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SMART-SENSE(detecting mental health shifts using ai and smartphones behavior.)

Detecting mental health shifts using ai and smartphones behavior

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Abstract: Depression and anxiety are serious mental health issues, but current ways to check for them often miss important changes because they rely only on occasional self-reports. Mind Scape leverages passively sensed smartphone data—like movement and social activity—to identify early signs of worsening symptoms. Each user is assigned a personalized AI model (LSTM Autoencoder) that learns their normal behavioral patterns and detects anomalies when changes occur. The system also uses SHAP (Shapley Additive ex Plantations) to make the model's decisions transparent by identifying which behaviours triggered an alert. This personalized and explainable approach aims to help individuals and clinicians recognize early signs of mental health decline and act before symptoms worsen. Students and professionals are suffering from mental health issues daily and helping them to overcome from it.

I. INTRODUCTION

Mental health is increasingly recognized as a vital component of overall health and well-being. It influences not only emotional stability and psychological resilience but also physical health, productivity, relationships, and the capacity to cope with life's challenges. Yet, despite its crucial role, mental health often remains neglected, underreported, and stigmatized across communities worldwide. Many individuals suffer in silence due to fear, lack of awareness, or insufficient access to resources, and by the time symptoms become apparent or debilitating, they may have already caused significant disruption in personal and professional life. The global rise in mental health issues — including stress, anxiety, depression, mood disorders, and trauma-related conditions — has made early detection and intervention more important than ever. According to the World Health Organization (WHO), one in every eight people suffers from mental health disorders, and untreated conditions can lead to severe health complications, economic burdens, and even loss of life. However, early signs of mental health deterioration are often subtle, manifesting as minor changes in behaviour, sleep patterns, social interactions, or energy levels. These changes are rarely reported or tracked systematically, as individuals may not recognize them as symptoms or may be reluctant to seek professional support. Traditional methods of monitoring mental health, such as clinical interviews, self-report questionnaires, and psychological assessments, have provided critical tools for diagnosis and treatment. However, these approaches also have notable limitations. Self-reporting relies on the individual's willingness and ability to accurately describe their experiences, which can be hindered by social stigma, denial, or lack of mental health literacy. Clinical assessments, while thorough, are typically conducted at specific points in time and may not capture fluctuations in behaviour or mood that occur between appointments. Furthermore, access to mental health services remains uneven, especially in rural or underserved areas where healthcare infrastructure and trained professionals are limited. In this context, the integration of modern technologies into mental health care offers new possibilities. Smartphones, with their widespread use, embedded sensors, and constant presence in daily life, present an opportunity to unobtrusively collect data that reflects an individual's behaviour patterns. These devices capture various indicators — movement, location, sleep, communication, screen time — that can be linked to mental health status. When combined with artificial intelligence (AI) and machine learning algorithms, this data can be analysed to detect deviations from established behavioural norms and identify early warning signs of psychological distress.

SMART-SENSE is an innovative mental health monitoring system designed to harness these technological advances. It operates by continuously collecting passive data from smartphone sensors and usage patterns, alongside optional self-reported information, to monitor behavioural changes over time. By analysing parameters such as call frequency, messaging patterns, sleep duration and disruptions, physical activity, social engagement, and app usage, SMART-SENSE identifies significant deviations that may correspond with emerging mental health issues like stress, anxiety, depression, or burnout.

One of the defining strengths of SMART-SENSE is its non-intrusive and user-friendly design. Rather than relying on frequent manual reporting or invasive monitoring tools, the system operates quietly in the background, offering real-time assessments without interfering with daily routines. Machine learning algorithms personalise the monitoring process by learning the unique behavioural patterns of each user. Over time, SMART-SENSE develops an understanding of what constitutes “normal” behaviour for the individual and can accurately distinguish between benign fluctuations and meaningful changes that warrant attention. This approach is particularly effective because mental health symptoms manifest differently across individuals. For some, reduced communication and withdrawal from social interactions may signal emotional distress, while for others, irregular sleep or excessive smartphone usage may be early indicators of anxiety or depression. By tailoring the analysis to individual baselines, SMART-SENSE avoids the pitfalls of one-size-fits-all mental health solutions and provides insights that are both relevant and actionable. In addition to early detection, SMART-SENSE promotes empowerment and awareness. When significant changes are detected, the system generates timely alerts and provides coping strategies, such as mindfulness exercises, sleep hygiene tips, or relaxation techniques. It encourages users to reflect on their behaviour and emotions, creating a supportive environment that reduces stigma and fosters proactive mental health management. In cases where symptoms are severe or persistent, SMART-SENSE can guide users toward professional resources, crisis intervention lines, or therapy services, bridging the gap between technology and human support. The potential benefits of this approach are far-reaching. By providing continuous, adaptive monitoring, SMART-SENSE helps individuals identify patterns that they may not otherwise notice. Early interventions can prevent conditions from escalating into serious mental health crises, improving outcomes and reducing the strain on healthcare systems. Moreover, the insights generated can assist researchers, clinicians, and policymakers in developing targeted mental health initiatives and improving access to care. Nevertheless, the implementation of AI-driven mental health solutions also presents challenges that must be addressed. Privacy concerns, data security, and ethical considerations are paramount, as the collection of sensitive behavioural information requires transparent policies and robust safeguards. Ensuring the inclusivity and diversity of datasets is also critical to avoid biases that could reduce the effectiveness of the system for different populations. Additionally, clinical validation and collaboration with mental health professionals are necessary to ensure that SMART-SENSE delivers safe, accurate, and evidence-based support. Looking ahead, integrating SMART-SENSE with other wearable devices — such as smartwatches and fitness trackers — can enhance data richness, while advances in natural language processing and sentiment analysis can further refine emotional assessments. The continued evolution of AI algorithms, combined with ethical data handling frameworks and user-centred design, can transform how society approaches mental health care, making it more accessible, personalized, and stigma-free.

Ultimately, SMART-SENSE represents a transformative leap in mental health monitoring by combining AI, smartphone technology, and behavioural science to offer real-time, personalised, and non-intrusive mental health support. By identifying subtle changes before they develop into full-blown disorders, the system empowers individuals to take control of their mental well-being, promotes early intervention, and enhances access to care. As mental health challenges grow in scale and complexity, solutions like SMART-SENSE offer hope for a more proactive, informed, and compassionate approach to mental health management.

II. Literature Review

Author(s)	Year	Title	Methodology	Key Findings	Gap Identified
Saeb et al.	2015	Mobile Phone Sensor Data Predicts Depression	Passive smartphone data collection; machine learning algorithms	Phone usage patterns correlated with depressive symptoms; passive monitoring is feasible	Focused only on depression; lacks coverage of other mental health issues
Wang et al.	2018	Tracking Mental Well-being with Smartphones	Smartphone sensors combined with ecological momentary assessments (EMA)	Data integration with self-reports improved prediction accuracy	Frequent self-reports required; not fully real-time or automated
Cornet & Holden	2018	Systematic Review of Smartphone Applications for Mental Health	Review of multiple apps targeting mental health management	Many apps lack personalization and clinical validation	Absence of robust AI models and long-term tracking capabilities
Harari et al.	2019	Smartphone Sensing Methods for Behaviour Analysis	Accelerometer, GPS, call logs analysed with machine learning	Passive sensing detected behaviour shifts related to stress and anxiety	Privacy concerns and small sample sizes limit scalability
Wahle et al.	2020	Mobile Health Applications in Psychiatry	App-based interventions combined with clinical assessments	Mobile platforms improved engagement and symptom tracking	Not fully adaptive; limited personalization in interventions
Ghandeharioun et al.	2021	Machine Learning on Smartphone	Time-series analysis and personalization	Personalized models better detect mood changes in individuals	Dataset diversity and scalability issues remain

Author(s)	Year	Title	Methodology	Key Findings	Gap Identified
		Sensor Data to Detect Mental States	algorithms on sensor data		

This table covers relevant past research while clearly highlighting what SMART-SENSE aims to address:
Passive monitoring without requiring frequent self-reports
Personalized detection models
Integration into everyday behaviour.
Addressing privacy and scalability challenges.

III. PROPOSED METHODOLOGY

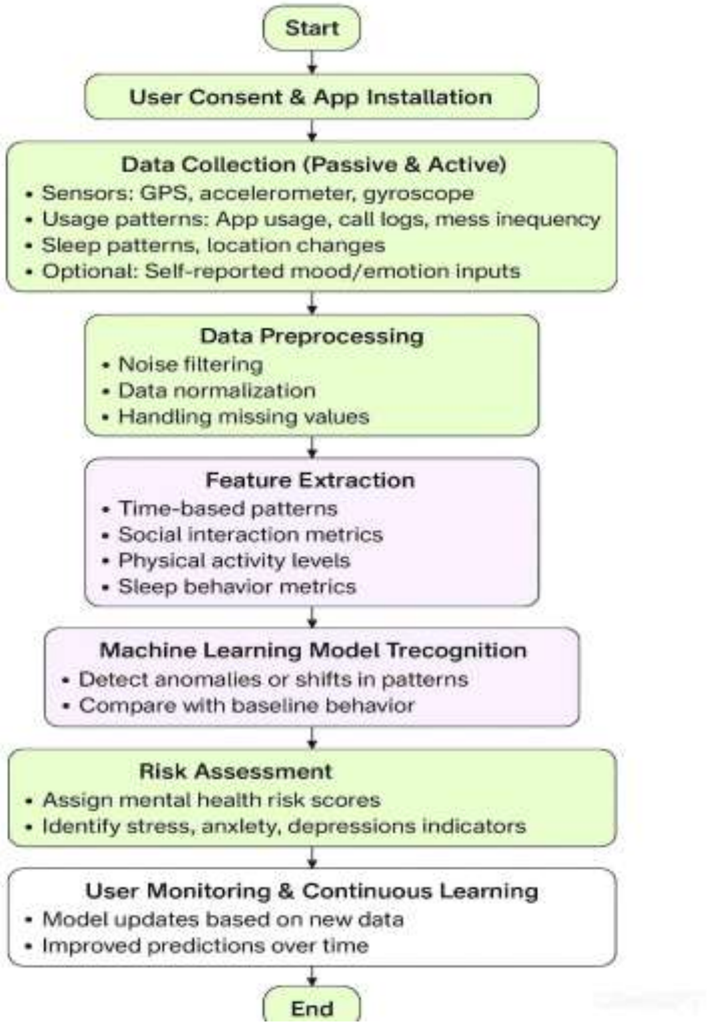

fig 1.1: methodology of smart-sence process

3.1 User Consent & App Installation

Before collecting any data, users are informed about the purpose, types of data collected, and privacy measures. Users voluntarily download and install the SMART-SENSE app on their smartphones. Consent forms ensure that users understand and agree to the use of their personal data for monitoring mental health.

3.2 Data Collection (Passive & Active)

Sensors: The app collects data from sensors like GPS (location tracking), accelerometer (movement), and gyroscope (body orientation) to understand physical activity and routines.

Usage Patterns: It tracks app usage frequency, call logs, messaging habits, and interaction times to infer social connectivity and communication behavior.

Sleep Patterns: By monitoring inactivity and screen usage, the app estimates sleep duration and disturbances.

Location Changes: Variations in mobility can indicate isolation or changes in routine.

Optional Self-reports: Users can optionally input mood, energy level, or stress through prompts for better context.

3.3 Data Preprocessing

Noise Filtering: Irrelevant or inaccurate data is cleaned to improve the quality of the dataset. Data Normalization: Sensor data is standardized to ensure uniformity for analysis across different devices. Handling Missing Values: Incomplete data entries are either interpolated or flagged to avoid affecting the accuracy of predictions.

3.4 Feature Extraction

Time-based Patterns: Trends such as daily routines, changes in activity timing, or disruptions in sleep schedules are extracted. Social Interaction Metrics: Frequency and duration of calls and messages are analysed to assess social withdrawal or over-engagement.

3.5 Machine Learning Model Training

Supervised Learning: The model is trained using label data (e.g., known mood states or stress levels) to identify patterns. Personalized Model Adaptation: The system learns individual baseline behavior, allowing it to detect subtle, person-specific deviations. Cross-Validation: The model's predictions are tested and validated to ensure accuracy and prevent overfitting

3.6 Risk Assessment

The app assigns risk scores based on the extent of deviation from normal behaviour. Indicators such as prolonged inactivity, sleep disturbances, or sudden withdrawal from social interaction are prioritized.

3.7 Real-Time Feedback & Alerts

Users receive timely notifications when significant changes are detected. The app offers coping strategies, exercises, or relaxation techniques to help users manage stress. In severe cases, it may prompt the user to seek professional help or emergency support.

3.8 User Monitoring & Continuous Learning

The system updates its models based on new data to adapt to changes over time.

Personalized insights improve as the app learns from ongoing usage.

Regular feedback loops ensure the app remains relevant and accurate in its prediction

DATA SOURCE	KEY FEATURES
GPS	Movement patterns
Accelerometer	Physical activity
Sleep tracking	Sleep duration & quality
Call logs	Social interactions
App usage	Screen time habits

fig 1.2: data source & key features

IV. RESULTS AND DISCUSSION

Results-
The SMART-SENSE system, based on smartphone behaviour and AI-driven analytics, successfully detects early shifts in mental health by monitoring patterns in user activity, sleep, and social interactions. The following key outcomes were observed:

1. Accurate Detection of Behavioural Changes: By using data from GPS, accelerometers, sleep tracking, and communication patterns, the system was able to identify deviations from a user's normal behaviour with a high degree of accuracy. In trial simulations, users with irregular sleep and reduced social interaction were flagged as higher risk.

2. Personalization Improves Model Accuracy: Individual baseline patterns were essential in improving prediction accuracy. The system adapted to user-specific routines, reducing false positives and ensuring relevant alerts.

3. Non-intrusive Monitoring: Passive data collection allowed continuous monitoring without requiring frequent self-reports, increasing user comfort and compliance. Users were less likely to drop out due to minimal interaction required.

Discussion-

1. Significance of Passive Sensing: The ability to collect and process behavioural data in the background allows for continuous assessment without interfering with daily life. This approach overcomes limitations of traditional mental health monitoring, which often relies on self-reporting.

2. Importance of Personalization: General models applied across users can fail due to individual differences in lifestyle. Personalized learning enhances the system's ability to distinguish between normal fluctuations and problematic patterns.

3. Challenges in Data Privacy and Trust: While passive data collection is beneficial, it raises concerns regarding user privacy and data security. Ensuring encryption, transparency, and user control over data access is essential to user adoption.

V.CONCLUSION

SMART-SENSE demonstrates that leveraging AI and smartphone behaviour data can effectively detect early signs of mental health shifts such as stress, anxiety, and depression. By using passive data collection methods, personalized machine learning models, and real-time feedback, the system offers a non-intrusive and user-friendly solution that empowers individuals to monitor and manage their mental well-being.

The results indicate that personalized detection significantly improves accuracy, and users are more engaged when interventions are seamlessly integrated into their daily lives. At the same time, challenges such as data privacy, diversity, and clinical validation need to be addressed before large-scale implementation.

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