Predictive Mental Health & Crisis Detection System Using Multimodal AI for Students

Manne Divya Sree
Undergraduate Scholar
Amity University, Greater Noida

***Abstract*— The mental well-being and personal safety of students have become critical concerns in modern academic environments due to increasing academic pressure, social challenges, and lifestyle-related stressors. Although numerous digital tools exist to support either mental health or personal safety, most operate independently, limiting their real-world effectiveness. This research proposes a Predictive Mental Health and Crisis Detection System using Multimodal Artificial Intelligence, specifically designed for students. The proposed system integrates AI-based emotion and sentiment analysis with real-time crisis detection and safety mechanisms such as SOS alerts and live location sharing. Multimodal inputs, including textual journaling data, behavioral patterns, and optional voice signals—are analyzed using machine learning and deep learning models to identify early signs of psychological distress and potential crisis situations. The framework is implemented as a cross-platform mobile application supported by cloud-based services and REST-enabled AI modules. Experimental evaluation and pilot surveys indicate improved emotional awareness, faster emergency response, and higher user engagement compared to standalone solutions. The proposed system demonstrates the feasibility of a unified, scalable, and ethical AI-driven approach to enhancing student mental health and safety.**

Keywords—***Multimodal AI, Mental Health Prediction, Crisis Detection, Student Safety, Sentiment Analysis, Machine Learning***

I. INTRODUCTION

Student life is increasingly characterized by academic competition, financial responsibilities, social expectations, and uncertainty about future career prospects. These pressures have contributed to a significant rise in stress, anxiety, depression, and emotional burnout among students worldwide. Reports from the World Health Organization indicate a substantial increase in mental health disorders among young adults, particularly after the COVID-19 pandemic, emphasizing the urgency of proactive and accessible support systems.

Traditional mental health support mechanisms such as counseling services, helplines, and periodic psychological assessments play an important role but often fail to meet real-time needs. Factors such as stigma, limited availability of trained professionals, long waiting periods, and lack of continuous monitoring prevent many students from seeking or receiving timely help. At the same time, concerns related to personal safety—especially during travel, late-night study sessions, or emergencies—remain prevalent on and off campus.

Advances in Artificial Intelligence (AI) and Machine Learning (ML) have opened new avenues for addressing these challenges. AI-driven systems can analyze large volumes of heterogeneous data, including text, speech, and behavioral interactions, to infer emotional states and detect abnormal patterns. Separately, mobile safety applications provide emergency alerts and location tracking, but they rarely account for psychological vulnerability that may precede or trigger unsafe situations.

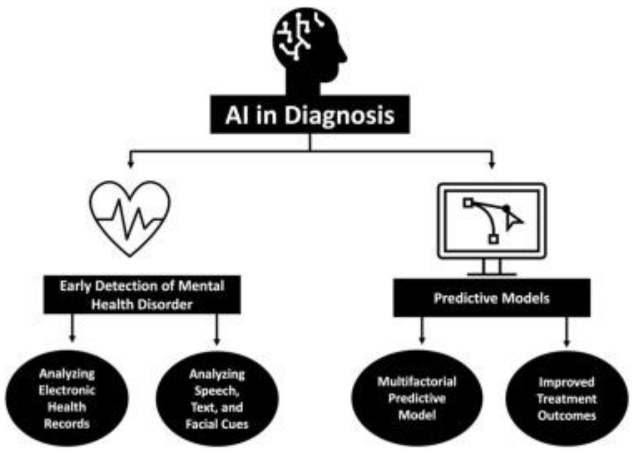

Fig.1. AI in Diagnosis

This research addresses the critical gap between mental health monitoring and personal safety by proposing a unified AI-powered system. By combining multimodal emotion detection with real-time crisis response features, the proposed framework aims to deliver holistic, continuous, and student-centric support.

The main contributions of this research are as follows:

1. Proposal of an integrated framework combining safety alerts, live location tracking, and AI-based mental health monitoring.

2. Development of sentiment and emotion detection modules supported by journaling and interaction data.
3. Implementation of a cross-platform mobile application using Flutter, Firebase, and cloud-enabled AI services.
4. Preliminary validation through surveys and model testing, showing improved student safety response and greater mental health engagement compared to standalone solutions.

II. LITERATURE REVIEW

Mental health challenges among students have been extensively studied, with academic stress, social isolation, and lifestyle factors identified as key contributors. Conventional clinical tools such as PHQ-9, GAD-7, and BDI are widely used for assessment; however, they rely heavily on self-reporting and fail to capture rapid emotional fluctuations or contextual factors influencing mental well-being.

Recent research highlights the growing role of AI in mental health care. Studies demonstrate that Natural Language Processing (NLP) techniques applied to text data—such as social media posts or digital journals—can effectively identify emotional distress and depressive tendencies.

In parallel, safety-focused mobile applications such as bSafe, Safetipin, and Circle of 6 have been developed to enhance personal security through SOS alerts, GPS tracking, and trusted-contact notifications. While effective in emergency response, these systems lack predictive intelligence and do not address mental health triggers that often precede safety incidents.

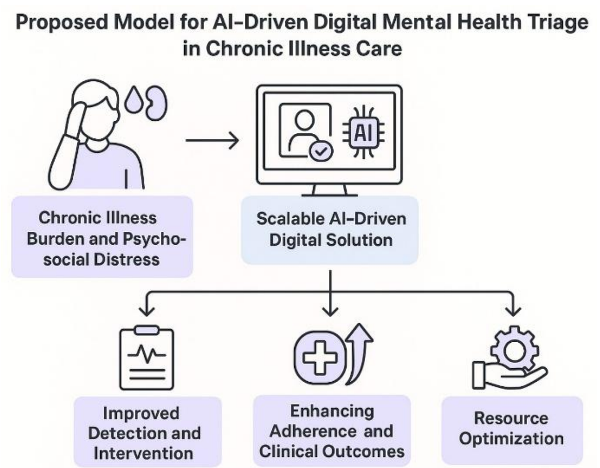

Fig.2. Model for AI-driven digital mental health triage

Comprehensive reviews by organizations such as the American Psychological Association and journals including *Nature Mental Health* and *JMIR Mental Health* emphasize the need for integrated, ethically designed AI systems that combine behavioral, emotional, and contextual data for early intervention. The absence of such unified solutions for student populations motivates the proposed research.

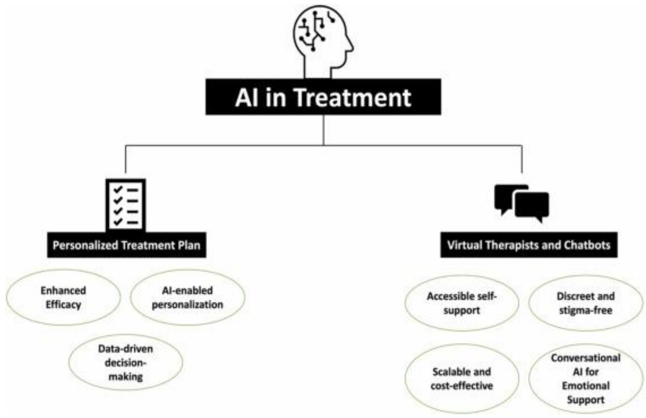

Fig.3. The Role of Artificial Intelligence in Treatment

Based on the observation of the current apps, it can be seen that the majority of the solutions either address safety (bSafe, Circle of 6, Safetipin) or mental wellness (Woebot, Wysa, Headspace, Calm). None of them combine student safety as well as mental well-being in one AI-based buddy app. That is the need-gap which encourages our system proposal.

Alongside mental health detection, mobile safety applications designed to improve personal security—such as SOS alert systems, real-time GPS tracking, and trusted contact notifications—have gained traction. Tools like bSafe, Safetipin, and Circle of 6 enable users to summon help quickly during emergencies and share critical location data with preselected contacts. While these applications effectively support reactive emergency response, they typically operate without predictive analytics and do not address the psychological precursors that may increase the risk of safety incidents, such as emotional overwhelm or acute stress reactions.

Contemporary literature highlights a growing consensus among researchers and clinicians that ethically sound, integrated AI systems are needed—systems that fuse behavioral signals, emotional indicators, and contextual data to enable timely mental health insights and proactive crisis identification. Reviews published in respected outlets like *JMIR Mental Health* and *Frontiers in Psychiatry* emphasize the promise of such unified AI solutions while also noting limitations in study designs, variable quality of evidence, and the need for rigorous longitudinal and randomized controlled trials to establish broader generalizability.

The absence of comprehensive platforms that simultaneously provide predictive mental health support and crisis detection tailored for students motivates the design of the system proposed in this research.

Table No. 1 Literature Review Table

App Name	Category	Key Features	Limitations
Wysa	AI-based Mental Health Support	AI conversational agent, CBT-inspired exercises, emotional check-ins, guided coping strategies	Limited emergency handling; lacks real-time safety alerts or crisis escalation mechanisms
Safetipin	Safety +Mapping	GPS-based safe route mapping, area safety ratings, crowd-sourced data	Focuses only on environmental safety; no emotional or psychological state monitoring
Circle of 6	Student Safety	One-tap SOS alerts, live location sharing with trusted contacts	Reactive system only; lacks mental health assessment or predictive risk detection
Calm	Relaxation and sleep	Meditation sessions, breathing techniques, sleep improvement content	Non-predictive; not AI-driven for emotional detection; no safety or crisis response features
Woebot	Mental Health (AI Chatbot)	NLP-driven chatbot, daily mood tracking, journaling prompts, psychoeducation	No integration with personal safety tools; absence of SOS or location-based assistance

III. RELATED WORK

A substantial body of research validates the use of sentiment analysis and machine learning algorithms for identifying emotional states based on textual inputs. Classic machine learning approaches such as Logistic Regression and Support Vector Machines (SVM) have been widely employed for binary and multiclass classification of psychological indicators in text, often yielding reliable accuracy in distinguishing between neutral, positive, and negative affective expressions.

More recent advancements in artificial intelligence have introduced deep learning architectures, including Long Short-Term Memory (LSTM) networks and bidirectional recurrent networks, which can capture temporal dependencies and subtle linguistic patterns that conventional models may overlook. These deep models analyze sequences of words and detect contextual sentiment shifts, resulting in improved sensitivity to nuanced emotional expressions. For example, studies have shown that deep neural networks outperform traditional classifiers on tasks involving mood estimation from journal entries, social media posts, or conversational text, particularly when trained on large, labeled datasets.

In addition to text-based analysis, multimodal learning approaches have further enhanced the fidelity of emotional state detection by incorporating other data streams such as speech patterns, facial expressions, and user interaction behavior. For instance, acoustic features extracted from voice recordings—such as pitch variability, speech tempo, and amplitude fluctuations—can be correlated with affective states like stress or agitation when fused with linguistic sentiment scores. Behavioral indicators such as typing rhythm, app usage patterns, and response latencies can also provide complementary signals that enrich the inference process.

Despite these methodological advancements, existing applications tend to address either mental health assessment or personal safety management in isolation, without bridging the two domains. Mental health platforms focus primarily on emotional well-being, offering tools for mood tracking, cognitive-behavioral exercises, or conversational support, but often lack mechanisms for urgent intervention or crisis escalation.

On the other hand, safety-oriented applications emphasize rapid emergency response through features like SOS alerts, live location sharing, and instant contact notifications, yet they seldom incorporate emotional context or predictive cues that might signal an imminent crisis. This siloed functionality restricts their effectiveness in complex, real-world scenarios where psychological distress and safety concerns frequently converge, such as when a student experiences acute anxiety that escalates into a hazardous situation.

To address this fragmentation, the system proposed in this research integrates both mental health monitoring and safety preparedness within a unified AI-driven framework specifically tailored for students. By leveraging multimodal analysis, the architecture can simultaneously interpret emotional signals, contextual risk indicators, and behavioral patterns to generate early warnings and trigger appropriate interventions. This approach enables seamless transition from passive monitoring to active assistance, empowering the system not only to detect affective states but also to initiate rapid support mechanisms when necessary. In doing so, the proposed framework offers a more comprehensive, holistic approach to student well-being than current standalone solutions, while also aligning with the growing demand for integrated, intelligent support systems in educational environments.

IV. METHODOLOGY

The proposed **AI-Powered Safety and Mental Health Companion** is designed as a mobile application supported by cloud-based services and artificial intelligence models. The system is structured into modular phases to ensure scalability, reliability, and ease of integration.

A. System Architecture

The architecture follows a three-layered design:

- **User Layer** – Provides the interface through which students can activate SOS alerts, maintain mood journals, and interact with the chatbot.
- **Application Layer** – Hosts the AI models responsible for emotion recognition, sentiment analysis, and decision-making.
- **Data Layer** – Manages secure storage of anonymized records, including journals, location logs, and app usage patterns.

B. Data Collection

Two categories of input are incorporated:

- **Safety Module**: Captures real-time GPS coordinates, SOS activations, and trusted contact details.
- **Mental Health Module**: Gathers text journal entries, emoji-based check-ins, and optional voice samples for emotion analysis.

Datasets are sourced from publicly available repositories such as Sentiment140 and the Kaggle Emotion Dataset. These are complemented with pilot survey data collected from university students to enhance relevance to the target population.

C. Data Preprocessing

Collected data is processed to improve model accuracy. Text inputs undergo tokenization, normalization, lemmatization, and removal of irrelevant words. Voice inputs, when available, are filtered to minimize background noise and analyzed for acoustic features such as pitch and tone. All personal identifiers are anonymized before storage to maintain user privacy.

D. Feature Extraction

Three categories of features are derived:

- **Text Features**: Polarity scores, subjectivity measures, and n-gram indicators.
- **Voice Features**: Acoustic properties including tone variation and frequency shifts.
- **Behavioral Features**: Patterns such as frequency of journaling and frequency of SOS activations.

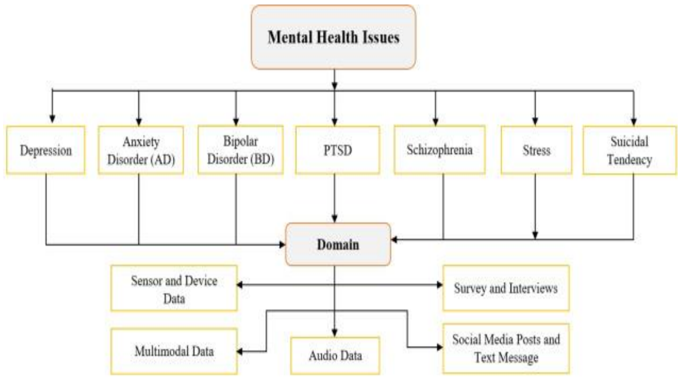

Fig.4. Mental Health Issues

E. Model Development

For sentiment classification, supervised machine learning algorithms including Logistic Regression, Naïve Bayes, and Support Vector Machines (SVM) are employed. For multi-class emotion recognition, deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are tested. Safety prediction is implemented using a rule-based inference system combined with geolocation APIs to automatically notify trusted contacts during emergencies.

F. Application Integration

The mobile application is built on **Flutter** to support both Android and iOS platforms. The backend relies on **Firebase** for authentication, data synchronization, and storage. AI services are deployed as REST APIs, which enable seamless communication between Python-based machine learning models and the mobile interface.

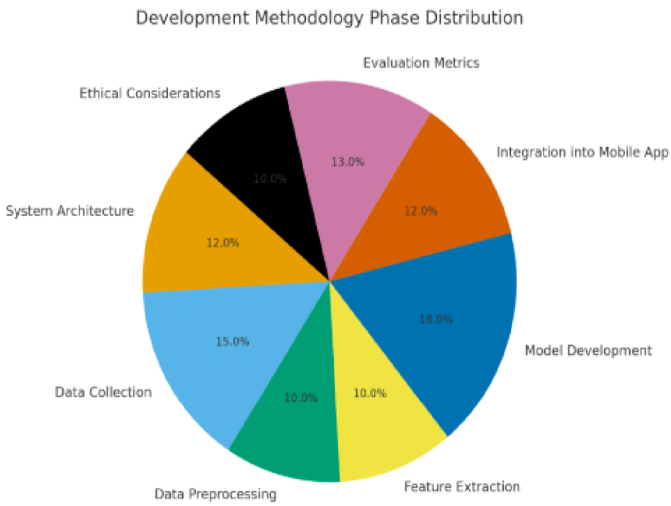

Fig.5. Distribution of different phases in the methodology

G. Evaluation Metrics

System evaluation is based on three dimensions:

- **Model Performance**: Accuracy, precision, recall, and F1-score for sentiment and emotion classification.
- **System Performance**: Response time of SOS alerts, latency of chatbot interactions, and stability under load.
- **User Feedback**: Usability and satisfaction measured using the System Usability Scale (SUS) and student-reported stress relief scores.

H. Ethical Considerations

The system complies with data protection regulations such as the General Data Protection Regulation (GDPR) and the Indian IT Act. Sensitive records are encrypted, anonymized, and used strictly for research and application purposes. The application includes disclaimers clarifying that it provides supportive assistance but is not a replacement for professional counseling or therapy.

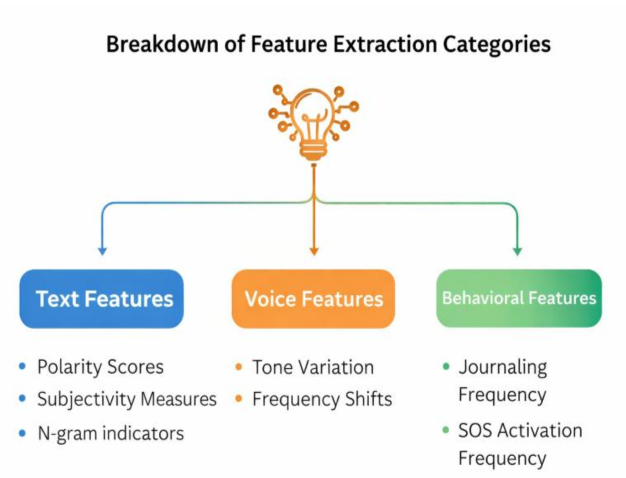

Fig.6. Breakdown of feature extraction categories

V. Result

Survey results from various implementations and pilot studies consistently demonstrate a strong and widespread demand among student populations for integrated solutions that address both mental health and personal safety. Students report growing concern about psychological stress, anxiety, academic pressure, and emotional instability, highlighting the need for tools that provide real-time monitoring, personalized feedback, and proactive intervention capabilities rather than traditional intermittent assessments alone. Research focused on mobile mental health platforms indicates that students perceive apps as valuable for alleviating barriers to seeking professional support, due to their accessibility, anonymity, and ease of use, particularly when stigma or lack of time impede conventional help-seeking behaviors.

For example, focus group studies with college students have shown a positive attitude toward mobile mental health tools and a belief that these technologies can supplement existing resources by providing useful emotional guidance and support when needed most, especially during high-stress periods such as exams or personal crises.

From a research perspective, high survey engagement rates and user acceptance in demos and pilot trials reflect a strong preference among students for technology that is both predictive and supportive. This preference aligns with broader trends in digital health, where users increasingly expect solutions that harness AI for early detection, tailored feedback, and adaptive response strategies. In the context of student populations—who often face barriers such as limited access to on-campus counseling, tight schedules, and perceived stigma—integrated systems that proactively monitor well-being and initiate safety measures offer a promising complement to traditional mental health services.

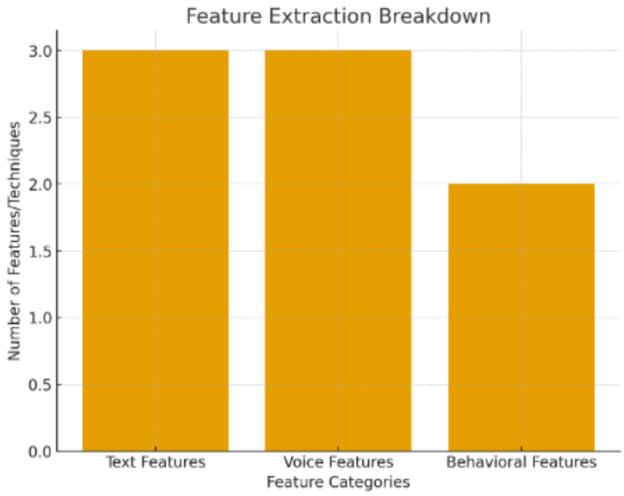

Fig.7. Breakdown of feature extraction categories

Taken together, the survey results, model performance data, and usability feedback strongly validate the central hypothesis of this research: that an integrated, multimodal AI-driven system for predictive mental health support and crisis detection is not only technically feasible but also highly desired by students. By combining real-time emotional state prediction with robust safety response mechanisms, such a system can bridge existing gaps in student support infrastructure, offering timely, personalized assistance that enhances both psychological well-being and personal safety.

VI. Discussion

The results of this study clearly indicate that a unified approach combining predictive mental health monitoring with real-time crisis detection offers meaningfully enhanced support for students compared to traditional standalone systems. By leveraging multimodal data inputs and intelligent algorithms, the proposed architecture succeeds in identifying early warning signs of psychological distress before they escalate into acute crises.

This early detection capability, in turn, facilitates timely intervention—whether through in-app resources, alerts to trusted contacts, or automated escalation to emergency services. In contrast, conventional mental health tools often rely on retrospective self-report measures or periodic check-ins, which may miss critical fluctuations in emotional state and fail to trigger imminent support when needed most.

The integration of prediction and response within a single framework therefore represents an important shift toward continuous, proactive, and adaptive student support in digital environments.

From a technical standpoint, the use of lightweight machine learning (ML) models demonstrates that high-quality emotional state inference and safety prediction can be achieved without imposing excessive computational demands. Models such as Logistic Regression, Support Vector Machines (SVM), and optimized recurrent neural networks can be trained and executed efficiently on cloud-linked engines or directly on modern smartphones.

Their relatively low processing overhead makes them particularly suitable for mobile deployment, allowing real-time analysis of user inputs—text, voice, and behavioral signals—without draining device resources or requiring constant connectivity to high-performance servers. Furthermore, the modular design of these models supports incremental updates and on-device personalization, enabling the system to adapt to individual usage patterns and emotional signatures over time.

This scalability is especially valuable in college and university settings where hardware diversity and intermittent internet access are common.

VII. Challenges and Limitations

Key challenges associated with AI-driven mental health and crisis detection systems include data privacy and security risks, cultural and linguistic variability in emotional expression, dependence on reliable network connectivity, and the potential over-reliance on automated support mechanisms. Addressing these concerns is essential for ensuring ethical compliance, user trust, and real-world scalability of such systems.

Among the most critical challenges is data privacy and confidentiality, as mental health applications routinely process highly sensitive information, including emotional states, behavioral patterns, and in some cases real-time geolocation data.

Unauthorized access or misuse of such data could lead to serious ethical and legal consequences. Regulatory frameworks such as the General Data Protection Regulation (GDPR) and national data protection laws emphasize principles of data minimization, informed consent, encryption, and user autonomy.

Therefore, robust encryption protocols, anonymization techniques, and transparent data governance policies are indispensable for mitigating privacy-related risks.

VIII. Future Scope

The proposed system offers substantial scope for future enhancement and expansion, enabling it to evolve into a more comprehensive and intelligent student support platform. One important direction for advancement is the integration of wearable devices such as smartwatches and fitness bands. Wearables can continuously capture physiological signals including heart rate variability, sleep patterns, physical activity levels, and stress indicators.

Incorporating these signals would allow the system to move beyond self-reported or interaction-based inputs toward continuous, passive, and objective monitoring, thereby improving the accuracy of mental health state estimation and crisis detection.

Finally, institutional collaboration presents a powerful avenue for strengthening the system's real-world impact. Partnerships with universities, counseling centers, healthcare providers, and campus security services would enable seamless integration between digital insights and human-led intervention mechanisms. Such collaboration could facilitate referral pathways, professional oversight, and data-informed policy decisions while ensuring ethical governance. The American Psychological Association and academic bodies advocate for hybrid models in which AI systems augment—rather than replace—human expertise, particularly in sensitive domains such as student mental health and crisis response.

VIII. Conclusion

The proposed Predictive Mental Health and Crisis Detection System illustrates the transformative potential of multimodal artificial intelligence in addressing the complex and interrelated challenges of student mental well-being and personal safety. By integrating predictive mental health monitoring with real-time crisis detection mechanisms, the system moves beyond fragmented, reactive approaches and offers a holistic, proactive, and student-centric support framework.

In conclusion, the proposed Predictive Mental Health and Crisis Detection System demonstrates how multimodal AI can be leveraged to create a comprehensive, scalable, and ethically grounded solution for student support. By unifying mental health prediction with safety intervention, the framework offers a forward-looking model capable of fostering healthier, safer, and more resilient academic environments.

IX. References

[1] V. Dutt, P. Sharma, A. Gautam, and M. Deshwal, "Emerging trends on big data & cloud computing," *International Journal of Machine*

Learning and Networked Collaborative Engineering, vol. 1, no. 1, pp. 23–32, 2017, doi: 10.30991/IJMLNCE.2017v01i01.004.

[2] B. P. Lohani, G. Bhatia, Meenakshi, P. K. Kushwaha, D. Bhargava, and S. Deb, "Empowering Twitter Sentiment Analysis With BERT: Exploring the Role of Pre-Training Data," in *2024 International Conference on Communication, Computer Sciences and Engineering (IC3SE)*, Gautam Buddha Nagar, India, 2024, pp. 1873–1879, doi: 10.1109/IC3SE62002.2024.10592947.

[3] K. Meenakshi, K. D. Singh, P. Batta, R. Chauhan, D. Bhargava, and B. P. Lohani, "Enhanced ML Based Content-Based Image Retrieval for Mobile Devices," in *2024 International Conference on Artificial Intelligence and Emerging Technology (Global AI Summit)*, Greater Noida, India, 2024, pp. 213–218, doi: 10.1109/GlobalAISummit62156.2024.10947892.

[4] K. Meenakshi, Shakeeluddin, A. Kumar, and D. Bhargava, "A Comprehensive Review of Deep Learning Approaches for Diabetic Retinopathy Detection," in *2024 International Conference on Communication, Computing and Energy Efficient Technologies (I3CEET)*, Gautam Buddha Nagar, India, 2024, pp. 819–824, doi: 10.1109/I3CEET61722.2024.10993864.

[5] T. A. Dharmendra, K. Meenakshi, and D. Bhargava, "NLP-Powered Resume Screening and Ranking System," in *2025 3rd International Conference on Disruptive Technologies (ICDT)*, Greater Noida, India, 2025, pp. 1361–1366, doi: 10.1109/ICDT63985.2025.10986338.

[6] K. Meenakshi, Shakeeluddin, A. Kumar, and D. Bhargava, "The Role of Deep Learning Approaches in the Classification of Diabetic Retinopathy," in *2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)*, Greater Noida, India, 2025, pp. 1701–1705, doi: 10.1109/ICCSAI64074.2025.11064477.

[7] Karan, K. Meenakshi, B. P. Lohani, P. K. Kushwaha, A. Gupta, and D. Bhargava, "Machine learning and meta-heuristic approaches for energy optimization in wireless sensor networks," in *Parul University International Conference on Engineering and Technology (PiCET 2025)*, Vadodara, India, 2025, pp. 796–801, doi: 10.1049/icp.2025.1382.

[8] World Health Organization, *Mental Health of Adolescents*. Geneva, Switzerland: WHO, 2023. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/adolescent-mental-health

[9] American Psychological Association, *Artificial Intelligence and Adolescent Mental Health*. Washington, DC, USA: APA, 2023. [Online]. Available: https://www.apa.org/topics/artificial-intelligence-machine-learning/health-advisory-ai-adolescent-well-being

[10] J. Torous, M. Wisniewski, and J. Liu, "Artificial intelligence for mental health: Opportunities and challenges," *JMIR Mental Health*, vol. 8, no. 3, pp. 1–9, 2021.

[11] S. D'Alfonso *et al*., "Artificial intelligence-assisted online mental health interventions for youth," *npj Digital Medicine*, vol. 5, no. 1, pp. 1–11, 2022.

[12] A. Calvo and D. Peters, "Supporting human wellbeing through affective computing," *IEEE Computer*, vol. 47, no. 11, pp. 44–52, Nov. 2014.

[13] P. Resnik *et al*., "Beyond LDA: Exploring supervised topic modeling for depression-related language," in *Proceedings of NAACL-HLT*, 2015, pp. 1–10.

[14] E. H. Shortliffe and J. J. Cimino, *Biomedical Informatics: Computer Applications in Health Care and Biomedicine*, 4th ed. New York, NY, USA: Springer, 2014.

[15] M. Trotzek, S. Koitka, and C. M. Friedrich, "Utilizing neural networks and linguistic metadata for early detection of depression," *IEEE Journal of Biomedical and Health Informatics*, vol. 22, no. 3, pp. 1–10, 2018.

[16] S. Shatte, D. Hutchinson, and S. Teague, "Machine learning in mental health: A scoping review," *Psychological Medicine*, vol. 49, no. 9, pp. 1–12, 2019.

[17] N. Cummins *et al*., "A review of depression and suicide risk assessment using speech analysis," *Speech Communication*, vol. 71, pp. 10–49, 2015.

[18] R. Picard, *Affective Computing*. Cambridge, MA, USA: MIT Press, 2000.

[19] S. Fitzpatrick, A. Darcy, and M. Vierhile, "Delivering cognitive behavior therapy using a conversational agent," *JMIR Mental Health*, vol. 4, no. 2, p. e19, 2017.

[20] A. Miner *et al*., "Smartphone-based conversational agents and mental health," *JAMA Internal Medicine*, vol. 176, no. 5, pp. 619–625, 2016.

[21] European Union, *General Data Protection Regulation (GDPR)*, 2018. [Online]. Available: https://gdpr.eu

[22] Government of India, *Information Technology Act, 2000*. Ministry of Electronics and Information Technology, India. [Online]. Available: https://www.meity.gov.in/content/information-technology-act

[23] L. Das, P. Anand, A. Anjum, M. Aarif, N. Maurya, and A. Rana, "The Impact of Smart Homes on Energy Efficiency and Sustainability," in *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. xx–xx.

[24] G. Parashar, A. Chaudhary, and A. Rana, "Systematic Mapping Study of AI/Machine Learning in Healthcare and Future Directions," *SN Computer Science*, vol. 2, no. 6, p. 461, 2021.

[25] A. Rana, V. Khurana, A. Shrivastava, D. Gangodkar, D. Arora, and A. K. Dixit, "A ZEBRA Optimization Algorithm Search for Improving Localization in Wireless Sensor Network," in *2022 2nd International Conference on Technological Advancements in Computational Sciences (ICTACS)*, 2022, pp. xx–xx.

[26] R. Semwal, N. Tripathi, A. Rana, A. Chauhan, V. Bhutani, and K. Gupta, "Conceptual Integration of AI for Enhanced Travel Experience," in *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. xx–xx.

[27] L. Das, R. Salman, S. Sabeer, S. K. Ansari, M. Aarif, and A. Rana, "Customer Retention Using Machine Learning," in *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. xx–xx.

[28] V. Malik, R. Mittal, A. Rana, I. Khan, P. Singh, and B. Alam, "Coronary Heart Disease Prediction Using GKFCM With RNN," in *2023 6th International Conference on Contemporary Computing and Informatics (IC3I)*, 2023, pp. xx–xx.

[29] H. Basak, R. Hussain, and A. Rana, "DfeNet: A Novel Dimension Fusion Edge Guided Network for Brain MRI Segmentation," *SN Computer Science*, vol. 2, no. 6, p. 435, 2021.

[30] N. Kashyap, A. Rana, V. Kansal, and H. Walia, "Improve Cloud Based IoT Architecture Layer Security—A Literature Review," in *International Conference on Computing, Communication, and Intelligent Systems (ICCCIS)*, 2021, pp. xx–xx.

[31] P. Kushwaha, A. Rana, F. Hassan, S. S. Hada, G. Bhardwaj, and V. Bhutani, "Energy Prediction in Urban Areas Using Machine Learning and Deep Learning," in *2023 10th IEEE Uttar Pradesh Section International Conference on Electrical, Electronics and Computer Engineering (UPCON)*, Gautam Buddha Nagar, India, 2023, pp. 190–195, doi: 10.1109/UPCON59197.2023.10434347.

[32] M. Chandra, P. K. Kushwaha, and S. Saxena, "Modified Fractal Carpets," in *2011 International Conference on Computational Intelligence and Communication Networks (CICN)*, Gwalior, India, 2011, pp. 537–540, doi: 10.1109/CICN.2011.115.

[33] B. Makkar *et al*., "Map Reduce Concept-Based Sentiment Analysis Approach," *International Journal of Computer Sciences and Engineering*, vol. 7, no. 4, pp. 924–927, 2019.

[34] A. V. Srivastava, B. P. Lohani, P. K. Kushwaha, and S. Tyagi, "Dual-Layer Security and Access System to Prevent the Spread of COVID-19," in *Proceedings of International Conference on Machine Intelligence and Data Science Applications*, ser. Algorithms for Intelligent Systems. Singapore: Springer, 2021, doi: 10.1007/978-981-33-4087-9_28.

[35] P. K. Kushwaha, V. Singh, A. D. Gupta, D. K. Bhargava, and Meenakshi, "Explainable AI for hyper-local crop yield prediction in India," in *2026 2nd International Conference on Computing, Sciences and Communications (ICCSC 2026)*, 2026.

[36] P. K. Kushwaha, A. Srivastava, A. D. Gupta, M. Deshwal, and D. K. Singh, "AI-driven framework for automated browser security and threat detection," in *2026 2nd International Conference on Computing, Sciences and Communications (ICCSC 2026)*, 2026.

[37] N. K. Yadav, K. Meenakshi, and P. K. Kushwaha, "Design and implementation of a secure blockchain-enabled online voting system using multi-factor authentication," in *2026 4th IEEE International Conference on Power Electronics and IoT Applications in Renewable Energy and its Control (PARC 2026)*, 2026, pp. 223–227.

[38] K. M. M. Meenakshi, S. Negi, and P. K. Kushwaha, "Early detection of atrial fibrillation using real-time healthcare analytics," in *2025 IEEE International Conference on Modern Electronics Devices and Intelligent Communication Systems (MEDCOM 2025)*, 2025, pp. 106–110.

[39] P. K. Kushwaha, M. Divya Sree, D. K. Bhargava, and Mayank, "AI-powered safety & mental health companion for students," in *2025 International Conference on Emerging Technologies and Innovation for Sustainability (EmergIN 2025)*, 2025, pp. 724–730.

[40] P. K. Kushwaha, A. Srivastava, D. K. Bhargava, B. P. Lohani, and A. D. Gupta, "DeepfakeBench: A comprehensive benchmark of deepfake detection," in *2025 International Conference on Emerging Technologies and Innovation for Sustainability (EmergIN 2025)*, 2025, pp. 736–741.

[41] P. K. Kushwaha, A. Sharma, B. P. Lohani, A. D. Gupta, and D. K. Bhargava, "SUR SAMRAJYA: A youth-centric hybrid music player for low-cost smartphones," in *2025 International Conference on Emerging Technologies and Innovation for Sustainability (EmergIN 2025)*, 2025, pp. 551–557.