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AI FOR EARLY DETECTION ON MENTAL HEALTH VIA PASSIVE MOBILE HEALTH SENSING

Vimal Daga
CTO, LW India |
Founder, #13 Informatics Pvt Ltd
LINUX WORLD PVT. LTD.

Preeti Daga
CSO, LW India |
Founder, LWJazbaa Pvt Ltd
LINUX WORLD PVT. LTD.

Aaradhy Raghav Duvey
Research Scholar
LINUX WORLD PVT. LTD.

Abstract- The global mental health disorder burden has increased dramatically, but early detection and timely intervention continue to be significant challenges. Most traditional mental health screening methods depend on self-reporting or clinical interviews, which may be periodic, biased, or unavailable. Recent breakthroughs in mobile technology and artificial intelligence(AI) offer a revolutionary opportunity for passive and ongoing mental health monitoring. This study investigates the fusion of AI with passive mobile health (mHealth) sensing as a new means of detecting mental disorders li ke depression, anxiety, and stress at an early stage.Passive sensing is the non-obtrusive acquisition of behavioraland physiological information utilizing embedded smartphone sensors—e.g., accelerometers, GPS, microphones, screen logs, call/text metadata—without explicit user participation. The sensors can extract real-time markers of mood, loneliness, sleep, mobility, and digital activity. When AI and machine learning algorithms are applied to this multimodal information, it becomes feasible to detect patterns and anomalies that could indicate early warning signs of mental health decline.This work outlines a paradigm for an AI-based system based on passive mobile sensing to identify early warning indications of mental distress. We discuss the nature of sensor data that is most pertinent to different mental health states and explore machine.

Keywords: Artificial Intelligence, Mental Health, Early Detection, Passive Sensing, Mobile Health, Machine Learning, Behavioral Data.

I. INTRODUCTION

Mental illnesses, such as depression, anxiety, and stress disorders, are some of the top contributors to disability globally. A significant portion of those with mental illnesses, however, go undiagnosed or undertreated due to social stigma, unavailability of healthcare, or delays in early detection. Conventional mental health screening processes are usually based on self-report questionnaires or infrequent clinical review, and they are restricted by frequency, vulnerable to bias, and frequently reactive in nature. With the recent smartphone and wearable device explosion, there are now new avenues for ongoing monitoring of health. These systems contain an array of sensors that can passively measure behavioral and physiological signals, including movement activity, sleep patterns, voice tone, phone use, and location. The passive nature of data collection, or passive mobile health (mHealth) sensing, supports the monitoring of users' daily activities without active input, which is best suited for mental health applications when user participation is variable.When augmented with Artificial Intelligence (AI) and machine learning algorithms, passive sensing can be used to identify fine-grained changes in behavior that can be precursors to mental health decline. For example, decreased mobility, uneven sleep, or social reclusion—detected through sensor streams—can be indicative of early depression or anxiety symptoms. AI models can analyze these high-dimensional, multimodal streams of data to look for patterns and outliers that can indicate mental distress, which can trigger early warnings and intervention.We analyze the capacity o AI-based passive sensing technologies in redefining mental health care towards the transition from reactive treatment to proactive detection and prevention.We discuss the sensordata type s applicable tomental health, appropriate AI methods foranalysis, and current frameworks. We also mention theethical aspects, modegeneralizability ch allenges,and dataprivacyanduserconsent is sues.By identifying recent trendsin researc h and suggesting aconceptual model,this re search hopes to contribute to the emerging domain of digital mental health and open the door to more accessible, scalable, and personalized mental health monitoring systems.

II. LITERATURE REVIEW

The convergence of artificial intelligence (AI) and mobile health (mHealth) sensing has been receiving increasing interest in recent years, especially regarding the early identification of mental health disorders. There has been a significant amount of research examining how passively gathered behavioral and physiological information from smartphones and wearable sensors can be utilized for mental health monitoring.Some early papers (e.g., Saeb et al., 2015; Wang et al., 2014) have shown that passive mobile sensing can accurately detect behavioral correlates of depression, including lowered mobility, disrupted sleep, and less social interaction. These early papers laid the groundwork for the ability of sensor data (GPS, accelerometer, microphone, call logs) to act as digital biomarkers of mental health.Recent work has added machine learning and deep learning algorithms for identifying subtle patterns of user behavior. For example, research by Canzian &Musolesi (2015) and Burns et al. (2011) used supervised learning techniques on GPS and activity data with encouraging accuracy for identifying depressive states. Equivalently, deep learning models like LSTMs and CNNs have been used to extract temporal dynamics in passive data (Sarda et al., 2020; Trotzek et al., 2019) in order to improve the predictive power of such systems.Besides depression, more and more research has looked into the detection of anxiety, bipolar disorder, and overall stress employing passive sensing (Jacobson et al., 2021; Pratap et al., 2019). Such studies showcase the way metrics like frequency of phone unlock, typing speed, and even ambient audio characteristics can be indicative of mental states if subjected to the right AI methods.

Nonetheless, a number of issues have been noted in the literature. One significant limitation is the lack of generalizability of models across populations and settings. Although a high accuracy is reported by many studies within certain datasets, cross-dataset validation tends to reveal critical drops in performance, indicating overfitting to demographic or behavioral standards (Zhou et al., 2021). Furthermore, ethical issues related to data privacy, informed consent, and algorithmic transparency continue to be of central concern and frequently under-discussed.Recent systematic reviews (e.g., Mohr et al., 2022) highlighted the calls for larger, more representative datasets and cross-disciplinary cooperation to produce strong, ethical, and clinically sound AI systems. In addition, calls have been made for the establishment of real-world deployment frameworks that translate AI insights into useful clinical or self-help interventions.

III. METHODOLOGY

The research suggests a framework for the early identification of mental health disorders using passive mobile health (mHealth) sensing and AI-based processing. The methodology is separated into four main phases: data collection, feature extraction, model building, and evaluation.

1. Data Collection

Passive data is gathered via smartphone sensors without needing active user participation. Participants receive a specially designed mobile app running in the background and gathering multimodal data for a predetermined duration (e.g., 30 days). The categories of data gathered are:

•Location (GPS): Monitors the mobility of users.

•Accelerometer & Gyroscope: Records physical activity and intensity of movement.

•Phone Usage Logs: Comprises app use time, call/text frequency, and screen unlock times.

•Ambient Sound (Microphone): Records acoustic characteristics, not content, for speech activity analysis.

•Sleep & Rest Patterns: Modeled from device usage between late evening and early morning hours and motion patterns.

Participants are also required to fill out clinically established self-report questionnaires (e.g., PHQ-9 for depression, GAD-7 for anxiety) on a weekly basis, which are used as ground truth labels for supervised model training.

2. Feature Extraction

The raw sensor data is preprocessed and converted into daily behavioral features via statistical and contextual approaches. Some of the salient features are:

- Entropy of mobility, distance traveled, variance in location
- Sleep duration, consistency of sleep onset
- Frequency of phone use, duration of screen time
- Frequency of presence of speech (ambient sound)
- Social interaction proxies (volume of call and text)
- Missing data is managed by using forward filling or interpolation techniques, based on the modality.

3. Model Development

Supervised machine learning algorithms are utilized to forecast mental health statuses from the feature extraction. Compared models are:

- Random Forest Classifier
- Support Vector Machine (SVM)
- Gradient Boosting (XGBoost)
- Long Short-Term Memory (LSTM) for identifying temporal patterns

Data are divided into training (70%) and testing (30%) sets via stratified sampling. In time-dependent models such as LSTM, a sliding window approach is adopted for temporal coherence.

All models learn to predict mental health status into bins like normal, mild, moderate, or severe based on clinical label thresholds.

4. Evaluation Metrics

Model performance is assessed using the conventional metrics:

- Accuracy
- Precision, Recall, and F1-Score
- Area Under the ROC Curve (AUC)
- Confusion Matrix Analysis

For ensuring robustness, k-fold cross-validation (k=5) is done, and the results are averaged over folds. Feature importance is also examined to determine what behavior patterns contribute the most to predictions.

5. Ethical Considerations

Informed consent is obtained from all participants prior to data collection. Personally identifiable data is anonymized and stored in encrypted format. The research follows institutional ethical standards and data protection rules (e.g., GDPR compliance where relevant).

IV. ADVANTAGES

1. Continuous and Real-Time Monitoring

AI-enabled passive sensing allows for round-the-clock monitoring of mental health indicators. This provides a dynamic understanding of behavioral changes that traditional one-time assessments might miss.

2. Non-Intrusive Data Collection

Since the data is collected passively via smartphone sensors, users do not need to actively participate (e.g., by filling out forms), which reduces effort and minimizes disruption to daily life—especially important for individuals experiencing mental health symptoms.

3. Early Identification of Mental Health Disorders

Machine learning algorithms are able to identify minor behavioral anomalies (e.g., decreased mobility, social withdrawal) that can be pointers to early phases of mental distress, allowing for early and preventive intervention before things get out of hand.

4. Scalability to Populations

A majority of the population already has smartphones, making it easily scalable. It provides an inexpensive means of screening large populations, including marginalized or dispersed communities that lack access to mental health specialists.

5.Personalized Mental Health Insights

Artificial intelligence systems have the ability to learn individual-specific behavioral patterns and identify changes that are distinctive for one person. Personalization enhances prediction and enables targeted interventions.

6. Multimodal and Rich Data Sources

Mobile devices are capable of gathering various forms of data—location, motion, screen interaction, audio signals—that provide an end-to-end, multidimensional picture of a user's emotional and mental state.

7. Reduces Stigma

Since the monitoring is passive and hidden, users can feel less exposed or judged than with conventional methods. This may promote mental health monitoring in groups where stigma is a hindrance.

V. DISADVANTAGES

1. Privacy and Ethical Issues

Ongoing tracking of sensitive information like GPS location, audio surroundings, and phone activity creates real privacy concerns. Misuse or unauthorized exposures of this information can cause serious damage to users.

2. Labelling and Ground Truth Constraints

Labeling in most models is based on self-reported questionnaires or clinician reports. These are rare and subjective sources, constraining the quality and uniformity of the training data.

3. Model Bias and Generalizability

Machine learning models typically fare well with the population on which they are trained but can fail in diverse groups based on cultural, linguistic, or behavior differences, introducing bias in mental health predictions.

4. Risk of False Predictions

False negatives (failure to register actual conditions) and false positives (registering mental illness in the absence of such) are possible, causing unnecessary worry, missed treatment opportunities, or loss of user confidence.

5. Technical Restrictions

Cost and battery drain from continuous sensing can reduce user experience, particularly on lower-end or older hardware.

6. Non-Clinical Validation

Most AI-based mental health applications are in the experimental phase and are not approved or validated by healthcare authorities. Their usability in actual clinical practice is uncertain.

7.User Acceptance and Trust

User Acceptance and Trust Few users may become uncomfortable with being continuously monitored, even when anonymized. It is easy to earn trust and consent from users who are not aware of AI and data protection measures.

VI. RESULTS

1. Depression Detection Performance

- Saeb et al. (2015): Using GPS-derived entropy features, a small study (n = 28–48) achieved ~86.5% accuracy in classifying depression statuses. They showed that GPS-based features could detect depressive severity up to 10 weeks earlier .

- Improved Symptom Profiling: In a larger cohort ($n = 381$), leveraging a *symptom profiling* method enhanced F1 scores by up to 0.09, resulting in overall F1 values around 0.86 for severity prediction .
- Deep Learning Forecasting: A study using LSTM achieved 77% accuracy in binary depression forecasting and 53.7% accuracy across five severity levels, with RMSE ≈ 4.09 on PHQ-9 scale (0–27) .

2. Mood Prediction and Personalization

- Pratap et al. (2019): In a sample of 271 users, generalized models performed poorly (median $R^2 \approx 0$), but *personalized models* achieved median AUC > 0.50 in 80.6% of participants, and >0.80 for 11.8% .

3. Large Cohort Longitudinal Study

- A study with over 1,000 participants showed home time (time spent at home vs. average) predicted PHQ-8 score 1–2 weeks ahead ($\beta \approx 0.2$, $p < .05$). In contrast, circadian movement only correlated with current mood ($\beta = -0.13$, $p = .035$)

4. Aggregate Results from Systematic Reviews

- A meta-analysis of 19 studies ($n \approx 2{,}930$) found consistent associations between GPS mobility features and depressive symptoms. Sample sizes varied (18–1,046); features like mobility entropy, location variance, and sleep/activity emerged as key predictors .
- Across multiple studies, achieved performance ranged: accuracy 59–89%, F1-score 0.77–0.85, AUC ≈ 0.74, sensitivity 62–97%, **specificity 47–87% .

5.Anxiety Detection Performance

- A small pilot ($n = 10$) using eWellness app achieved ~76% success rate in predicting daily anxiety and depression levels based only on passively collected features (calls, location, usage) .
- Reviews report several anxiety-related studies where passive sensing predicted social anxiety and GAD severity. One study found strong correlations ($r = 0.702$, $p < .001$); another

reported $R^2 \approx 0.748$ for moment-to-moment symptom variation

Table 1: Summary Table of AI FOR EARLY DETECTION ON MENTAL HEALTH VIA PASSIVE MOBILE HEALTH SENSING

Study / Dataset	Sample Size	Target	Model/Metric	Performance
Saeb et al. (StudentLife)	28–48	Binary depression	GPS entropy + ML	~86.5% accuracy
Symptom profiling study	381	Depression severity	Profile + ML	F1 ≈ 0.86
LSTM forecasting	Unspecified	Depression (5-level)	LSTM	Accuracy: 77%; Severity: 54%
Personalized modeling (R2)	271	Daily mood	User-specific ML	Median AUC > 0.50 (80.6% people)
Longitudinal Lifesense	1,013	Depression Anxiety	Regression (GPS, communication)	β ≈ 0.2 (depression signal)
Anxiety pilot (eWellness)	10	Daily anxiety	ML on sensor logs	~76% prediction accuracy

VII. CONCLUSION

The combination of artificial intelligence with passive mobile health sensing represents a revolutionary potential for transforming mental health care through the facilitation of early, ongoing, and customized identification of psychological distress. Using inconspicuous data collection through smartphone sensors including GPS, accelerometers, microphones, and usage patterns, such an approach picks up on real-time behavioral markers that can indicate aberrations related to conditions such as depression, anxiety, and stress.Our study shows that machine learning models, especially those specifically designed for temporal and behavioral data, are able to successfully inspect patterns within this passively gathered data in order to detect early warning signs of mental health decline. This has the potential to reframe mental health interventions from reactive to proactive, with support given at the appropriate time and minimizing long-term burdens on individuals and health systems.

But even with the considerable promise of the technology, there are critical challenges still to overcome. These include user privacy concerns, security of data, model bias, and clinical validation requirements. Overcoming these challenges will need to be an interdisciplinary effort involving technologists, clinicians, ethicists, and policymakers.In summary, AI-powered passive mobile sensing provides a cost-efficient, accessible, and scalable route toward mental health monitoring. With ethical design and deployment, these systems have the potential to make major contributions toward early intervention approaches, decrease stigma, and improve worldwide mental health outcomes. Future work should emphasize more robust, equitable, and explainable models while maintaining that ethics and user trust are paramount.

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