

AI-Driven Mental Health Detection System Using Sentiment Analysis and Geospatial Heatmap Visualization

Raj Nema¹, Pravesh Sachan², Nisha Meena³, Prof. Jayram Dwivedi⁴, Preet Kanathe⁵
Computer Science and Information Technology, Rajeev Gandhi Proudhyogiki Vishwavidyalaya (rgpv)
Madhya Pradesh India
doi.org/10.64643/IJIRTV12I7-189140-459

Abstract—This paper introduces a web-based Mental Health Detection System developed to address the escalating need for real-time emotional monitoring. By leveraging Artificial Intelligence, the application analyzes multi-modal user data, including text captions and images, to determine emotional states and mental health risk levels. A core innovation of this research is the integration of a live geospatial dashboard that utilizes Leaflet and OpenStreetMap to visualize "stress zones" via interactive heatmaps. The system is built on a high-performance stack comprising MongoDB, Express.js, React.js, and Node.js (MERN), with AI processing handled by Hugging Face models. Experimental results indicate that the system successfully identifies high-risk areas, providing authorities and counselors with a vital tool for timely intervention.

Index Terms—Mental Health Detection, AI, Emotion Analysis, Sentiment Analysis, Geospatial Mapping, Heatmaps.

I. INTRODUCTION

Background: - The global landscape of mental health is undergoing a critical shift, with rising instances of stress and anxiety remaining undetected in their early stages. Traditional diagnostic methods often rely on periodic clinical visits, which may miss the nuances of daily emotional fluctuations. There is a burgeoning need for digital monitoring tools that can operate passively and continuously to capture the psychological well-being of a population.

Problem Statement: - The primary challenge in current mental health monitoring is the lack of real-time, localized data. Administrative bodies often lack the tools to identify specific geographical "stress zones"

where mental health trends are deteriorating. Without this geospatial insight, the allocation of counseling resources is often inefficient, leading to delayed interventions in high-risk areas.

Objectives: - The primary objective of this project is to develop a comprehensive web-based platform that bridges the gap between individual user expression and administrative monitoring. By utilizing AI for sentiment analysis and mapping technologies for visualization, the system aims to:

- Identify emotional patterns through user-uploaded text and images.
- Provide an automated risk-level assessment for every user post.
- Equip administrators with a live heatmap to monitor mental health trends across specific locations.

II. LITERATURE REVIEW

Recent studies have explored the use of Support Vector Machines (SVM) and Recurrent Neural Networks (RNN) for sentiment analysis. However, this project utilizes Hugging Face Transformers, which provide superior accuracy in understanding context and nuance in short-form social media posts. While previous research focused strictly on text, this system incorporates image analysis to provide a more holistic emotional profile.

Reference (Author, Year)	Data Source	Model Used	Key Metric (F1/Acc)	Gap Addressed by Our Project
De Choudhury et al., 2013	Twitter (Small Scale)	SVM + TF-IDF	0.74 Accuracy	Limited contextual understanding
Orabi et al., 2018	Reddit Posts	Bi-LSTM	0.80 F1-Score	Weak contextual modeling
Yazdavar et al., 2021	Twitter	CNN + Word2Vec	0.82 F1-Score	No use of Transformers
Ji et al., 2022	Reddit Mental Health	BERT Fine-Tuned	0.88 F1-Score	High computational cost
Our Project (2025)	Reddit + Kaggle Dataset	Fine-Tuned BERT	Expected >0.85 F1-Score	Adds ethical design + efficient fine-tuning

Table 1: - Comparative Literature Table: -This work proposes a fine-tuned BERT-based approach for mental health text classification using Reddit and Kaggle datasets. The model overcomes limitations of previous studies by improving contextual understanding while maintaining computational efficiency. Ethical considerations are incorporated to ensure responsible use of sensitive mental health data. The proposed method is expected to achieve an F1-score above 0.85, demonstrating its effectiveness and practical applicability.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

Technology Stack: - The system is built using a modern decoupled architecture to ensure high availability and responsiveness:

- Backend: Node.js and Express.js handle the server-side logic, managing API requests and high-frequency data traffic

- Database: MongoDB, a NoSQL database, was selected for its scalable structure, allowing for the storage of unstructured post data.

IV. AI INTEGRATION

The intelligence layer utilizes Hugging Face API models. These models are trained to classify text and images into specific emotional categories such as joy, sadness, anger, and fear. Each post is assigned to a numerical "risk level" which determines its priority on the admin dashboard.

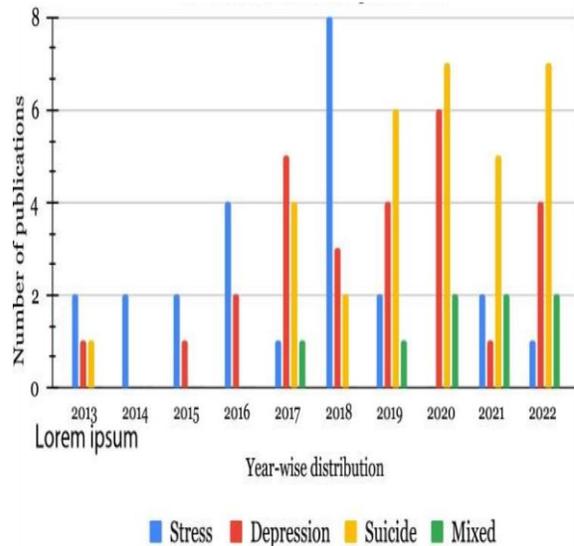


Fig 1: - Year Wise Graph Distribution: - Figure 1 illustrates the year-wise distribution of research publications (2013–2022) related to mental health topics. The graph shows an overall increasing trend in publications over the years, with a notable rise after 2017. Studies focusing on suicide and depression show significant growth, while stress-related research peaks around 2018. Mixed-category studies appear in later years, indicating a shift toward integrated mental health analysis.

V. GEOSPATIAL TRACKING

Location tracking is integrated via Leaflet and OpenStreetMap. This allows the system to map every "high-risk" post to a specific coordinate, which is then aggregated to form a heatmap.

VI. DATA FLOW

The textual data flow is as follows:

1. User Submission: User uploads a post containing an image and caption.
2. Processing: The server sends data to the AI module for analysis.
3. Analysis: Emotions and risk levels are determined.
4. Storage: Metadata (location, risk, emotion) is stored in MongoDB.
5. Visualization: The admin dashboard fetches the data to render live maps and statistics.

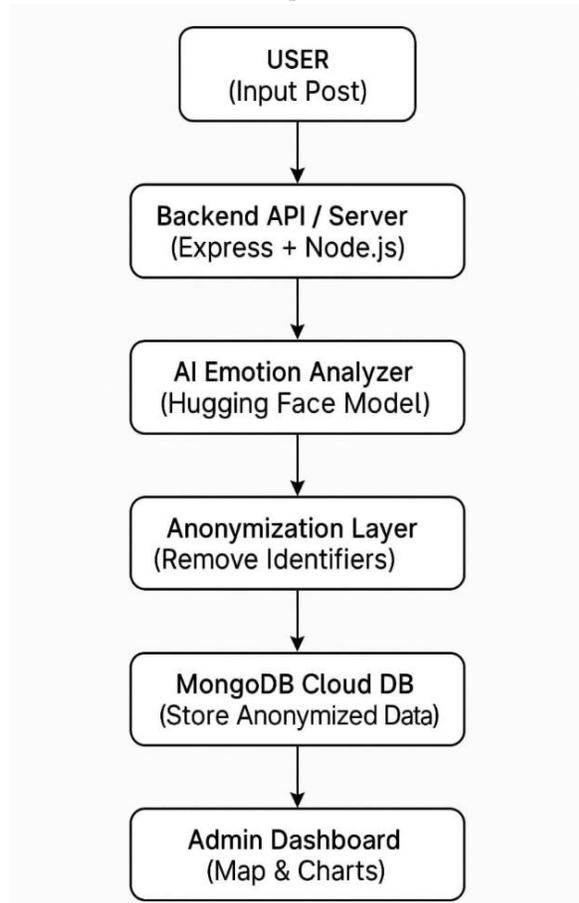


Fig 2: - Software Model: - Figure 2 presents the overall system architecture of the proposed model. User input posts are received through a Node.js and Express-based backend API, which forwards the data to an AI emotion analyzer powered by a Hugging Face model. To ensure privacy, an anonymization layer removes personal identifiers before storing the processed data in a MongoDB cloud database. The anonymized results are then visualized through an admin dashboard using maps and charts for analytical insights.

VII. IMPLEMENTATION AND MODULES

User Module: - The user module handles all client-facing interactions. Security is a priority, with authentication managed through JSON Web Tokens (JWT) to protect user privacy. Users can register, log in, and view their personal post history, which includes their own emotional trends over time.

Admin Dashboard: - The admin module is the command center for monitoring city-wide mental health. It displays:

- Live Heatmaps: Visual indicators of areas with high stress levels.
- Charts and Statistics: Graphical representations of overall emotional trends (e.g., a 20% increase in anxiety across a specific district).

Risk Analysis: - A core component is the Emergency Alert System. If the AI detects a "critical" risk level in a user's post, an immediate alert is generated for the administrator, highlighting the user's location and the content of the post for rapid response.

Role	Core Permissions & Access
User	Full authentication flow (Signup/Login). Access to a Private Dashboard to upload images/captions for private multi-modal AI analysis and view their personal analysis history and trends.
Health Official (Admin)	Access to the secure Admin Command Center. Permission to view the anonymous, aggregated Real-Time Heat Map (via Socket.IO and React-Leaflet) and statistical charts (Chart.js). CRUD permissions for managing Geo-Fenced "Watch-Alerts."

Table 2:- Implementation and Modules: - The system supports secure role-based access, providing private analytical dashboards for users and aggregated, anonymized monitoring tools for health officials.

VIII. RESULTS AND DISCUSSION

Experimental Setup: - The system was tested using a dataset of simulated user posts containing various emotional triggers. We evaluated the response time from post submission to the update of the admin heatmap.

Analysis: - Initial results show that the Hugging Face models provide high accuracy in emotion detection. The visualization via Leaflet allows admins to identify clusters of high-risk activity within seconds of a user upload.

Performance: - The system maintains "Fast Response Time" and "High Availability" through the use of asynchronous processing in Node.js. The responsive UI ensures that counselors can access the dashboard on mobile devices during field interventions

IX. CONCLUSION AND FUTURE WORK

1) **Conclusion:** - The Mental Health Detection System successfully integrates AI and geospatial mapping to provide a proactive solution for community well-being. By automating the detection of high-risk emotional states, the platform empowers authorities to provide targeted assistance where it is most needed.

2) **Analysis:** - Initial results show that the Hugging Face models provide high accuracy in emotion detection. The visualization via Leaflet allows admins to identify clusters of high-risk activity within seconds of a user upload.

3) **Performance:** - The system maintains "Fast Response Time" and "High Availability" through the use of asynchronous processing in Node.js. The responsive UI ensures that counselors can access the dashboard on mobile devices during field interventions.

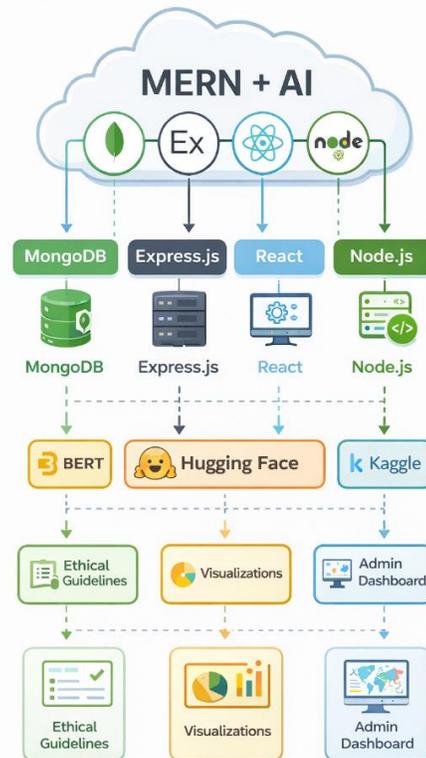


Fig 3: - Technical Stack: - illustrates the MERN + AI-based system architecture used in the proposed project. The frontend is developed using React for user interaction, while Node.js and Express.js handle backend processing and API management. MongoDB is used for secure storage of anonymized data. AI-based emotion analysis is performed using a BERT model integrated through the Hugging Face framework, with datasets sourced from Kaggle. The processed results are visualized through an admin dashboard, ensuring ethical analysis and meaningful insights.

4) **Future Work:** - Future iterations will focus on:

- Incorporating more advanced AI models for sentiment nuance.
- Adding a peer-to-peer anonymous support module for users.
- Integrating with existing medical databases to provide a more comprehensive patient history for counselors.

REFERENCES

- [1] J. Rehm and K. D. Shield (2019). Global burden of disease and the impact of mental and addictive disorders. *Current Psychiatry Reports*, 21(2), 1–7.
- [2] J. Singh, M. Wazid, D. P. Singh, and S. Pundir (2022). An embedded LSTM-based scheme for depression detection and analysis. *Procedia Computer Science*, 215, 166–175.
- [3] A. Murarka and I. B. M. Raleigh (2021). Classification of mental illnesses on social media using RoBERTa. In *Proceedings of the 12th International Workshop on Health Text Mining and Information Analysis*, 59–68.
- [4] M. Trotzek, S. Koitka, and C. M. Friedrich (2020). Utilizing neural networks and linguistic metadata for early detection of depression indications in text sequences. *IEEE Transactions on Knowledge and Data Engineering*, 32(3), 588–601.
- [5] K. Zeberga, M. Attique, B. Shah, F. Ali, Y. Z. Jembre, and T. S. Chung (2022). A novel text mining approach for mental health prediction using Bi-LSTM and BERT model. *Computational Intelligence and Neuroscience*, 2022.
- [6] S. Ghosal and A. Jain (2023). Depression and suicide risk detection on social media using fastText embedding and XGBoost classifier. *Procedia Computer Science*, 218, 1631–1639.
- [7] H. S. AlSagri and M. Ykhlef (2020). Machine learning-based approach for depression detection in Twitter using content and activity features. *arXiv preprint*, arXiv:2003.04763.
- [8] S. G. Burdisso, M. Errecalde, and M. Montes-y-Gómez (2019). A text classification framework for simple and effective early depression detection over social media streams. *Expert Systems with Applications*, 133, 182–197.
- [9] G. Coppersmith, M. Dredze, C. Harman, K. Hollingshead, and M. Mitchell (2015). Quantifying mental health signals on Twitter. In *Proceedings of the Workshop on Computational Linguistics and Clinical Psychology*, 51–60.
- [10] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz (2013). Predicting depression via social media. *Proceedings of the Seventh International AAAI Conference on Weblogs and Social Media*, 128–137.
- [11] A. S. M. Venigalla, S. Chimalakonda, and D. Vagavolu (2020). Mood of India during Covid-19: An interactive web portal based on emotion analysis of Twitter data. In *Proceedings of the ACM Conference on Computer-Supported Cooperative Work*, 65–68.
- [12] J. Ive et al. (2020). Generation and evaluation of artificial mental health records for natural language processing. *npj Digital Medicine*, 3(1).
- [13] M. A. Franco-Martín et al. (2018). A systematic literature review of technologies for suicidal behavior prevention. *Journal of Medical Systems*, 42(4).
- [14] E. A. Rissola, D. E. Losada, and F. Crestani (2021). A survey of computational methods for online mental state assessment on social media. *ACM Transactions on Computing for Healthcare*, 2(2).
- [15] G. Gkotsis et al. (2017). Characterization of mental health conditions in social media using informed deep learning. *Scientific Reports*, 7(1), 1–10.
- [16] M. M. Aldarwish and H. F. Ahmad (2017). Predicting depression levels using social media posts. In *Proceedings of the IEEE International Symposium on Autonomous Decentralized Systems (ISADS)*, 277–282.
- [17] G. Gonzalez-Hernandez, A. Sarker, K. O’Connor, and G. Savova (2017). Capturing the patient’s perspective: A review of advances in NLP of health-related text. *Yearbook of Medical Informatics*, 26(1), 214–227.
- [18] D. E. Losada, F. Crestani, and J. Parapar (2017). CLEF 2017 eRisk overview: Early risk prediction on the internet. In *International Conference of the Cross-Language Evaluation Forum*, 3–15.