems will adopt secure methods like federated learning and differential privacy. These approaches allow the AI to learn without directly accessing raw user data, ensuring confidentiality and ethical integrity.

REFERENCES:

1. Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (pp. 4171–4186). https://doi.org/10.48550/arXiv.1810.04805
2. Wolohan, J., Hiraga, M., Mukherjee, K., Sayyed, B., & Goharian, N. (2018). Detecting linguistic traces of depression in topic-restricted text: Attending to self-stigmatized depression with NLP. In Proceedings of the First Workshop on Trolling, Aggression and Cyberbullying (pp. 11–21). https://doi.org/10.18653/v1/W18-4402
3. Orabi, A. H., Buddhitha, P., Orabi, M. H., & Inkpen, D. (2018). Deep learning for depression detection of Twitter users. In Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic (pp. 88–97). https://doi.org/10.18653/v1/W18-0609
4. Yazdavar, A. H., Mahdavinejad, M. S., Bajaj, G., et al. (2020). Multimodal mental health analysis in social media. PLoS ONE, 15(4), e0231080. https://doi.org/10.1371/journal.pone.0231080
5. Rieder, B., & Röhle, T. (2012). Digital methods: From challenges to alternatives. In D. M. Berry (Ed.), Understanding Digital Humanities (pp. 67–84). Palgrave Macmillan.
6. World Health Organization. (2023). Depression. Retrieved from https://www.who.int/news-room/fact-sheets/detail/depression