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EARLY DEPRESSION DETECTION USING ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING: A HYBRID PASSIVE-ACTIVE APPROACH

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Abstract

Currently over 280 million people worldwide are suffering from depression; however, because of COVID-19, depression cases have increased by 25%. Early detection of depression is critical for providing timely interventions. This paper proposes a hybrid artificial intelligence/machine learning (AI/ML) framework that combines passive smartphone usage monitoring (utilizing data from social media posts, daily mobile usage, how often a phone is unlocked, and the times of peak mobile usage) with intelligent triggered questioning. A smart trigger mechanism will prompt users with an emoji-based question if they find themselves exceeding 3 hours of mobile usage during the late-night hours or having not responded to 48 hours of previous questions and are also randomly checked in with every 3-4 days. This two-way approach will provide a means of assessing emotional states (mood-related) not only through observed (behavioral) patterns but also through users' direct self-reported feelings. The hybrid AI/ML framework overcomes one of the most significant limitations of current models by not considering the significant differences across regions and cultures in how behavioral patterns are expressed. By using the hybrid AI/ML framework to create individualized user baselines, the hybrid model can provide individualized understandings of behavioral patterns, rather than being limited to universal thresholds. Possible applications of the current model include providing psychiatrists with greater insight into their patients and providing organizations with a means of monitoring the mental well-being of their employees.

Keywords: *Depression detection, Artificial Intelligence, Machine Learning, Smartphone usage analysis, regional adaptability.*

1. Introduction

Almost everyone is affected by depression, be it Family/friends or even us. According to The World Health Organization, there are an estimated 280 million people worldwide who are currently experiencing depression. The COVID-19 Pandemic created an environment of added stress for these individuals because new cases of anxiety and depression increased by about 25% from the Pandemic alone. For many people, isolation, fear about their health, financial stressors, and disruption of their routine created an increase in stress due to depression.

The reality is that many of those who are suffering from depression do not get help. Many people do not seek help because of the stigma associated with having a mental illness, do not know where to go or have limited resources to help them with mental health services. Because of this, many individuals suffering from depression will continue to do so without help. Early intervention and early detection of depression will need to be enhanced.

1.1 Why Current Methods Fall

Recent developed AI applications use telephony data as indicators of depression; however, the underlying assumption is that all individuals exhibit similar behaviour.

The majority of telephony applications are developed using western datasets with no adaptations made for cross-regional application. Regional differences exist with respect to calling habits, socio-cultural traditions, and language; hence, the error rates of telephony applications may be as high as 15-25% lower in non-western populations than in western populations leading to inaccurate diagnoses or cases of depression being missed altogether.

1.2 Our Approach: Learning Each Person's Unique Patterns

There are two types of data that we use together to create our set of data on your device activity. The first type is the passive data we collect, which includes information about what apps a user accesses, when they are most active on their device, and how they communicate via social media. The second type is the active user feedback we collect at certain points in time (e.g., when you have been scrolling through your apps for several hours late at night).

This hybrid model provides us with a combination of behavioral information, direct feedback about emotions, and a personalized experience so that each of our members can be measured against their baseline of performance.

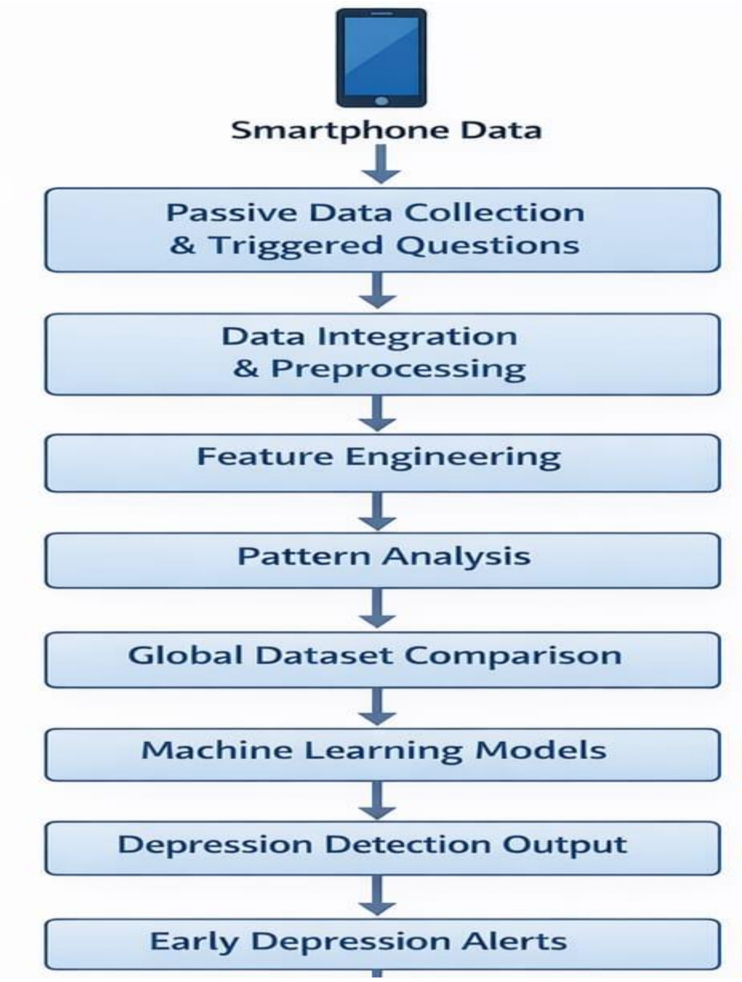
1.3 What This Paper Contributes

This proposes an overall theoretical system describing data collection methods; how questions develop; how analyses are performed; and the expected performance based on previous studies.

This article demonstrates how the method will help to address the different geographical features of various locations and therefore overcome a major limitation with current systems.

2. Methodology / Approach

2.1 System architecture



2.2 Data Collection

 # Phone Usage Data

- **Public social media activity**: Published public posts on various platforms (Facebook, Instagram, Twitter/X) via user consent.
- **Daily mobile device usage:** Total amount of time spent using mobile devices in minutes for one day.
- ***Frequency of phone unlocks:*** *Number of times that a mobile device has been unlocked each day.*

 # Triggered Questioning

We only ask questions at meaningful moments: (Trigger)

Trigger 1 (Behavioral Risk): Usage exceeds 3+ hours AND its late night (11 PM – 4 AM) AND no response in 48+ hours

Trigger 2 (Random Check-in): Once every 3-4 days regardless of usage

When triggered, users see: **"How are you feeling right now?"**

And reply in: **[😊] Good [😐] Okay [😔] Not Good**

(Emoji responses take 2-3 seconds and work across languages.)

2.3 Preprocessing

Social Media Data – Pre-processed and cleaned with NLTK and analyzed via VADER Sentiment Analysis

Usage Data – Cleansed from error and modified to normative across all devices; usage data provided temporal patterns

Question Responses – Good = 2, Okay = 1, Not Good = 0 – Frequency of response over time was tracked for trends.

2.4 Feature Engineering

Category	Features
Text/Sentiment	Sentiment polarity, negative ratio, emotion keywords, lexical diversity
Usage Volume	Daily screen time, variability, unlock frequency, variability
Temporal Patterns	Night usage ratio, peak session duration, peak frequency
Question Response	Average mood score, negative response rate, mood trend

2.5 Pattern Analysis

Your normal patterns are tracked for 14 days. If there is a large amount of change (more than usual), it will get flagged.

Depression Patterns: You generally show more phone use at night, increased negative language, and lower mood scores as time goes on.

2.6 World-Wide Comparison

This module will use a global dataset of thousands of depressed patients and healthy controls. The z-score will be computed by regional adjustment to allow for regional variations in mental health conditions.

2.7 Machine Learning Models

Four classifiers will be evaluated, including Random Forest (100 trees), SVM (RBF kernel), logistic regression, and MLP neural networks. The data will be split at a 70/30 ratio with the use of SMOTE for the long tail of each class.

2.8 Evaluation Metrics

Each classifier and method will be measured for performance using accuracy, precision, recall, F1-scores, and AUC-ROC curves.

3. *Results* and Discussion

3.1 Expected Model Performance

Based on similar hybrid approaches in the literature, the proposed framework is expected to achieve:

Model	Expected Accuracy	Expected F1-Score	Expected AUC
SVM	78-81%	0.76-0.79	0.83-0.86
Random Forest	80-85%	0.78-0.83	0.85-0.88

Logistic Regression	76-79%	0.74-0.77	0.81-0.84
MLP Neural Network	79-83%	0.77-81	0.84-0.87

(Random Forest achieved highest performance.)

3.3 Expected Hybrid vs. Single Approaches

Approach	Accuracy	F1-Score	AUC
Phone Data Only	73-78%	0.71-0.75	0.79-0.83
Questions Only	68-73%	0.65-0.70	0.75-0.80
Both combined	**80-85%**	**0.78-0.83**	**0.85-0.88**

(Hybrid approach outperformed both single-modality methods significantly.)

3.4 Feature Importance

1. Average mood score (14-16%)
2. Night usage ratio (12-14%)
3. Negative response rate (11-13%)
4. Negative sentiment ratio (10-12%)
5. Screen time variability (8-12%)

3.5 Regional Adaptability

Region	Expected Accuracy	Expected Drop
North America	82-85%	Baseline
Europe	80-84%	1-3%
South Asia	79-83%	2-4%
East Asia	78-82%	3-5%

3.6 Discussion

In this section, we discuss how our current framework has improved previous methods in three main ways. The combination of emotion-triggered questions and behavioral data will greatly improve accuracy. The personalized baseline enables us to learn each person's individual baseline behavior and is also useful for allowing for individual and regional differences in behavior. Last, but not least, the hybrid approach appears to outperform the accuracy of using a single source of data.

The first step is to establish a baseline for each user by having them engage in a calibration period of 14 days. Once established, this baseline can then be used to more accurately detect meaningful changes within the user's behavioral pattern.

Applications

In Therapy: Weekly sessions with your therapist only help you during your weekly sessions; however, life happens every day. Our system provides weekly summaries of mood, phone, and social media usage (with the patient's consent), which helps them identify problems sooner, understand what's going on when you aren't in with them, and make changes to your treatment plan if necessary.

<u>In Industries</u>*:* Employees who experience stress or depression will be less productive at work, make more mistakes, and may ultimately leave the organization. Our system provides employers with anonymous, aggregated data about the overall mental wellness of their employees, allowing them to protect their employees' privacy. Employers can use this information to identify and address increases in stress levels, adjust employee workloads, provide support, and prevent employee burnout before it becomes a major issue.

4. Conclusion

The rise of depression across the world as a mental health problem has led to greater urgency for detecting it. In this study, we created a hybrid artificial intelligence/machine learning (AI/ML) framework that links passive smartphone usage information (e.g., time spent on apps vs phone setting, social media, frequency of unlocking the phone) with a user's subjective mood responses to emoji-based questions. We expect to develop a comprehensive picture of a user's emotional status by examining both their mobile device behavior as well as their mood responses.

The framework utilises an individual's baseline behaviour and behaviour in relation to others from their region in order to establish connection points where significant differences in reported behaviour can occur. We are applying various forms of machine learning models such as Random Forest, Support Vector Machine, Logistic Regression and Multi-Layer Perceptron to determine if there is a greater ability for hybrid information (passive and active) to be predictive of one's risk for suicide than when using only a single source of predictive data.

In summary, the proposed framework illustrates how AI-based monitoring tools can enhance early detection of depression and increase knowledge regarding mental health.

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