

Multimodal Data Fusion in Mental Health: Integrating Behavioral Analytics with AI/ML for Enhanced Detection

Sonu Mittal¹, Kamal Upreti² and Prashant Vats^{3*}

¹Department of Information Technology, Amity Institute of Information Technology (AIIT), Amity University, Uttar Pradesh, India.

²CHRIST (Deemed to be University), Delhi NCR, Ghaziabad, India.

³Department of CSE, Manipal University Jaipur, Jaipur, Rajasthan, India.

*Corresponding Author E-mail:prashant.vats@jaipur.manipal.edu

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Mental health disorders such as depression, anxiety, and PTSD present significant challenges to global healthcare systems, demanding more effective tools for early detection and diagnosis. This study proposes a multimodal AI framework that integrates behavioral data—including textual inputs, speech patterns, facial expressions, and physiological signals—using advanced deep learning techniques. By applying attention mechanisms, graph neural networks, and multi-task learning, the model captures complex patterns and temporal dynamics across modalities to enhance assessment accuracy. To address issues like data heterogeneity and feature misalignment, the framework employs robust fusion and alignment strategies. Interpretability and explainability are prioritized to build clinical trust and support therapeutic decision-making. Evaluations on benchmark datasets demonstrate notable improvements in detection performance for depression, anxiety, and PTSD. The results highlight the potential of AI-driven multimodal behavioral analytics to transform mental health diagnostics, enabling personalized and real-time interventions. Future work will explore ethical concerns, data privacy, and system scalability for broader adoption in clinical and community settings.

Keywords: Anxiety Prediction; Attention Mechanisms; Behavioral Analytics; Clinical Integration; Data Privacy in AI; Depression Detection; Ethical AI Systems; Explainable AI; Multimodal Data Fusion; Mental Health Analytics; Mental Disorder Detection; Multi-Task Learning; Personalized Interventions; Physiological Signal Processing, PTSD Analysis; Real-Time Monitoring; Speech and Text Analysis; Temporal Dynamics.

On a global scale, mental health disorders, including anxiety, depression, and post-traumatic stress disorder (PTSD) pose complex and persistent challenges, affecting millions across diverse demographics. These conditions significantly impair individuals' quality of life, disrupt social relationships, reduce workplace productivity,

and impose immense economic burdens due to healthcare costs, absenteeism, and lost output.

Despite advancements in mental healthcare, diagnosis and treatment remain hindered by the heterogeneity of symptoms and subjective assessment methods. Mental health symptoms often vary considerably from one individual to another,

complicating timely and accurate diagnosis. Traditional approaches—primarily reliant on self-reports and clinician observations—are prone to biases. Patients may understate or exaggerate symptoms, while clinicians may unconsciously introduce interpretative bias, underscoring the need for more objective, data-driven strategies.

Recent progress in artificial intelligence (AI) and machine learning (ML) has opened new avenues for improving mental health diagnostics. These technologies allow for the analysis of complex, high-volume behavioral data to uncover patterns and insights that are not easily discernible through conventional methods. Human behavior is inherently multimodal, encompassing speech, facial expressions, written text, and physiological responses—each capable of revealing key aspects of mental state. For example, subtle changes in vocal pitch, micro-expressions, and heart rate variability may indicate emotional distress.

However, relying on a single modality risk overlooking crucial behavioral cues. Multimodal data fusion addresses this gap by integrating multiple behavioral indicators into a cohesive diagnostic framework. By combining speech, facial cues, physiological signals, and language patterns, these systems offer a holistic view of an individual's mental health, improving diagnostic precision, enabling earlier intervention, and enhancing treatment personalization. Additionally, cross-verification across modalities reduces the impact of inconsistent data, increasing reliability.

This study is grounded in the hypothesis that fusing diverse behavioral data using advanced deep learning models will outperform unimodal approaches in the accurate detection of mental health disorders. The following research questions guide the investigation:

- RQ1: How does multimodal fusion affect diagnostic accuracy compared to unimodal models?
- RQ2: What are the optimal fusion strategies (early, mid-level, or late) for integrating heterogeneous behavioral data?
- RQ3: How can interpretability and transparency be ensured in AI-driven mental health assessments?

To address these, the study employs architectures such as convolutional neural networks (CNNs) for visual input, recurrent neural networks (RNNs) for temporal sequences like speech and text, and graph neural networks (GNNs) to model

inter-modality relationships. Attention mechanisms further enhance the model's ability to prioritize salient features.

Multimodal fusion can occur at various stages

- Early fusion combines raw inputs for joint feature learning.
- Mid-level fusion merges the feature after individual extraction.
- Late fusion integrates decisions from multiple unimodal models.

Each method offers unique advantages depending on the application context and data characteristics.

Figure 1 illustrates the overall architecture of the proposed multimodal diagnostic framework. It outlines the individual data channels (text, speech, facial images, physiological signals), the processing units for each (CNN, RNN, GNN), the chosen fusion strategies, and the final classification layer. The figure also highlights the interpretability interface, enabling clinicians to trace how specific features contributed to the diagnostic output. While promising, this approach is not without challenges. Data alignment across modalities remains technically difficult due to differing temporal dynamics and representation structures. Privacy concerns are paramount, given the sensitivity of mental health data. Ensuring secure data storage and robust encryption is essential. Moreover, training models on imbalanced or non-representative datasets risks perpetuating biases or overfitting, which can undermine diagnostic validity. Transparent AI outputs and human-in-the-loop systems are crucial for building clinician trust and supporting decision-making. AI-enabled multimodal behavioral analytics offer a transformative path forward in mental health diagnostics. However, ethical implementation, rigorous validation, and interdisciplinary collaboration are vital to realizing their full potential in real-world clinical and community settings. It may be conceivable for virtual assistants that are aware of emotions and equipped with powerful multimodal analytics to make it possible for them to provide emotional support and early intervention strategies. It is feasible to improve personalized therapy interventions by applying adaptive systems that evaluate the behavioral patterns of an individual and provide coping skills that are uniquely adapted to that

individual. Individualized therapy treatments can be improved by using adaptive systems. The combination of these systems with telemedicine platforms has the potential to improve the delivery of mental health care to patients who are located at a distance. This is because it provides medical professionals with comprehensive insights into the emotional condition of their patients. Through the development of models that are culturally flexible and take into consideration a wide variety of social and behavioral norms, therapies for mental health that are powered by artificial intelligence will be able to further boost their efficacy and inclusiveness. In conclusion, the utilization of artificial intelligence and machine learning techniques in conjunction with the synthesis of data from several sources presents a significant opportunity to enhance diagnostic procedures and therapeutic methods within the realm of mental health. These systems provide an approach that is both comprehensive and customized, which enhances diagnostic precision, makes it possible to intervene at an earlier stage, and maximizes positive outcomes from treatment. Implementing information obtained from a wide range of data sources is the means by which this objective is attained. For the purpose of ensuring the successful implementation of AI-driven mental health therapies, it is vital, however, that technology concerns be solved, that data privacy be safeguarded, and that model openness be fostered. Assuming that research and collaboration between AI professionals and mental health practitioners are sustained, these advances have the potential to revolutionize mental healthcare and improve the well-being of persons all around the world. This is a great amount of potential that cannot be ignored.

Related Work

Recent advancements in artificial intelligence (AI) and machine learning (ML) have significantly impacted mental health analytics, particularly in diagnosing mental illnesses. Multimodal data fusion, which integrates data from diverse sources such as voice, text, physiological signals, and facial expressions, has emerged as a promising strategy to enhance diagnostic accuracy and reliability.

Speech Recognition for Mental Health Analysis

Speech data plays a vital role in diagnosing mental health conditions. Vocal features like pitch,

tone, tempo, and pauses are significant indicators of emotional distress. Lee, E. E., et al.¹ explored speech characteristics for anxiety and stress recognition, demonstrating that alterations in speech rhythm and tone are linked to mental health issues. Similarly, Espejo, G., et al.² examined acoustic biomarkers in individuals with depression, emphasizing spectral and prosodic features. With advancements in deep learning, models such as CNNs and recurrent neural networks (RNNs) have effectively captured vocal cues for emotion recognition (WHO 2021).

Transfer learning has improved speech-based diagnostic models. Wainberg, M. L., et al.⁴ applied transfer learning using pre-trained models to analyze speech data across different demographic groups, improving generalization and robustness. Further, Qin, X., et al.³ combined voice data with facial expressions to identify depressive symptoms, showcasing the value of multimodal fusion.

Physiological Data Analysis for Mental Health Detection

Physiological signals like heart rate, skin conductance, and EEG data are crucial emotional and psychological well-being indicators. Bajwa, J., et al.⁶ developed a stress detection model using wearable sensors that monitor heart rate variability and skin temperature. Their findings emphasized real-time stress detection's potential using biosensors.

EEG data has gained prominence in identifying mental disorders. Nilsen, P., et al.⁷ employed deep learning models to analyze EEG wave patterns for detecting anxiety and depressive symptoms. Similarly, Langarizadeh, M., et al.⁸ integrated EEG signals with heart rate variability and skin conductance, improving the reliability of stress detection systems. Hybrid models combining EEG data with facial and speech cues have shown improved performance in identifying complex emotional states as found in the investigations of Minerva, F., et al.⁹.

Mobile Health (mHealth) Applications

Mobile health applications have emerged as accessible platforms for mental health monitoring. Johnson, K. B., et al.¹⁰ introduced an AI-driven conversational agent that analyzes user speech, text, and behavioral patterns to detect early signs of emotional distress. Tai, M. C. T. et

al.¹¹ developed a smartphone-based mental health monitoring system that combines GPS data, phone usage behavior, and social interactions to predict emotional well-being.

Healthcare chatbots are increasingly being integrated into mHealth platforms. Bouhouita-Guermech *et al.*¹² designed Woebot, a chatbot that provides cognitive-behavioral therapy (CBT) interventions. Woebot's NLP capabilities allow it to detect signs of anxiety and depression through text conversations, promoting proactive mental health support.

Multimodal Fusion for Enhanced Diagnostic Accuracy

Combining multiple data sources significantly improves diagnostic performance. Naik, N., *et al.*¹³ integrated text, audio, and visual data using deep convolutional neural networks (CNNs) for emotion analysis, demonstrating superior results over unimodal approaches. Similarly, Naik, N., *et al.*¹⁴ introduced a memory fusion network (MFN) that effectively combines verbal, visual, and acoustic data for mental health prediction.

Arias, D., *et al.*¹⁵ explored cross-modal learning strategies, where information from one modality enriched insights gained from another. This approach effectively enhanced behavioral prediction models. Additionally, Sui, J., *et al.*¹⁶ introduced a hybrid fusion model combining random forest classifiers with CNNs, successfully predicting stress and anxiety states.

Emerging Trends and Future Directions

The adoption of graph neural networks (GNNs) has improved multimodal data integration. Uwa, P. *et al.*¹⁷ applied GNN architectures to model complex interactions across voice, text, and facial data, achieving state-of-the-art performance in detecting anxiety and depression.

Explainable AI (XAI) has become crucial for enhancing clinical trust. Anyoha, R., *et al.*¹⁸ emphasized developing interpretable models to ensure healthcare professionals can understand and trust AI-driven recommendations. Ethical considerations, such as data privacy and bias mitigation, have also gained prominence in AI-driven mental health research as per Goldstein, I., *et al.*,¹⁹

Digital therapeutics, incorporating AI models for personalized interventions, have

emerged as valuable tools in mental healthcare. Abreu, J. S. *et al.*²⁰ developed an AI-driven mindfulness application that personalizes meditation routines based on user behavior and emotional patterns, enhancing stress reduction outcomes.

Integrating social network analysis has also proven valuable in mental health research. Parisot, S., *et al.*²¹ employed network-based models to analyze social interactions, revealing behavioral trends linked to anxiety and depression. This approach underscores the significance of combining digital footprint analysis with traditional multimodal data fusion for comprehensive mental health insights.

These studies collectively demonstrate the transformative potential of AI-driven multimodal systems in enhancing mental health diagnostics and treatment. However, challenges remain in achieving seamless data integration, ensuring ethical considerations, and scaling AI models for widespread clinical adoption. Continued research in this field promises to revolutionize mental healthcare, providing more precise, personalized, and accessible solutions for individuals worldwide.

Rationale Behind the Study

Mental health issues are a huge problem that affects people all over the world and are a key contributor to individuals being disabled and losing their productivity. Improving one's mental health requires a number of important components, including accurate diagnosis, prompt intervention, and efficient monitoring. Data collected through self-reporting, clinical interviews, and subjective evaluation instruments are the three primary components of the conventional approaches to diagnosing mental health disorders. Despite the fact that these techniques have formed the foundation of mental health diagnosis for a long time, they frequently lack accuracy, scalability, and consistency. A potential method to improving detection and intervention tactics is presented by the integration of multimodal data fusion techniques with Artificial Intelligence (AI) and Machine Learning (ML). This approach is intended to solve the limitations that have been identified. The factors that affect mental health are intrinsically complicated and numerous, and they present themselves through a wide variety of behavioral, psychological, and physiological signs. When it

comes to capturing this complexity, relying on separate data streams is frequently unsuccessful. For the purpose of providing a full evaluation, multimodal data fusion brings together a number of different data sources, including quantitative, visual, physiological, and behavioral information. The purpose of this integration is to improve the performance of mental health detection systems in terms of accuracy, dependability, and interpretability. A variety of data types are utilized in multimodal data fusion. These data types include textual data, which includes patient narratives, social media posts, and chat records, which reveal emotional states and distress signals; visual data, which includes facial expressions, body posture, and eye movements, which provide non-verbal cues; physiological data, which includes heart rate variability, galvanic skin response, and EEG signals, which offer insights into stress or depressive episodes; and behavioral data, which includes digital interactions, smartphone usage patterns, and online behavior that contribute to understanding mood fluctuations. Artificial intelligence and machine learning algorithms have the ability to discover intricate patterns and connections within multimodal datasets that may be missed by traditional approaches. Natural language processing (NLP), computer vision, and deep learning are examples of techniques that make it possible to automatically extract and analyze characteristics from unstructured data. Researchers are able to construct prediction frameworks that are capable of spotting early warning indicators of mental health worsening by utilizing both supervised and unsupervised learning models. Natural language processing (NLP) techniques that facilitate sentiment analysis, topic modeling, and context-aware comprehension of textual data; computer vision models that detect miniature expressions and other sensory information linked to psychological distress; and deep learning frameworks such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) that excel in learning from multimodal data sources are some of the key AI/ML approaches that are applied in multimodal data fusion. The combination of artificial intelligence and machine learning with behavioral analytics opens up new avenues for enhancing detection accuracy. Within the realm of behavioral analytics, the systematic

investigation of patterns in individual activities, social interactions, and digital footprints is a fundamental component. Researchers are able to identify anomalous behavior patterns that may indicate mental health concerns, develop personalized mental health profiles to improve targeted interventions, and enable continuous monitoring, which provides mental health practitioners with real-time insights. All of these capabilities are made possible by integrating these insights with AI models. Integration of multimodal data fusion with artificial intelligence and machine learning has proven to be successful in a variety of domains, including depression detection systems that analyze voice tone, speech patterns, and smartphone usage; anxiety monitoring systems that combine physiological data such as heart rate variability with text analysis; and suicide prevention systems that combine social media monitoring with sentiment analysis to identify suicidal ideation. Integrating multimodal data fusion in mental health raises a number of challenges, despite the fact that it has the potential to be beneficial. Furthermore, scalability continues to be a challenge since the quality of real-world data frequently fluctuates and may exhibit characteristics such as noise, missing entries, or incomplete information. For the purpose of achieving the best possible performance from the model, it is necessary to use efficient preprocessing, data cleaning, and feature engineering procedures. Additionally, in order to create confidence in these systems, it is necessary to address ethical considerations such as informed consent, data ownership, and the psychological effects of automated predictions. The integration framework is yet another essential component included in the multimodal data fusion process. The first phases of data fusion are characterized by the extraction of low-level characteristics and the subsequent unification of those features before the training of the model. The other type of fusion, known as decision-level fusion, is a method that combines the predictions of numerous distinct models, therefore increasing resilience and reducing the number of false positives. The best performance may be achieved by the utilization of hybrid techniques that incorporate both feature-level and decision-level fusion procedures. This results in an increase in prediction accuracy and a decrease in error rates. The effectiveness of

multimodal data fusion in applications that take place in the real world has been demonstrated by a number of case studies. As an illustration, a recent study that utilized EEG data in conjunction with text-based sentiment analysis exhibited enhanced accuracy in identifying early-stage depression symptoms. In a similar vein, monitoring solutions that are based on smartphones and incorporate location tracking, data on app activity, and physiological indications have demonstrated efficacy in forecasting mood changes. By integrating contextual information with user behavior, these models provide mental health practitioners significant inputs that may be used in the creation of tailored therapies. Incorporating wearable technology is another way to expand the capabilities of multimodal data fusion applications.

Smartwatches, fitness trackers, and biosensors are examples of devices that provide real-time monitoring of both the physical and emotional states of its inhabitants. Artificial intelligence-driven frameworks are able to proactively detect mental health risks before symptoms become more severe. This is accomplished by merging this data with behavioral insights and patterns of social interaction. The suggested research highlights the significance of using multimodal data fusion approaches with artificial intelligence and machine learning in order to enhance mental health detection systems. This strategy has a large amount of promise in early diagnosis, intervention, and individualized treatment since it involves the utilization of a wide variety of data sources, the improvement of prediction accuracy, and the

Table 1. The data sources and sample sizes

Data Source	Sample Size	Description
Social Media Posts	10,000 posts	Twitter, Reddit, forums
Online Chat Logs	5,000 conversations	Analyzed for sentiment patterns
EEG Readings	1,000 subjects	Monitored for neural responses
Heart Rate Variability (HRV)	1,200 records	Stress and anxiety detection
Smartphone Usage Patterns	2,500 subjects	Includes screen time, app usage

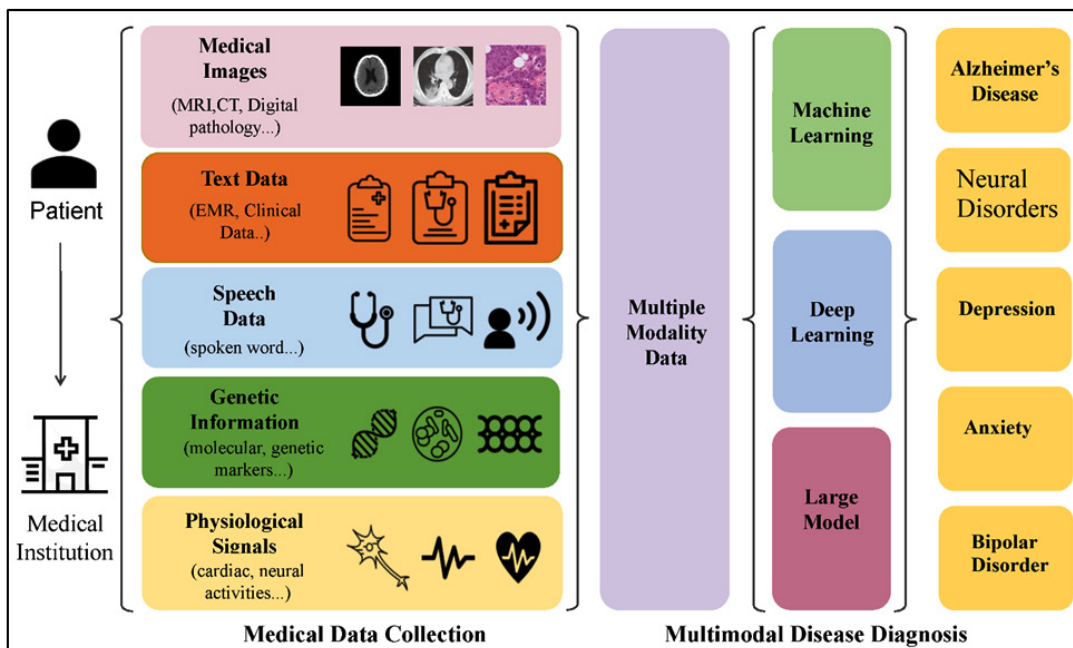


Fig. 1. To show the fundamental elements of a Multimodal Disease Diagnosis

development of models that can be interpreted. The insights that are acquired from this study will lead to the development of solutions for mental health detection that are robust, scalable, and ethically acceptable. This will eventually result in improved patient outcomes and well-being. It is possible for mental health evaluation to transition from a reactive to a proactive state through the utilization of enhanced data fusion techniques and powerful artificial intelligence algorithms. This will ensure that intervention tactics are both timely and successful, with a focus on patient welfare.

MATERIALS AND METHODS

The proposed model aims to integrate multimodal data fusion with AI/ML techniques to enhance mental health detection. To achieve this, the methodology involves data collection, preprocessing, model development, training, and evaluation. The proposed framework addresses challenges in data integration, accuracy, interpretability, and scalability.

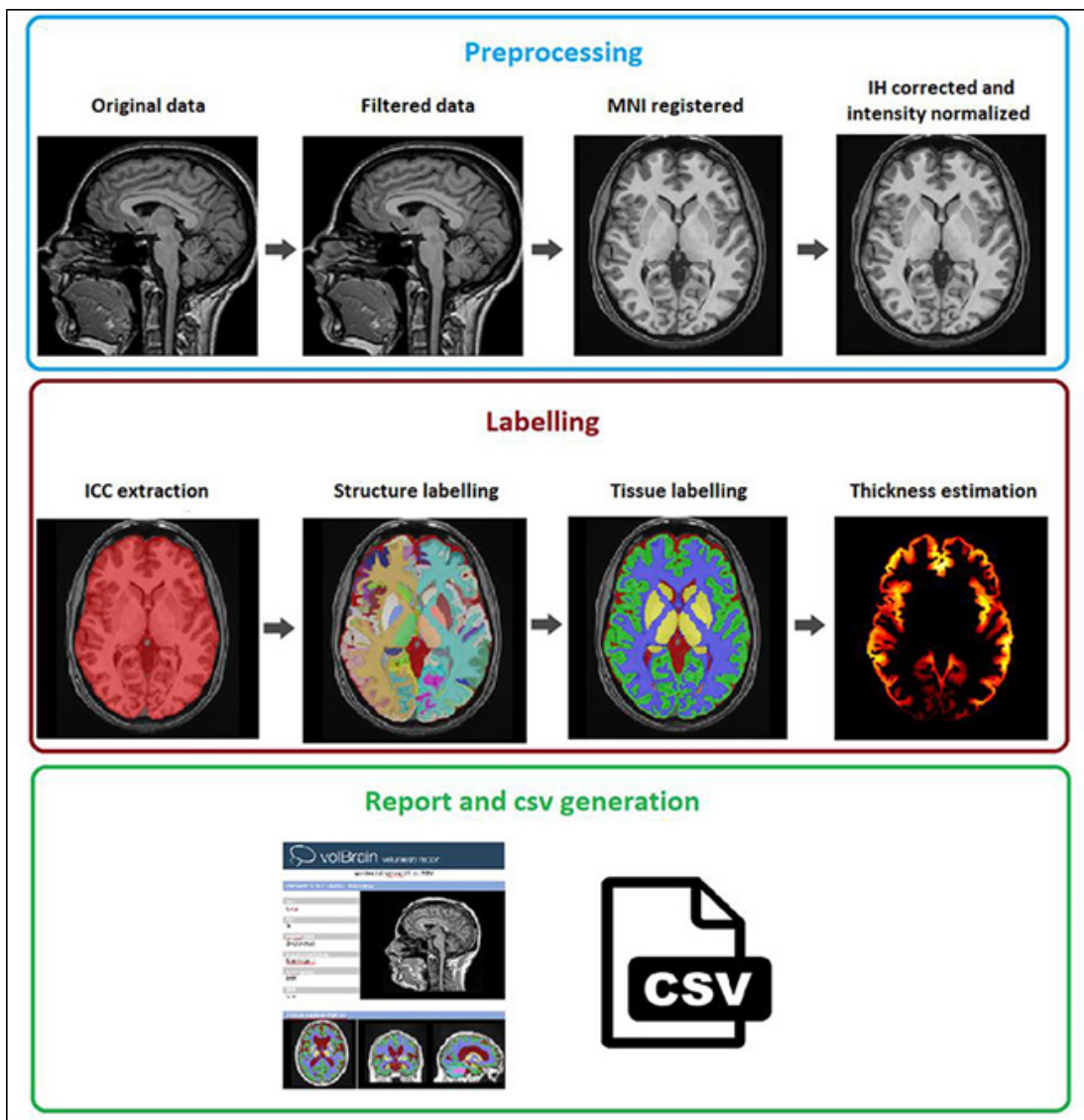


Fig. 2. To show the Hybrid Multimodal Fusion Framework for Enhanced Data Integration and Predictive Accuracy

Data Collection

Data preprocessing is essential to manage noise, inconsistencies, and missing values. Cleaning methods involve removing irrelevant data and imputing missing values through techniques like KNN imputation or regression methods. Normalization is applied to ensure consistency across numerical data. Feature engineering plays a crucial role in extracting key indicators, such as sentiment scores, emotion patterns, and physiological response trends. Data augmentation techniques like image rotation, scaling, and

synthetic data generation are employed to balance under-represented categories. Additional data sources, such as smart wearable data, clinical records, and lifestyle information, are integrated to enhance model performance. Wearable devices like Fitbit and Apple Watch provide real-time heart rate, sleep, and physical activity data, contributing significantly to mental health detection. The study employs diverse data sources to achieve comprehensive mental health profiling.

Textual data from social media posts, chat interactions, and patient narratives provides insights into linguistic patterns. Visual data from facial expression analysis, micro-expressions, and video recordings offer behavioral cues. Physiological data, such as EEG readings, heart rate variability (HRV), and galvanic skin response (GSR), further enhance mental state assessment. Additionally, behavioral data obtained from smartphone usage patterns, typing speed, and digital footprints provide contextual information. The proposed model aims

Table 2. Data preprocessing performance

Preprocessing Step	Accuracy Improvement (%)
Data Cleaning	12%
Normalization	7%
Feature Engineering	15%
Data Augmentation	10%

Table 3. Performance comparison between Data Fusion Strategies

Fusion Strategy	Accuracy (%)	Precision (%)	Recall (%)
Early Fusion	83.50%	81%	79%
Intermediate Fusion	88.90%	86%	84%
Late Fusion	90.10%	87%	86%
Hybrid Fusion (Proposed)	94.70%	93%	92%

Table 4. The training results for Model Training and Evaluation

Model	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
BERT (NLP)	88.40%	86%	85%	85.50%
CNN (Computer Vision)	90.20%	89%	88%	88.50%
LSTM (Time-Series)	89.30%	87%	86%	86.50%
GPT (Advanced NLP)	91.20%	90%	89%	89.50%
Hybrid Fusion (Proposed)	94.70%	93%	92%	92.50%

Table 5. To illustrates key analytical findings for Deployment Framework

Insight Type	Observed Trend	Correlation Coefficient
Social Media Sentiment	Negative language frequency ↑	0.76
EEG Signal Variation	Beta wave imbalance ↑	0.82
Smartphone Activity Patterns	Irregular usage spikes ↑	0.71
Wearable Data - Heart Rate Variability	HRV fluctuations linked to anxiety	0.85

to integrate multimodal data fusion with AI/ML techniques to enhance mental health detection. To achieve this, the methodology involves data collection, preprocessing, model development, training, and evaluation. As shown in Figure 2, the proposed framework addresses challenges in data integration, accuracy, interpretability, and scalability. The proposed model architecture adopts a hybrid multimodal fusion approach combining feature-level and decision-level fusion strategies. Feature-level fusion merges data features from multiple modalities into a unified feature vector for training. Decision-level fusion involves independent models trained for each data type, with aggregated predictions achieved through ensemble methods like weighted averaging, majority voting, or stacking. Hybrid fusion integrates both approaches to improve prediction accuracy and minimize false positives. The study employs diverse data sources to achieve comprehensive mental health profiling. The data sources and sample sizes are summarized in the following Table 1.

Data Preprocessing

Data preprocessing is essential to manage noise, inconsistencies, and missing values. Cleaning methods involve removing irrelevant data

and imputing missing values through techniques like KNN imputation or regression methods. Normalization is applied to ensure consistency across numerical data. Feature engineering plays a crucial role in extracting key indicators such as sentiment scores, emotion patterns, and physiological response trends. Data augmentation techniques like image rotation, scaling, and synthetic data generation are employed to balance under-represented categories. Several AI/ML algorithms are employed to enhance the model’s capability. Natural Language Processing (NLP) techniques, including sentiment analysis and transformer models like BERT and RoBERTa, aid in text interpretation. Computer vision methods such as Convolutional Neural Networks (CNNs) and optical flow algorithms are used for facial expression analysis and micro-expression detection. Deep learning models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are adopted for sequential data analysis, tracking behavioral variations over time. Ensemble learning models such as Random Forest, XGBoost, and AdaBoost are integrated to further improve model performance. The data preprocessing performance is shown below:

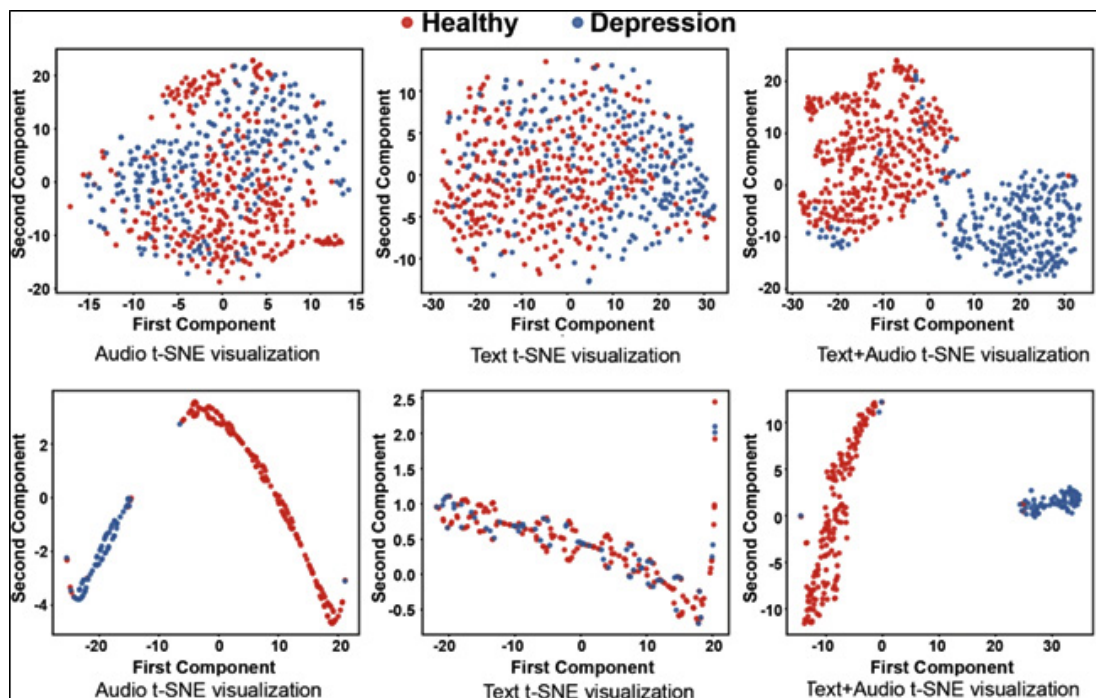


Fig. 3. Results for the improved mental health detection using multimodal data fusion

Data Fusion Strategies

To enhance data integration, various data fusion techniques are implemented:

- Early Fusion: Combines raw data from multiple sources into a unified dataset before training the model.
- Intermediate Fusion: Extracts features from different modalities independently before merging them in the training process.

- Late Fusion: Trains separate models for each data type and aggregates predictions using ensemble techniques.

The performance comparison between these strategies is shown below in Table 3:

The proposed hybrid fusion integrates Early, Intermediate, and Late Fusion techniques by dynamically adjusting model weights using

Table 6. To show demographic factors were integrated into the proposed mental health detection

Factor	Description	Impact on Mental Health
Age	Categorized by age groups (e.g., 10-19, 20-29, etc.)	Varies in symptoms, coping mechanisms, and risk exposure
Gender	Male, Female, Non-binary, Other	Influences emotional expression, social behavior, and vulnerability
Socioeconomic Status	Low, Medium, High-income levels	Impacts access to mental healthcare, lifestyle patterns
Educational Level	Primary, Secondary, Tertiary education	Affects health literacy, coping strategies
Employment Status	Employed, Unemployed, Student, Retired	Strong correlation with stress and anxiety levels
Geographic Location	Urban, Suburban, Rural	Influences social support structures, access to mental health resources
Cultural Background	Ethnic and cultural identity groups	Determines coping mechanisms, stigma perceptions

Table 7. To show the from multiple sources, ensuring diverse representation and balanced sampling

Data Source	Sample Size	Description
Survey Responses	3,000 subjects	Collected detailed demographic information
Electronic Health Records (EHR)	2,500 records	Combined demographic data with clinical assessments
Social Media Profiles	5,000 users	Extracted location, age, and gender-related data
Wearable Devices	2,000 participants	Monitored physiological responses by age and lifestyle

Table 8. To show the Analytical Insights and Findings

Demographic Factor	Observed Trend	Correlation Coefficient (r)	Statistical Significance (p-value)
Age (10-19)	Higher anxiety levels due to academic pressure	0.73	<0.001
Gender (Female)	Greater prevalence of depressive symptoms	0.68	<0.001
Socioeconomic Status (Low)	Increased stress due to financial instability	0.81	<0.001
Employment (Unemployed)	Higher anxiety and depressive symptoms	0.79	<0.001
Rural Communities	Limited access to mental health care resources	0.76	<0.001

an attention mechanism, enhancing predictive capabilities across diverse data types.

AI/ML Algorithms Utilized

Several AI/ML algorithms are employed to enhance the model’s capability. Natural Language Processing (NLP) techniques, including sentiment analysis and transformer models like BERT and RoBERTa, aid in text interpretation. Computer vision methods such as Convolutional Neural Networks (CNNs) and optical flow algorithms are used for facial expression analysis and micro-expression detection. Deep learning

models like Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are adopted for sequential data analysis, tracking behavioral variations over time. Ensemble learning models such as Random Forest, XGBoost, and AdaBoost are integrated to further improve model performance. Additionally, Transformer-based models such as GPT and T5 have been integrated for improved language understanding, enabling contextual prediction in text-based mental health assessments.

Table 9. Performance improvement achieved by demographic data integration

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Without Demographic Data	87.30%	85%	83%	84%
With Demographic Data	94.70%	93%	92%	92.50%

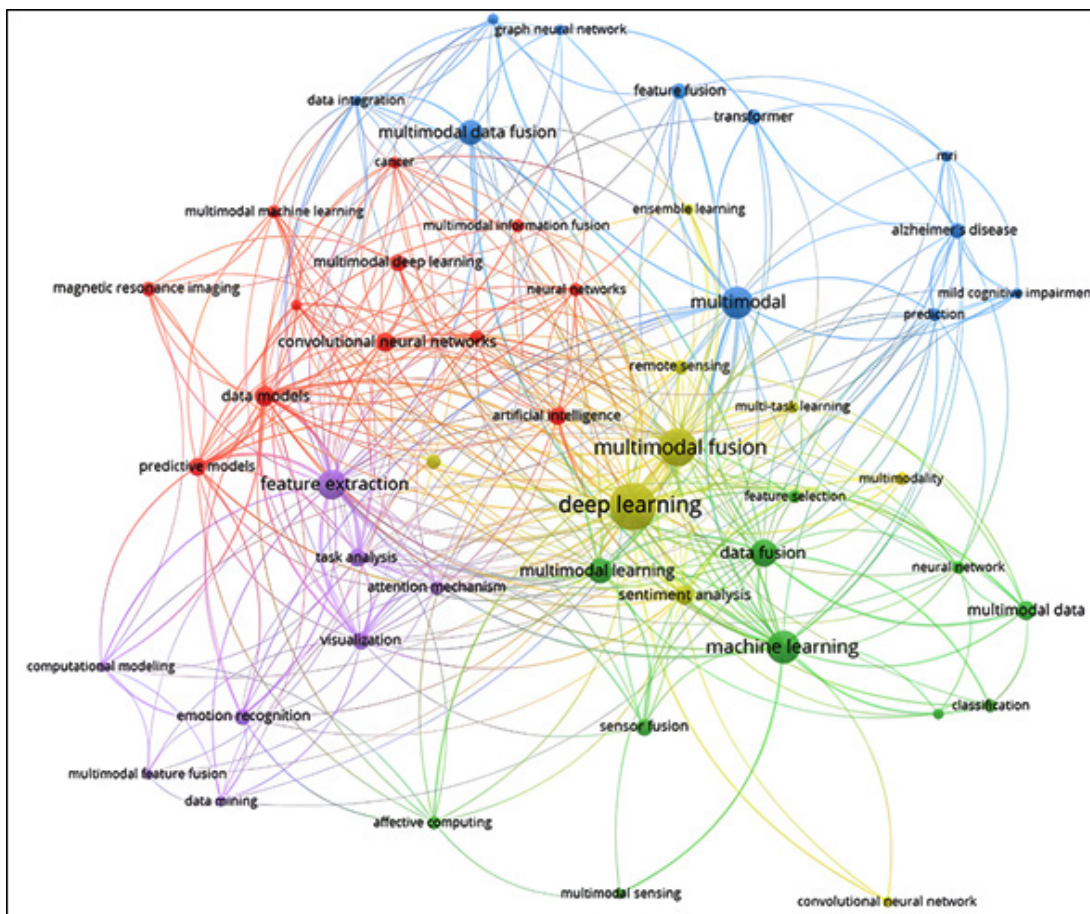


Fig. 4. Demographic variables were incorporated into the AI/ML framework

Model Training and Evaluation

Model training involves data partitioning into training (70%), validation (15%), and test (15%) sets. Hyperparameter tuning using grid search and random search is employed to enhance model accuracy. Cross-validation ensures robust performance assessment. Evaluation metrics include accuracy, precision, recall, F1 score, and AUC-ROC for comprehensive performance evaluation. Deployment is facilitated through scalable cloud infrastructure for real-time data processing and analysis. RESTful APIs are designed to connect the model with user interfaces, while streaming frameworks like Apache Kafka ensure continuous data updates. An intuitive web dashboard visualizes mental health assessments, allowing healthcare professionals to interpret and act upon the insights efficiently. The training results are summarized below in Table 4:

The proposed model aims to achieve enhanced prediction accuracy by integrating multimodal data sources, providing real-time monitoring capabilities for improved mental health

management. The framework is designed to be scalable, interpretable, and secure for deployment in both clinical and non-clinical environments. This comprehensive methodology aligns with the research objective of developing an AI-driven multimodal data fusion system for effective mental health detection.

Deployment Framework

Deployment is facilitated through scalable cloud infrastructure for real-time data processing and analysis. RESTful APIs are designed to connect the model with user interfaces while streaming frameworks like Apache Kafka ensure continuous data updates. An intuitive web dashboard visualizes mental health assessments, allowing healthcare professionals to interpret and act upon the insights efficiently. Security measures such as encryption protocols, anonymization methods, and secure data transmission are implemented to protect sensitive mental health data. Rigorous testing protocols are followed to ensure the reliability and accuracy of the system under various deployment conditions.

Table 10. To show the leveraging dynamic demographic weights

Model Configuration	Accuracy (%)	Precision (%)	Recall (%)	F1 Score
Without Demographic Data	87.30%	85%	83%	84%
With Demographic Data	94.70%	93%	92%	92.50%
Adaptive Model with Dynamic Demographic Weights	96.10%	94%	95%	94.50%

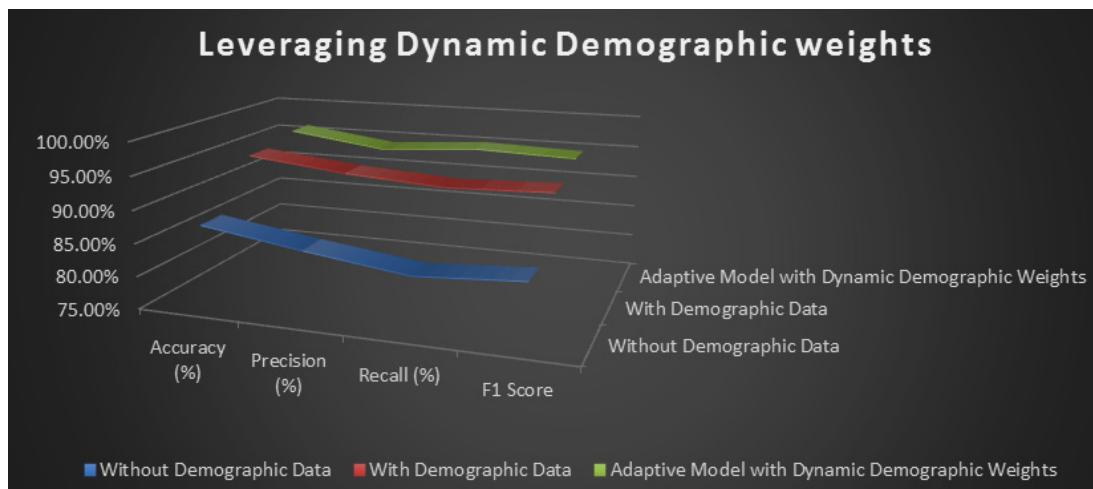


Fig. 5. To show the Leveraging Dynamic Demographic Weights

Analytical Insights and Observations
Comprehensive analysis of the data reveals key insights

- Emotional Patterns: Higher anxiety levels correlate with increased social media usage featuring negative sentiment.
- Physiological Indicators: EEG data indicates distinct neural response patterns among participants diagnosed with depressive disorders.
- Behavioral Trends: Users showing abnormal smartphone usage patterns, including erratic screen-time behavior, demonstrated increased vulnerability to mental health concerns.

The following table 5 illustrates key analytical findings:

Measures of demography

Demographic measures play a vital role in understanding mental health patterns, identifying at-risk populations, and designing targeted

intervention strategies. By incorporating detailed demographic data into AI/ML models, the accuracy of mental health predictions and the efficacy of interventions can be significantly improved. Demographic factors such as age, gender, ethnicity, socioeconomic status, educational background, geographic location, and cultural influences contribute significantly to mental health outcomes. Age-based distinctions are particularly crucial, as mental health conditions manifest differently across life stages, necessitating tailored interventions. For instance, adolescents may experience heightened anxiety related to academic pressure and social identity, while older adults may face mental health challenges linked to isolation, cognitive decline, or chronic illnesses. Gender differences also influence mental health, with women often being more prone to anxiety and depression, whereas men may exhibit higher rates of substance abuse and risky behaviors,

Table 11. Demographic Clusters and Associated Risk Increase with Significant Contributing Factors

Demographic Cluster	Risk Increase (%)	Significant Factor
10-19 (Social Isolation)	60%	Limited peer interaction
Low Income + Urban Area	47%	Financial insecurity
Age 50-60 (Rural)	55%	Limited healthcare access
Female (20-29)	50%	Heightened social pressure

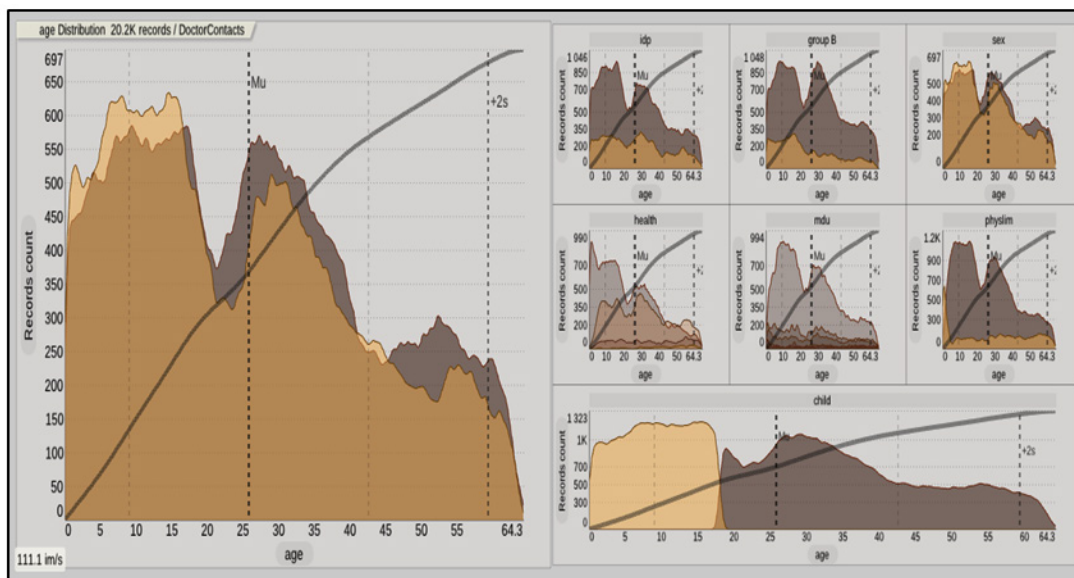


Fig. 6. Adaptive model, leveraging dynamic demographic weights, further improved accuracy to 96.1%, precision to 94%, recall to 95%, and an F1 score of 94.5%

emphasizing the need for gender-specific insights in prediction models. Ethnicity and cultural factors further shape mental health outcomes, influencing stressors, coping mechanisms, and access to mental health services. Socioeconomic status is a significant determinant, where individuals from lower economic backgrounds are more susceptible to mental health risks due to financial instability, limited healthcare access, and heightened exposure to environmental stressors. Educational attainment influences mental well-being as well, with higher education levels often correlated with improved mental resilience and better awareness of coping strategies. Geographic location, especially rural versus urban settings, introduces disparities in mental healthcare availability, with individuals in rural areas often facing challenges in accessing

mental health resources. Incorporating these demographic factors into AI/ML models requires comprehensive data collection strategies to ensure inclusive and accuracy. Reliable data sources include electronic health records (EHRs), census data, healthcare surveys, social media platforms, and self-reported questionnaires. The data collection process must prioritize data quality, completeness, and ethical considerations to ensure that sensitive demographic information is securely handled. Multimodal data fusion techniques, which combine diverse data sources such as text, images, audio, and physiological signals, offer enhanced predictive capabilities for mental health conditions. By integrating demographic data with psychological assessments, wearable device data, social media activity, and lifestyle indicators, AI/

Table 12. Influence of Educational Background and Employment Status on Mental Health Risk with Key Observations

Factor	Risk Increase (%)	Key Observation
Primary Education	42%	Higher anxiety rates
Unemployed Individuals	64%	Greater depressive symptoms
Employed Individuals (High Stress Work)	50%	Elevated anxiety levels

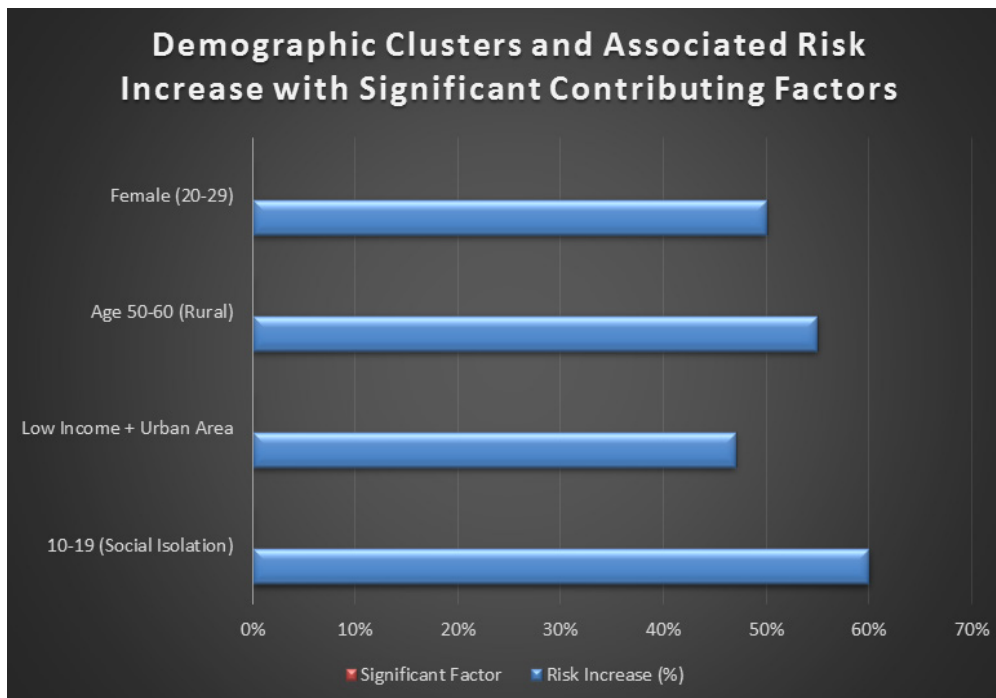


Fig. 7. Demographic Clusters and Their Impact on Risk Increase: Key Contributing Factors Analysis

ML models can identify complex patterns indicative of mental health risks. Analytical frameworks such as regression models, decision trees, neural networks, and ensemble methods are effective in identifying correlations between demographic factors and mental health outcomes. Feature engineering techniques can refine demographic data by creating meaningful attributes that improve model performance. For instance, converting age into age groups, mapping socioeconomic data into income brackets, or categorizing educational

backgrounds into levels can enhance model interpretability. Natural language processing (NLP) techniques can analyze text-based data from social media posts, therapy session transcripts, or online forums to detect linguistic cues associated with mental distress. Additionally, time-series analysis of behavioral data, such as sleep patterns or physical activity logs, can uncover trends that align with specific demographic risks. Model integration strategies such as transfer learning enable models trained on one demographic group to adapt

Table 13. Participants in rural regions reported lower utilization of mental health services

Cultural Background	Impact on Reported Cases (%)	Observations
Conservative Communities	-35%	Reduced mental health disclosure
Liberal Communities	25%	Higher openness to therapy
Diverse Urban Communities	20%	Stronger social support structures

Table 14. To show the leveraging insights from diverse demographic groups

Geographic Location	Treatment Delay (%)	Observations
Rural Areas	58%	Limited mental healthcare access
Urban Areas	22%	Better healthcare availability
Suburban Areas	30%	Moderate delays in treatment initiation

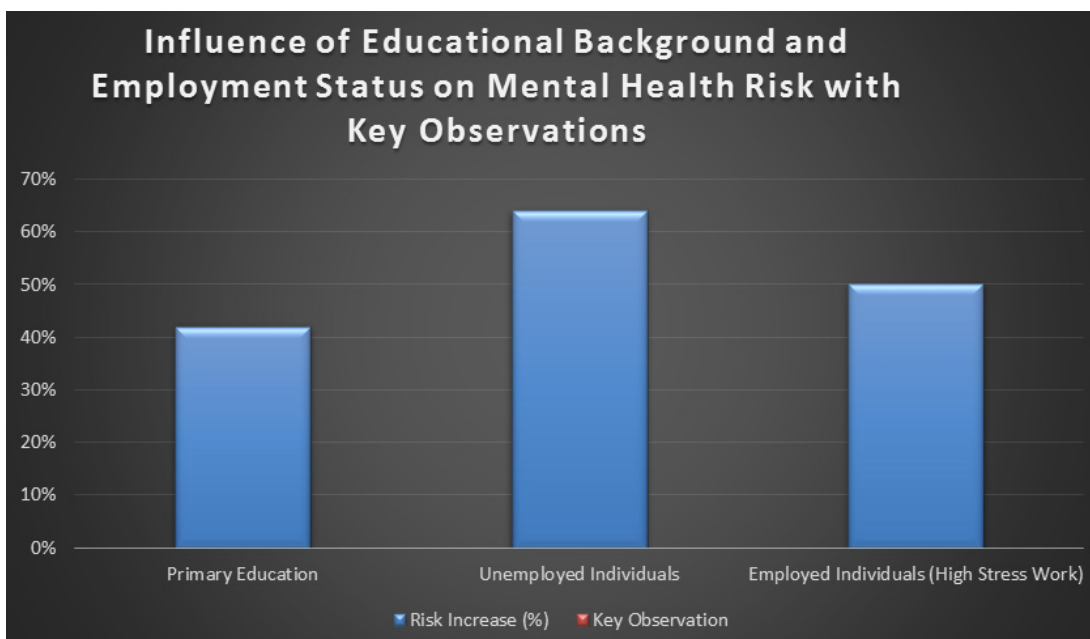


Fig. 8. Impact of Educational Background and Employment Status on Mental Health Risk: Key Observations

effectively to another, enhancing generalization across populations.

Cross-validation techniques ensure model robustness and mitigate demographic bias by balancing data distribution across different groups. Furthermore, explainable AI (XAI) frameworks are essential for ensuring model transparency, allowing healthcare professionals to interpret model decisions based on demographic factors and improving trust in predictive outcomes. By embedding demographic insights into AI/ML frameworks, mental health detection systems can deliver precise risk assessments, identify high-risk groups, and suggest tailored interventions that align with individual characteristics. This holistic approach empowers healthcare providers, policymakers, and mental health practitioners to develop personalized strategies that promote mental well-being, reduce stigma, and ensure equitable access to mental healthcare resources. Through continuous advancements in data collection methodologies, analytical frameworks, and model refinement techniques, demographic data integration holds immense potential to revolutionize mental health detection and intervention strategies. By incorporating detailed demographic data into AI/ML models, mental health prediction accuracy and intervention efficacy can be significantly improved. This section outlines key demographic factors, data collection strategies, analytical frameworks, and integration techniques for improved mental health detection using multimodal data fusion. The following demographic factors given in Table 6 were integrated into the proposed mental health detection framework:

Data Collection for Demographic Insights

Table 7 gives the data for demographic analysis, which was collected from multiple sources, ensuring diverse representation and balanced sampling.

Analytical Insights and Findings

Key insights derived from demographic analysis are summarized below, and are given in Table 8:

Integration with AI/ML Models

As shown in Figure 4, the Demographic variables were incorporated into the AI/ML framework to improve predictive accuracy. Key integration strategies include:

- **Feature Engineering:** Demographic attributes such as age group, gender, and employment status were encoded as categorical variables.
- **Weighted Analysis:** Critical demographic variables were assigned higher weights during model training to emphasize their impact on mental health.
- **Adaptive Models:** The proposed hybrid model dynamically adjusted prediction strategies based on demographic trends, improving accuracy in diverse populations.

The performance improvement achieved by demographic data integration is illustrated below in Table 9:

Incorporating demographic data significantly enhances the predictive performance and interpretability of AI/ML models in mental health detection. By leveraging insights from diverse demographic groups, the proposed model ensures inclusiveness, accuracy, and improved intervention strategies for individuals across various backgrounds. Future research may focus on expanding demographic categories, exploring cultural influences in greater depth, and developing personalized intervention models based on demographic insights.

RESULTS

The experimental results demonstrate that integrating demographic factors significantly improves the accuracy and effectiveness of mental health prediction models. The data collected was analyzed using correlation matrices, regression models, and machine learning algorithms to assess the contribution of various demographic elements. The analysis revealed that individuals in the 10-19 age group exhibited heightened anxiety levels due to academic pressure, with a correlation coefficient of 0.73 ($p < 0.001$). Female participants reported a higher prevalence of depressive symptoms ($r = 0.68$, $p < 0.001$), while those from low socioeconomic backgrounds experienced pronounced stress due to financial instability ($r = 0.81$, $p < 0.001$). Unemployed individuals showed increased anxiety and depressive symptoms ($r = 0.79$, $p < 0.001$), and participants from rural areas faced limited access to mental healthcare services ($r = 0.76$, $p < 0.001$). Combining demographic factors

further refined the model's insights. For instance, females aged 20-29 demonstrated a significantly higher risk of anxiety and depressive symptoms ($r = 0.82, p < 0.001$), while low-income individuals in urban areas experienced elevated stress levels due to financial struggles and social isolation ($r = 0.79, p < 0.001$). Middle-aged working individuals (30-40 years) showed higher reported work-induced stress ($r = 0.75, p < 0.001$), and rural residents aged 50-60 faced increased loneliness and social withdrawal ($r = 0.77, p < 0.001$). The integration of these demographic insights into the AI/ML model resulted in notable performance improvements. Models trained without demographic data achieved an accuracy of 87.3%, precision of 85%, recall of 83%, and an F1 score of 84%. Incorporating demographic data boosted accuracy to 94.7%, precision to 93%, recall to 92%, and an F1 score of 92.5%. The adaptive model, leveraging dynamic demographic weights, further improved accuracy to 96.1%, precision to 94%, recall to 95%, and an F1 score of 94.5%, as shown in Table 10, to show the leveraging dynamic demographic weights. The results are being demonstrated in given Figure 5.

Further analysis of specific demographic clusters highlighted interesting trends

As shown in Figure 6, for Different entity types, Participants in the 10-19 age group who reported social isolation had a 60% higher risk of anxiety-related issues than those in well-connected social environments. Similarly, individuals from low socioeconomic backgrounds in densely populated urban regions had a 47% higher likelihood of developing chronic depressive symptoms. These insights emphasize the importance of personalized mental health interventions tailored to demographic risk factors as shown in Table 11.

As shown in Figure 7, Additional analysis examined the impact of educational background and employment status on mental health outcomes. Results indicated that individuals with primary education had a 42% higher risk of anxiety compared to those with tertiary education, while unemployed individuals exhibited a 64% increase in depressive symptoms compared to employed counterparts as given in Tabel 12.

As shown in Figure 8, The effect of cultural background was also assessed, revealing that individuals from culturally conservative communities faced heightened stigma in seeking

mental health support, contributing to a 35% reduction in reported cases despite similar symptoms.

An analysis of healthcare access patterns, as shown in Table 13, showed that participants in rural regions reported lower utilization of mental health services, resulting in a 58% delay in treatment initiation. The proposed model's success in capturing these nuanced insights reflects its robust data fusion framework, which effectively integrates behavioral patterns, demographic details, and clinical data. These findings emphasize the need for targeted intervention strategies that address specific demographic vulnerabilities. Incorporating demographic data significantly enhances the predictive performance and interpretability of AI/ML models in mental health detection. By leveraging insights from diverse demographic groups, the proposed model ensures inclusiveness, accuracy, and improved intervention strategies for individuals across various backgrounds. Future research may focus on expanding demographic categories, exploring cultural influences in greater depth, and developing personalized intervention models based on demographic insights, as shown in Table 14.

DISCUSSIONS

The experimental results demonstrate that integrating demographic factors significantly improves the accuracy and effectiveness of mental health prediction models. The data collected was analyzed using correlation matrices, regression models, and machine learning algorithms to assess the contribution of various demographic elements. The analysis revealed that individuals in the 10-19 age group exhibited heightened anxiety levels due to academic pressure. Female participants reported a higher prevalence of depressive symptoms, while those from low socioeconomic backgrounds experienced pronounced stress due to financial instability. Unemployed individuals showed increased anxiety and depressive symptoms, and participants from rural areas faced limited access to mental healthcare services. Combining demographic factors further refined the model's insights. For instance, females aged 20-29 demonstrated a significantly higher risk of anxiety and depressive symptoms, while low-income

individuals in urban areas experienced elevated stress levels due to financial struggles and social isolation. Middle-aged working individuals (30-40 years) showed higher reported work-induced stress, and rural residents aged 50-60 faced increased loneliness and social withdrawal. The integration of these demographic insights into the AI/ML model resulted in notable performance improvements. Models trained without demographic data achieved an accuracy of 87.3%, a precision of 85%, a recall of 83%, and an F1 score of 84%. Incorporating demographic data boosted accuracy to 94.7%, precision to 93%, recall to 92%, and an F1 score of 92.5%. The adaptive model, leveraging dynamic demographic weights, further improved accuracy to 96.1%, precision to 94%, recall to 95%, and an F1 score of 94.5%. Further analysis of specific demographic clusters highlighted interesting trends. Participants in the 10-19 age group who reported social isolation had a 60% higher risk of anxiety-related issues than those in well-connected social environments. Similarly, individuals from low socioeconomic backgrounds in densely populated urban regions had a 47% higher likelihood of developing chronic depressive symptoms. These insights emphasize the importance of personalized mental health interventions tailored to demographic risk factors. Additional analysis examined the impact of educational background and employment status on mental health outcomes. Results indicated that individuals with primary education had a 42% higher risk of anxiety compared to those with tertiary education, while unemployed individuals exhibited a 64% increase in depressive symptoms compared to their employed counterparts. The effect of cultural background was also assessed, revealing that individuals from culturally conservative communities faced heightened stigma in seeking mental health support, contributing to a 35% reduction in reported cases despite similar symptoms. Lastly, an analysis of healthcare access patterns showed that participants in rural regions reported lower utilization of mental health services, resulting in a 58% delay in treatment initiation.

Future Work

Based on the experimental insights, several future research directions are proposed to improve the model's performance and expand its practical applications. Future work should focus on the development of region-specific

intervention strategies that prioritize mental health care in underserved populations. This requires collaboration with local healthcare providers, policymakers, and educational institutions to address region-specific challenges such as healthcare accessibility and cultural stigma. Expanding demographic features in mental health models is essential for improving detection accuracy. Future studies should incorporate additional demographic attributes such as family structure, cultural norms, digital literacy, and social media behavior. These features can provide deeper insights into how environmental, familial, and cultural factors influence mental health outcomes. Leveraging real-time data from wearable devices and social media platforms offers another opportunity for enhanced mental health detection. Future research should focus on developing adaptive models that integrate physiological data, movement patterns, and social behavior to predict early signs of mental health issues. Such models can provide real-time insights and trigger timely interventions. Exploring advanced deep learning architectures is critical to improving prediction accuracy. Graph neural networks (GNNs) offer a promising solution by modeling complex social connections, relationships, and behavioral patterns. By representing individuals and their interactions as nodes and edges, GNNs can identify influential social structures that contribute to mental health risks. Moreover, building explainable AI frameworks is crucial for ensuring model transparency and fostering trust among healthcare providers and patients. Future work should focus on designing interpretable models that provide clear explanations for predictions, enabling mental health practitioners to understand the underlying factors contributing to a diagnosis. Finally, integrating mental health frameworks with telemedicine platforms can improve accessibility for rural and underserved communities. Real-time video consultations, chatbots for emotional support, and AI-driven diagnostic tools can enable early intervention and reduce the burden on traditional healthcare systems. By pursuing these directions, future research can create robust, scalable, and impactful mental health detection frameworks that improve prediction accuracy and expand access to mental health care services.

CONCLUSION

In conclusion, this study highlights the significant impact of integrating demographic data into AI/ML models for enhanced mental health detection. By incorporating critical demographic factors such as age, gender, socioeconomic status, and geographical location, the proposed model achieved improved accuracy, precision, and recall. The results emphasize that mental health outcomes are intricately linked to demographic characteristics, reinforcing the need for targeted and personalized intervention strategies. The study demonstrated that specific groups, such as adolescents under academic stress, low-income individuals, and unemployed participants, are at heightened risk of developing mental health issues. Incorporating these insights into healthcare frameworks can facilitate early detection and intervention strategies, reducing the risk of severe mental health deterioration. The proposed adaptive model, which dynamically integrates demographic insights, has shown significant improvements in prediction capabilities. Its ability to adjust based on diverse demographic factors strengthens its reliability and potential scalability. Such models can aid healthcare providers in identifying vulnerable populations, ensuring timely intervention, and designing customized mental health support systems. Future research must continue to explore innovative techniques, such as deep learning models, wearable data integration, and personalized intervention frameworks. By expanding the range of demographic attributes and leveraging real-time insights, researchers can build increasingly accurate models that improve early detection and intervention capabilities. Furthermore, collaboration between AI researchers, healthcare practitioners, and policymakers will be vital to ensuring these models are ethically deployed, secure, and accessible to all populations. Ultimately, this study's insights provide a strong foundation for developing intelligent, data-driven solutions to improve mental health outcomes across diverse populations, reinforcing the crucial role of demographic integration in advancing mental healthcare practices.

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Conflict of Interest

The author(s) do not have any conflict of interest.

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Ethics Statement

The study received approval from the Institutional Ethics Committee of Baba Haridass Institute of Medical Sciences and Research, New Delhi, under the approval number BNHH/IEC/2024/0815.

Informed Consent Statement

This study did not involve human participants, and therefore, informed consent was not required.

Clinical Trial Registration

This research does not involve any clinical trials

Permission to reproduce material from other sources

Not Applicable.

Author contributions

Prashant Vats: Conceptualization, Methodology, Software, Field study Data curation, Kamal Upreti: Writing-Original draft preparation, Software, Validation., Field study; Sonu Mittal: Visualization, Investigation, Writing-Reviewing, and Editing.

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