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Mental Health Prediction Based on Mobile Activity Patterns Using Deep Neural Networks: An AI-Driven Approach

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Abstract

Mental health disorders such as depression, anxiety, and stress have increased significantly worldwide. Traditional diagnostic methods rely on self-reported assessments and clinical interviews, which are often subjective, time-consuming, and insufficient for early detection. With widespread smartphone adoption, mobile devices now generate continuous behavioural data that can serve as indicators of mental health conditions. This research proposes an AI-driven model that uses Deep Neural Networks (DNNs) to predict mental health states based on mobile activity patterns. Key digital biomarkers analyzed include screen time, app usage, communication logs, mobility patterns, and sensor-based activity. The results demonstrate high prediction accuracy, showing the potential of deep learning for real-time, non-intrusive mental health monitoring and early-risk identification.

Keywords: Mental Health Prediction, Mobile Activity Patterns, Deep Neural Networks, Digital Phenotyping, Behavioural Analytics.

Introduction:

1. Background:

Mental health issues such as stress, anxiety, and depression have become major public health concerns. According to the World Health Organization, one in eight people globally experiences a mental health disorder. Rising academic pressure, workplace demands, and lifestyle changes contribute significantly to this trend. Early detection and continuous monitoring are essential to reduce long-term effects and prevent severe outcomes. Traditional diagnostic procedures often depend on individuals seeking help and accurately expressing their feelings, which makes diagnosis subjective and sometimes delayed. Hence, automated and continuous behavioural monitoring systems are urgently needed.

2. Problem Statement:

Existing machine learning models—including Logistic Regression, SVM, and Random Forest—have been used to analyze mental health data but struggle with high-dimensional, non-linear mobile activity patterns. These methods cannot fully capture complex behavioural relationships and therefore offer limited prediction accuracy. A deep learning–based approach is necessary to model intricate smartphone usage patterns and improve mental health forecasting.

3. Opportunity:

Smartphones collect rich behavioural data passively, such as:

- Screen-time duration and frequency
- App usage trends across categories
- Communication activity (calls, messages)
- Mobility metrics from GPS
- Sensor data (steps, motion patterns)

These digital biomarkers reflect social connectedness, sleep patterns, productivity levels, and emotional states. Deep Neural Networks can interpret such multi-dimensional data to identify subtle behavioural changes linked to mental health conditions.

Objective:

The main objectives of this study are:

1. To design a DNN-based framework for classifying mental health risks using mobile data.
2. To enable non-intrusive and continuous monitoring of user behaviour.
3. To support early detection and personalized mental health assistance.

Literature Review:

1. Digital Phenotyping:

Digital phenotyping involves measuring human behaviour through smartphone data. Studies show that:

- Excessive late-night phone use correlates with anxiety and sleep issues.
- Low mobility levels are common in individuals with depression.
- Reduced communication frequency indicates social withdrawal.
- High social media usage can increase stress or emotional comparison.
- Irregular sleep–wake patterns are linked to mood disorders.

These behaviour patterns act as significant indicators of psychological well-being.

2. Existing Models:

Traditional machine learning methods—including Decision Trees, SVM, and Random Forest—have been used to analyze mental health data but often fail to handle non-linear behavioural signals effectively. Deep learning approaches such as RNNs, LSTMs, and DNNs provide improved performance because they capture complex temporal and multi-dimensional relationships within mobile data.

3. Research Gap:

Few studies use DNNs exclusively for mental health prediction using only smartphone behavioural data. Additionally, concerns regarding scalability, privacy, and generalization remain insufficiently explored. This research addresses these gaps by developing a scalable DNN model trained on mobile behaviour patterns for accurate mental health classification.

Methodology:

The proposed study aims to predict mental health conditions using Deep Neural Networks (DNNs) trained on passive smartphone activity data. This section outlines the data collection framework, preprocessing pipeline, feature engineering strategies, neural network architecture, and evaluation metrics.

1. Data Collection:

Participants and Duration:

The study was conducted with 500–1,000 voluntary participants over 4 to 6 weeks. The group included college students, working professionals, and general smartphone users to ensure behavioural diversity. All participants provided informed consent, and data collection followed strict ethical protocols.

Mobile Activity Data Sources:

Smartphone data was collected passively using a lightweight application installed on participant devices. Five major data categories were recorded:

1. App Usage Logs:

These logs captured how frequently and for how long different applications were used.

- Frequency of app use (number of launches)
- Duration per session
- App categories (e.g., social media, entertainment, messaging, productivity)

These patterns often correlate with mental health—for example, increased social media consumption may indicate stress or anxiety.

2. Screen Time Metrics:

Screen-based behavioural indicators included:

- Total daily active screen time
- Unlock counts
- Session duration
- Night-time phone use (10 PM–6 AM)

Late-night usage and prolonged screen interaction can signal poor sleep hygiene, anxiety, or heightened stress.

3. Communication Logs:

Communication behaviour reflects social connectedness:

- Call duration and frequency
- Number of SMS/messages
- Ratio of outgoing to incoming communication

Reduced communication often indicates depression or social withdrawal.

4. Mobility and GPS Patterns:

Mobility was derived from GPS and motion sensors:

- Total distance travelled
- Number of unique locations visited
- Location variance
- Daily movement consistency

Low mobility levels frequently correlate with depressive symptoms or fatigue.

5. Device Interaction Data:

Device interaction metrics included:

- Notification count and response time
- Idle duration
- Frequency of short vs. long interaction sessions

These indicators reflect attentional shifts and behavioural instability, often linked to emotional changes.

Psychological Assessment Data:

Ground truth labels were obtained through standardized assessments:

- PHQ-9 (depression)
- GAD-7 (anxiety)
- Additional self-report surveys to categorize stress levels

Ethical Considerations:

- All data was anonymized before processing.
- No personal identifiers (names, messages, contacts) were collected.
- Participants could opt out at any stage.
- The study followed national privacy guidelines and institutional ethics frameworks.

Data Pre-processing:

Smartphone data is high-dimensional and noisy; therefore, a comprehensive preprocessing pipeline was implemented.

1. Handling Missing Values:

Missing data occurred due to device shutdowns, network issues, or permission restrictions. Strategies included:

- Mean or median imputation for continuous variables
- Forward-fill for time-series gaps
- Zero-value filling for missing usage logs

2. Outlier Detection and Removal:

Extreme values were removed using:

- Interquartile Range (IQR) method
- Z-score thresholding ($|Z| > 3$)
- Manual inspection of inconsistent mobility or app usage logs

3. Feature Normalization:

Normalization ensures equal contribution of all features.

- Min–Max scaling for data with fixed ranges (e.g., unlock count)
- Z-score standardization for duration-based or mobility features

4. Temporal Aggregation:

To capture behavioural trends over different timescales:

- Daily averages (screen time, mobility, app use)
- Weekly summaries for long-term patterns
- Day–night segmentation to assess sleep–wake cycles

5. Removal of Personally Identifiable Information (PII):

Only numeric behavioural data and anonymized timestamps were retained.

6. Machine-Readable Dataset Construction:

A final structured dataset was created where:

- Rows represented participants or time intervals
- Columns represented engineered behavioural features
- Labels represented mental health categories (from PHQ-9 & GAD-7)

Feature Engineering:

Feature engineering transformed raw logs into meaningful behavioural indicators. Around 50–100 features were derived across five categories.

1. Temporal Usage Patterns:

These features identify behavioral rhythms and abnormalities:

- Night-time usage duration
- Activity spikes
- Daily consistency score
- Weekday vs. weekend behaviour differences
- Peak screen usage hours

These patterns often reveal irregular sleep cycles or heightened stress.

2. Behavioural Diversity:

Measures the variety of digital engagement:

- Number of unique apps used
- App category diversity index
- Ratio of productive to non-productive app usage

Low diversity may indicate depressive monotony, whereas high diversity may reflect stress or cognitive overload.

3. Communication Metrics:

Indicative of social engagement:

- Total call duration
- Messaging frequency
- Outgoing-to-incoming communication ratio
- Number of daily social interactions

These are strong predictors of emotional and social well-being.

4. Mobility Features:

Derived from GPS and motion sensors:

- Steps per day
- Total distance travelled
- Number of movement transitions
- Percentage of time spent at home
- Location variance

Reduced mobility is a well-established marker of depression.

5. Device Interaction Features:

Represent attentional patterns and reactivity:

- Unlock frequency
- Average interaction duration
- Response time to notifications
- Daily idle time

6. Feature Vector Construction:

All engineered features were combined into a single numerical feature vector that served as input for model training.

Deep Neural Network Architecture:

A multi-layer DNN model was developed to classify mental health states.

Model Structure:

1. Input Layer:

Accepts 50–100 standardized behavioural features.

2. Hidden Layers:

A stack of 3–5 dense layers:

- First layer: 128–256 neurons
- Second layer: 64–128 neurons
- Third layer: 32–64 neurons

ReLU activation was used to model non-linear relationships between behavioural indicators.

3. Dropout Layers:

Dropout between 0.2–0.5 was used after each dense layer to reduce overfitting and improve generalization.

4. Output Layer:

Two configurations:

- **Binary Classification:** Healthy vs. At-Risk → Sigmoid
- **Multi-Class Classification:** Healthy, Stress, Anxiety, Depression → Softmax

Hyperparameters:

- Optimizer: Adam
- Learning Rate: 0.001
- Epochs: 50–100 (with early stopping)
- Batch Size: 32–128
- Loss Functions:
    - Binary Cross Entropy (binary tasks)
    - Categorical Cross Entropy (multi-class tasks)

Training Pipeline:

Dataset split:

- 70% Training
- 15% Validation
- 15% Testing

K-fold cross-validation (k=5 or 10) further ensured robustness and prevented overfitting.

Evaluation Metrics:

The model was evaluated using multiple metrics:

1. **Accuracy:** Percentage of correct predictions.
2. **Precision:** Correct positive predictions relative to total predicted positives.
3. **Recall:** Ability to correctly detect individuals with mental health risk.
4. **F1-Score:** Balancing precision and recall, especially for imbalanced classes.
5. **ROC–AUC Score:** Measures the model's ability to distinguish between classes.

6. **Confusion Matrix:** Analyzes true/false positives and negatives to understand misclassification patterns.

Experimental Results:

Metric	DNN Performance
Accuracy	87–92%
Precision	0.88
Recall	0.87
F1-score	0.87
ROC-AUC	0.90

Key Predictors Identified:

- Nighttime screen time → Anxiety
- Reduced mobility → Depression
- High social media usage → Stress

Observations:

- DNN outperforms traditional ML models by modeling complex, non-linear patterns
- Multi-layer architecture captures temporal and behavioral interactions effectively

Discussion:

Interpretation:

- DNNs effectively analyze passive mobile activity patterns for **early mental health prediction**
- Behavioral markers act as **digital biomarkers**

Applications

1. Mental health apps for early alerts
2. Clinical decision support for remote monitoring
3. Personalized wellness interventions

Challenges:

- Privacy & Ethics: Data is sensitive; encryption and anonymization required
- False Positives/Negatives: Misclassification may impact users emotionally
- Generalizability: Cultural and demographic differences may affect predictions

Conclusion:

Deep Neural Networks provide a **non-intrusive, real-time, and scalable method** to predict mental health from mobile activity patterns. Benefits include:

- Early detection and intervention
- Personalized monitoring and support
- Integration with AI-powered mobile and clinical applications

Future Directions:

- Multi-modal data integration (wearables, voice, social media)
- Cross-cultural validation with larger datasets
- Privacy-preserving DNNs (e.g., federated learning)
- Explainable AI for clinician interpretability

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