

A MULTI-DIMENSIONAL FRAMEWORK FOR MENTAL HEALTH PREDICTION USING BEHAVIORAL, PSYCHOLOGICAL AND SOCIAL NETWORK DATA

Dr. Deepika Lokesh

Department of AIML

C Byregowda Institute of Technology

Kolar 563010

ushalokesh@gmail.com

Vijetha K

Department of AIML

C Byregowda Institute of Technology

Kolar 563010

vijetha.cbit@gmail.com

Abstract: Mental health is a vital component of overall well-being, particularly among university students who face diverse academic and social challenges. Conventional methods for stress and mental health assessment often depend on a single type of data, limiting their ability to capture the complexity of human behavior. This study proposes a multi-dimensional framework to improve the accuracy of mental health and stress prediction. The framework integrates heterogeneous data sources, including behavioral patterns, psychological attributes, social interactions, and environmental factors. Data is collected from mobile usage records, transactional data, self-reported surveys, and online platforms to extract both static features and temporal behavioral trends. A neural network-based model is utilized to identify complex relationships among variables, while a complementary statistical approach ensures scalability and computational efficiency. Temporal analysis is incorporated to track behavioral changes over time, enabling better understanding of evolving mental states. Experimental results show that combining multiple data sources significantly enhances prediction performance. Key indicators include behavioral consistency, social engagement, and interaction patterns. The proposed system provides a scalable and non-invasive solution for early detection and personalized mental health monitoring.

Keywords: Terms-Mental Health, Stress Detection, Social Networks, Behavioral Analysis, Machine Learning, Neural Networks, Temporal Analysis

I. INTRODUCTION

The prevalence of mental health disorders has increased significantly across the world, particularly following the COVID-19 pandemic, and are expected to contribute substantially to global healthcare burdens in the coming years. Ensuring psychological well-being has therefore become a major public health priority. However, identifying the factors that influence mental health remains a complex task, which is essential for enabling early diagnosis, prevention, and timely intervention.

Previous studies have shown that mental health is shaped by a combination of personal and social factors, including income level, physical health, behavioral habits, and personality characteristics. Most existing research has typically examined these factors independently, which limits the overall

understanding of mental health conditions. Recent findings suggest that combining multiple categories of information leads to more accurate and reliable mental health assessment. In particular, social relationships—such as trust, communication, and cooperation within networks—provide important insights into an individual's psychological condition, although they are often not fully integrated with other influencing factors.

The widespread use of smartphones has created new possibilities for collecting real-world behavioral data in a non-intrusive manner. With large-scale smartphone adoption, it is now possible to analyze communication logs, mobility patterns, and daily routines to infer emotional states and behavioral changes. Such data has proven useful in identifying stress and related mental health conditions, offering a scalable alternative to traditional monitoring methods that rely on medical sensors or clinical assessments.

Environmental conditions and individual personality traits also play a significant role in shaping mental health outcomes. External factors such as weather variations can influence mood and stress levels, while personality differences determine how individuals respond to similar situations. Additionally, online social platforms provide valuable information about psychological states, as changes in interaction patterns—such as sudden increases or decreases in activity—may indicate emotional distress or behavioral shifts.

Research in social network analysis further shows that an individual's position within a network and their interactions with others are closely linked to mental health outcomes. The combination of social influence and similarity among individuals helps explain how psychological conditions can spread or evolve within communities. Studying multiple types of relationships within complex networks offers a clearer understanding of these dynamics.

Motivated by Based on these observations, this study proposes amulti-factor mental health prediction framework that integrates behavioral data, personality traits, and social network information. Using datasets collected from university students, including digital activity logs, psychological assessments, and social interaction networks, a neural network-based model is developed to predict conditions such as depression symptoms, suicidal tendencies, aggression, and internet addiction. By combining diverse sources of information, the proposed approach yields a more comprehensive and accurate analysis of mental health, demonstrating the value of multi-dimensional modeling for real-world psychological prediction tasks.

II. RELATED WORK

Behavioral Patterns and Mental Health

A substantial body of research has examined the link between human behavior and mental health conditions, especially among students. Numerous studies have highlighted a rise in depression, anxiety, and stress levels within this population college students, often linked with lifestyle-related behaviors such as irregular sleep, substance use, poor dietary habits, reduced physical activity, and excessive internet usage.

Behavioral clustering techniques, including latent class analysis, have been used to identify groups of co-occurring risky behaviors. These studies indicate that unhealthy habits often appear in combination rather than isolation, significantly increasing the likelihood of mental health problems. In addition, digital behavior analysis shows that online activity patterns—such as frequent profile changes, excessive engagement, or abnormal interaction behavior—can serve as indicators of psychological distress. In more severe cases, certain behavioral patterns have also been associated with suicidal tendencies, highlighting the importance of early detection through behavioral signals.

Psychological Factors and Personality Traits

Psychological characteristics and personality traits play a crucial role in determining mental health outcomes. Research across cognitive, emotional, and social domains has demonstrated strong associations between personality dimensions and mental well-being.

Low self-esteem is consistently linked with higher levels of depression and anxiety, while traits such as neuroticism are positively correlated with psychological distress. On the other hand, extraversion is generally associated with better emotional stability and lower stress levels. Longitudinal studies further suggest that self-perception and individual psychological evaluation significantly influence mental health over time. Moreover, personality traits often interact with external factors, modifying their impact on mental health conditions. These findings indicate that psychological attributes form a stable but influential component in mental health analysis.

Social Networks and Mental Health

Social relationships and network structures have been widely recognized as important indicators of mental health. Individuals with weaker social connections or isolated positions in a network are more likely to experience stress-related conditions and psychological disorders.

Recent studies have utilized mobile sensing technologies, such as smartphone logs and Bluetooth-based proximity data, to analyze social interactions and infer mental health states. Changes in communication frequency and interaction patterns often reflect shifts in emotional well-being. However, analyzing social networks remains challenging due to their dynamic and complex nature. Traditional studies often focus on static structures, whereas more recent approaches emphasize time-evolving networks to better capture behavioral changes.

Stress Detection and Sensing Techniques

Conventional stress detection methods primarily rely on physiological signals such as heart rate variability, skin conductance, and respiration rate. While these techniques can achieve high accuracy, they require wearable devices, which limit their practicality for continuous real-world monitoring. Alternative methods based on speech analysis and facial expression recognition have also been proposed. Although these approaches can detect stress-related cues, they are often affected by environmental noise, privacy concerns, and variability among individuals. More recent research has shifted toward smartphone-based sensing systems, which utilize call logs, messaging patterns, application usage, and mobility data to infer emotional states. These methods are more scalable and less intrusive, but challenges related to data quality and generalization still remain.

Temporal and Network-Based Analysis

Temporal analysis of online behavior has been widely used to study user engagement patterns over time. These approaches capture both short-term fluctuations and long-term behavioral trends. However, many existing studies rely on fixed time windows, which may fail to represent irregular or event-driven behavioral changes accurately.

Social network analysis can be categorized into three major perspectives: static versus dynamic structures, homogeneous versus heterogeneous interactions, and global versus local analysis. Static models provide an overall view of interactions, while dynamic models capture temporal evolution. Similarly, heterogeneous networks consider multiple types of relationships, whereas homogeneous models focus on a single interaction type. Despite advancements, most existing work focuses on global-level analysis, with limited attention given to local behavioral changes and their relation to psychological attributes.

Research Gaps

Despite significant progress in mental health prediction research, several limitations still exist:

- Over-reliance on static or single-type network representations
- Limited integration of behavioral, psychological, and social dimensions
- Insufficient modeling of temporal dynamics in user behavior
- Lack of focus on local-level network evolution and individual variability
- Weak integration of heterogeneous real-world data sources

These gaps highlight the need for a comprehensive multi-dimensional framework that combines behavioral data, personality traits, and dynamic social network analysis. Such integration can lead to more accurate and reliable mental health prediction systems.

III. DATA COLLECTION

This study adopts a heterogeneous, multi-source dataset to represent the complex and interconnected nature of mental health among university students. The dataset integrates behavioral, psychological, social, environmental, and temporal information collected over a continuous observation period.

Participants

A group of university students ($N \approx 100\text{--}200$) was recruited for the study. Participation was voluntary, and All participants provided informed consent prior to participation individuals before data acquisition. To ensure data reliability, only participants with at least two consecutive weeks of complete and consistent records were used in the final analysis dataset.

Behavioral Data

Behavioral information was obtained through smartphone sensing systems and institutional records. This includes:

- Mobile usage patterns such as call frequency, messaging activity, app usage duration, and screen time
- Mobility behavior derived from GPS/Wi-Fi signals and daily movement tracking
- Institutional records such as library visits, attendance logs, and cafeteria usage

These features provide a detailed view of daily routines, activity levels, and behavioral consistency.

Psychological Data

Psychological attributes were collected through standardized self-report questionnaires conducted periodically. These include:

- Stress levels measured using a 7-point Likert scale
- Personality traits assessed using established models such as the Big Five framework
- Mental health indicators including depression, anxiety, and self-esteem scores

These variables serve as ground truth labels for model training and evaluation.

Social Network Data

Social interaction patterns were derived from multiple sources:

- Communication networks based on call and message exchanges
- Physical proximity data collected through Bluetooth-based detection
- Online interaction patterns from digital platforms and peer communication systems

These datasets were used to construct multiplex social networks representing different types of relationships such as friendship, communication, and co-presence.

Environmental Data

External contextual factors were incorporated to capture environmental influences on mental health, including:

- Weather conditions such as temperature, humidity, and rainfall
- Academic schedule information including examinations, deadlines, and holidays

These variables help model external stressors affecting behavioral and psychological states.

Temporal Data

All collected datasets were time-aligned using timestamps to enable temporal analysis. Behavioral and social patterns were examined across:

- Short-term intervals (daily and weekly variations)
- Medium-term trends (behavioral bursts and inactivity periods)

This enables detection of dynamic changes in mental health states over time.

Data Pre-processing

To ensure data quality and consistency, several preprocessing steps were applied:

- Handling missing values through interpolation and data cleaning techniques
- Normalization and standardization of numerical features

- Segmentation of time-series data into structured observation windows

Ethical Considerations

The study followed strict ethical guidelines:

- Every participant granted informed consent before involvementAll personal identifiers were anonymized
- Data was securely stored and used exclusively for academic research

IV. METHODOLOGY

This section describes the proposed multi-dimensional framework designed for mental health prediction by integrating behavioral, psychological, social, and contextual data sources.

System Overview

The proposed framework integrates heterogeneous data into a unified predictive system. It captures both:

- Static attributes (e.g., personality traits)
- Dynamic behaviors (e.g., daily activity and social interaction changes)

The overall pipeline includes data preprocessing, feature extraction, model training, and prediction.

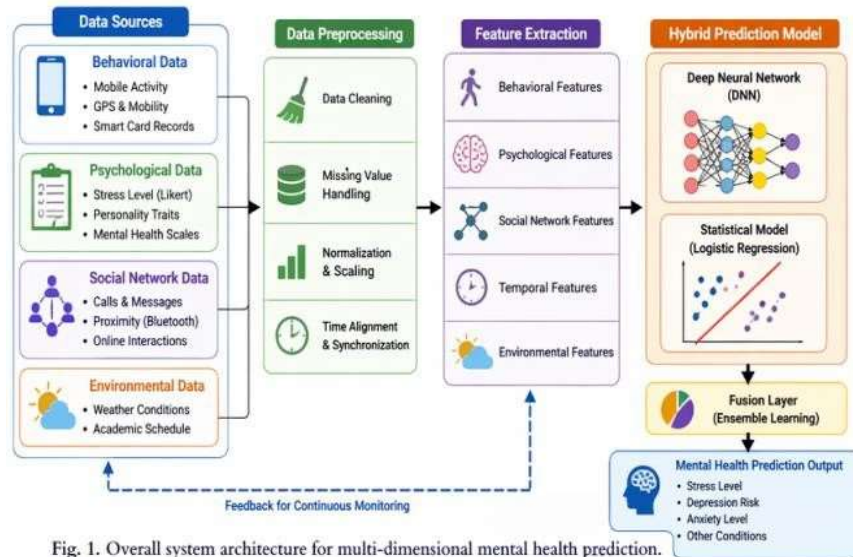


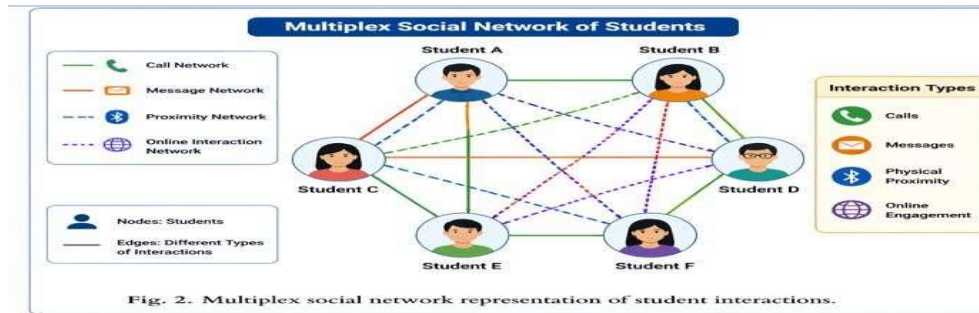
Fig. 1. Overall system architecture for multi-dimensional mental health prediction.

Data Representation

All data sources are transformed into structured formats:

- Behavioral data are aggregated into daily and weekly summaries such as activity levels and mobility range
- Psychological features remain relatively stable and are directly included as input variables
- Social interactions are modeled using graph structures where nodes represent individuals and edges represent interactions
- Environmental variables are encoded as contextual inputs

Missing values are addressed using statistical imputation, and all features are normalized for consistency.



Feature Engineering Behavioral Features

Key behavioral indicators include:

- Routine stability and activity variation
- Sleep and mobility behavior patterns
- Digital engagement intensity and diversity

Psychological Features

Psychological inputs include personality traits and self-reported stress levels, which help capture individual differences in emotional response and coping behavior.

Social Network Features

Social structures are analyzed using multiplex networks, capturing multiple interaction types. Extracted features include:

- Node centrality measures
- Interaction strength and frequency
- Network density and connectivity patterns

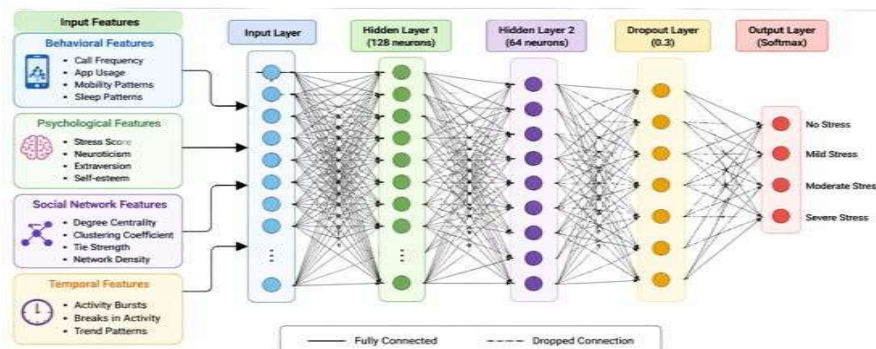
Temporal Features

Time-based behavioral dynamics are extracted by analyzing:

- Activity bursts and inactivity periods
- Short-term and medium-term behavioral trends
- Variability in social engagement over time

Model Architecture

A hybrid modeling framework is used to integrate multi-source data.



Deep Neural Network

A deep neural network is employed to capture complex nonlinear relationships. It consists of:

- Input layer combining all feature types
- Multiple hidden layers for representation learning
- Dropout layers to reduce overfitting
- Output layer for classification of mental health states

Statistical Model

A simpler statistical model (e.g., logistic regression) is also used to:

- Improve interpretability
- Reduce computational complexity
- Identify dominant predictive features

Fusion Strategy

Outputs from both models are combined using an ensemble-based fusion approach to improve robustness and overall prediction accuracy.

Training Process

- Dataset split: training, validation, and testing sets
- Cross-validation applied to ensure generalization
- Optimization performed using gradient-based methods such as Adam
- Loss function: cross-entropy for classification tasks

Evaluation Metrics

Model performance is evaluated using:

- Accuracy
- Precision
- Recall
- F1-score
- ROC-AUC

Implementation

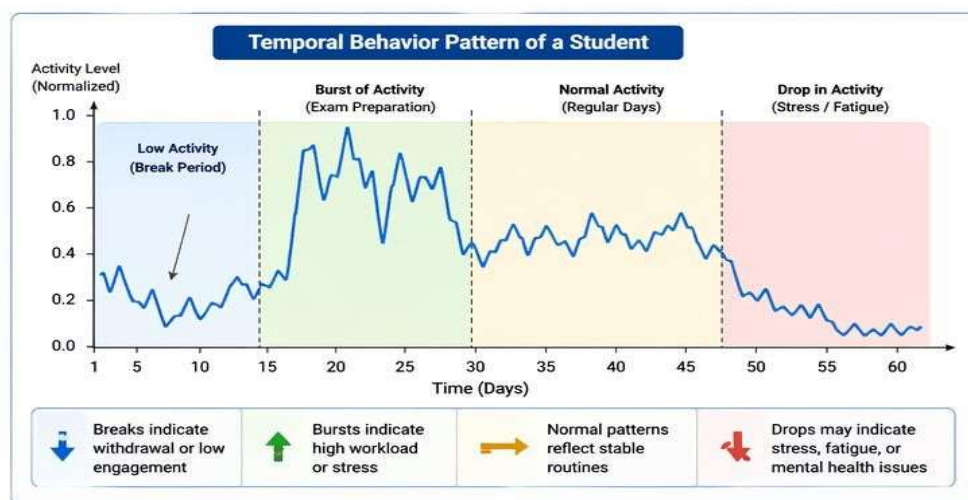


Fig. 4. Temporal variation in behavioral activity patterns over time

The framework is implemented using modern machine learning libraries such as PyTorch or TensorFlow, along with standard data processing tools. Experiments are executed on high-performance computing systems capable of handling large-scale multi-dimensional data

V. CHALLENGES

Although the proposed multi-dimensional framework demonstrates strong effectiveness in mental health prediction, several practical, technical, and ethical challenges arise during its development and deployment in real-world environments.

Heterogeneous Data Integration

A key difficulty lies in combining data from multiple heterogeneous sources such as behavioral logs, psychological assessments, social interaction graphs, and environmental indicators. These datasets vary significantly in format, resolution, and collection frequency. Transforming them into a consistent representation can introduce complexity and may result in partial information loss during preprocessing stages.

Noisy and Incomplete Data

Real-world datasets are often affected by missing values, inconsistencies, and noise. For instance, smartphone-based records may contain gaps due to device inactivity, while self-reported psychological responses may vary in reliability. Even though imputation and cleaning techniques are applied, they can still introduce estimation errors that influence model accuracy.

Privacy and Ethical Issues

The framework relies on highly sensitive personal information, including communication behavior, mobility traces, and mental health indicators. Protecting user privacy and ensuring secure data handling is therefore a major concern. Despite anonymization methods, the possibility of re-identifying individuals in large-scale datasets cannot be completely eliminated, making ethical compliance essential.

Limited Generalization Capability

The current model is trained using data collected from university students, which may restrict its applicability to other demographic groups such as working adults or elderly populations. Variations in lifestyle patterns, cultural behavior, and digital engagement may reduce model performance when applied beyond the original dataset.

Capturing Irregular Temporal Behavior

Human behavioral patterns are highly dynamic and often unpredictable. Fixed time-interval segmentation may fail to capture sudden emotional or behavioral

shifts. Effectively modeling both short-term fluctuations and long-term trends remains a challenging problem in temporal analysis.

Lack of Full Interpretability

Although the hybrid approach combines neural networks with statistical models, the deep learning component still functions as a black-box system to some extent. This reduces transparency in decision-making, which is particularly critical in mental health applications where interpretability is important for trust and validation.

Imbalanced Class Distribution

Mental health datasets typically exhibit uneven class distributions, where normal cases dominate over rare but critical conditions such as severe depression or suicidal behavior. This imbalance can bias the model toward majority classes and reduce sensitivity in detecting high-risk cases.

Scalability and Real-Time Constraints

Processing and analyzing large-scale multi-source data requires significant computational resources. Implementing the framework in real-time systems introduces challenges related to latency, memory usage, and efficient optimization, especially in resource-constrained environments such as mobile applications.

High Dimensionality and Redundant Features

The integration of multiple data sources leads to a high-dimensional feature space. Many features may be redundant or weakly informative, increasing computational cost and potentially degrading model performance. Effective feature selection techniques are therefore necessary to improve efficiency and accuracy.

VI. CONCLUSION

This study presented a comprehensive multi-dimensional framework for predicting mental health conditions by integrating behavioral signals, psychological characteristics, social network structures, environmental influences, and temporal dynamics. Unlike conventional approaches that depend on a single type of data, the proposed system captures the complex and interconnected nature of human behavior through multi-source data fusion.

The experimental analysis demonstrates that combining heterogeneous information significantly enhances prediction performance for stress detection and mental health classification tasks. Behavioral indicators such as daily activity patterns, social engagement levels, and interaction frequency were found to be strong predictors of psychological states. In addition, psychological traits provided long-term stability in prediction, while social network features contributed valuable insights into interpersonal influence and emotional connectivity.

The hybrid modeling strategy, which combines deep neural networks with statistical learning techniques, ensures both high predictive accuracy and improved interpretability. Furthermore, the incorporation of temporal analysis enables the system to capture dynamic changes in mental health conditions over time, making it more suitable for real-world monitoring scenarios.

Overall, the proposed framework demonstrates that a multi-dimensional approach offers a more reliable, scalable, and non-invasive solution for mental health assessment, particularly in environments such as universities where early detection is crucial.

VII. FUTURE WORK

Although the proposed framework achieves promising results, several directions can be explored to further enhance its performance and applicability. Future research will focus on expanding the dataset to include a more diverse population beyond university students, enabling better generalization across different age groups, professions, and cultural backgrounds. This will help improve the robustness of the model in real-world deployment.

Advanced deep learning architectures such as transformer-based models and graph neural networks can be incorporated to better capture long-range temporal dependencies and complex social interactions. These models are expected to improve representation learning from both sequential and network-based data.

Real-time mental health monitoring is another important direction. Developing lightweight and efficient models capable of operating on mobile or edge devices will make the system more practical for continuous monitoring applications.

Privacy preservation will also be a key focus area. Techniques such as federated learning, differential privacy, and secure multi-party computation can be integrated to ensure that sensitive user data remains protected while still enabling collaborative model training.

Additionally, future work can explore multimodal extensions by incorporating wearable sensor data, speech signals, facial expressions, and physiological measurements. These additional modalities can provide deeper insights into emotional and cognitive states.

Finally, improving model interpretability is essential for healthcare applications. Developing explainable AI techniques will help clinicians and users understand the reasoning behind predictions, thereby increasing trust and adoption of such systems.

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