

# A Multi-Layer Perceptron Model for Predicting Smartphone Addiction Levels

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**Keywords:** Machine Learning, Behavioral Analysis, Predictive Model, Digital Well-Being, Classification Algorithms, User Behavior, Artificial Intelligence, Neural Networks (ANNs), Mental Health.

**Abstract:** Smartphone addiction is a serious issue, with adverse effects on mental health, academic achievement, sleep and social relationships. Conventional self-reported questionnaires tend to be inaccurate and susceptible to bias, requiring automated approaches. This research suggests a machine learning model to forecast smartphone addiction based on behavioral metrics like screen time, app usage, social media usage, call duration, and phone unlock frequency. Psychological variables from well-validated questionnaires are also included to enhance prediction accuracy. Different machine learning algorithms such as Decision Trees, SVM, Random Forests, and Neural Networks are experimented with on a labeled dataset. Accuracy, precision, recall, and F1-score are used to evaluate the models, and the results indicate that ensemble methods such as Random Forests work best. The system allows real-time tracking of smartphone addiction risks. It provides an early intervention proactive approach and management of addiction. It can be implemented into digital health applications for users, educators, and healthcare providers. It ultimately seeks to enable healthier smartphone use and digital well-being.

## 1 INTRODUCTION

In recent years, smartphones have transformed from mere communication tools into indispensable digital companions. Their integration into everyday life ranging from social networking and entertainment to education and business has created a deep reliance on mobile devices. While smartphones offer immense convenience and connectivity, their overuse has given rise to a modern behavioral disorder known as smartphone addiction. This addiction is characterized by compulsive and excessive use of smartphones, leading to negative impacts on mental health, interpersonal relationships, and overall productivity.

Numerous studies have shown a significant correlation between excessive smartphone usage and issues such as anxiety, depression, sleep disturbances, and poor academic or professional performance. Particularly among adolescents and young adults, the increasing screen time and engagement in digital platforms have raised concerns about behavioral dependence. Traditional diagnostic methods such as surveys and psychological evaluations are effective but often limited by subjective interpretation, delayed

analysis, and the inability to monitor behavioral patterns in real-time.

The rise of artificial intelligence and machine learning technologies presents an opportunity to address this issue in a more dynamic and data-driven manner. Machine learning algorithms can analyze large volumes of behavioral data to uncover patterns and detect signs of addictive behavior. By utilizing smartphone usage metrics such as app usage duration, screen time frequency, social media interactions, and phone unlock counts along with psychological inputs, machine learning models can provide an accurate and automated assessment of smartphone addiction risk levels.

This project aims to develop a machine learning model capable of predicting smartphone addiction by analyzing behavioral and psychological data. The model is trained on datasets collected from smartphone users, incorporating both usage logs and responses from validated psychological questionnaires. Various supervised learning algorithms, including Decision Trees, Support Vector Machines (SVM), Random Forest, and Neural Networks, are employed and evaluated to determine

the most effective method for classification and prediction.

The goal of this study is not only to enhance the early detection of smartphone addiction but also to support the development of preventive tools and digital well-being solutions. By integrating such a system into mobile applications, users can receive timely alerts and recommendations for healthier smartphone habits. Additionally, educators, psychologists, and health professionals can use the insights generated by the model to guide individuals toward more balanced digital lifestyles and reduce the long-term consequences of technology overdependence.

## 2 RELATED WORKS

Several studies have explored smartphone addiction prediction using machine learning. Research by Kim et al. (2018) used Decision Trees and Logistic Regression on usage data, showing high correlation with addiction levels. Wang et al. (2020) applied SVM and Random Forest for addiction classification, achieving considerable accuracy. Lee & Lee (2021) improved predictions by combining behavioral and psychological data, while Chen et al. (2022) emphasized the role of feature selection in model performance. This study builds upon existing research by integrating behavioral metrics with psychological assessments and evaluating multiple machine learning algorithms for robust addiction prediction.

## 3 METHODOLOGY

### 3.1 Theoretical Structure

The research methodology adopted for this study involves a systematic approach to collecting, processing, and analyzing smartphone usage and psychological data to develop a machine learning model capable of predicting smartphone addiction. The first phase involves data collection from participants using both primary and secondary sources. Primary data is gathered through smartphone usage monitoring applications that log features such as screen time, app usage frequency, call and message duration, and unlock counts. Simultaneously, participants are asked to complete validated psychological questionnaires such as the Smartphone

Addiction Scale (SAS), which helps in labeling the addiction severity.

In the second phase, the collected data is preprocessed to ensure consistency and reliability. Data cleaning techniques are applied to remove duplicates, handle missing values, and standardize feature values. Feature engineering is performed to select the most relevant attributes that contribute significantly to addiction prediction. This phase also includes normalization and encoding of categorical data to prepare the dataset for machine learning algorithms.

The third phase focuses on model development and training. Several supervised learning algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forest, Logistic Regression, and Artificial Neural Networks are implemented using programming tools like Python and machine learning libraries such as Scikit-learn and TensorFlow. The dataset is split into training and testing sets to evaluate model performance. Hyperparameter tuning and cross-validation techniques are applied to enhance the accuracy and generalization of the models.

Finally, model evaluation is conducted using performance metrics such as Accuracy, Precision, Recall, F1-score, and ROC-AUC. The model with the highest predictive performance is selected as the final model. The results are interpreted to determine the patterns and factors contributing most significantly to smartphone addiction. The methodology ensures a robust, data-driven, and repeatable process for developing a predictive tool that can be. Figure 1 Shows the Schematic Flow of Theoretical Structure.

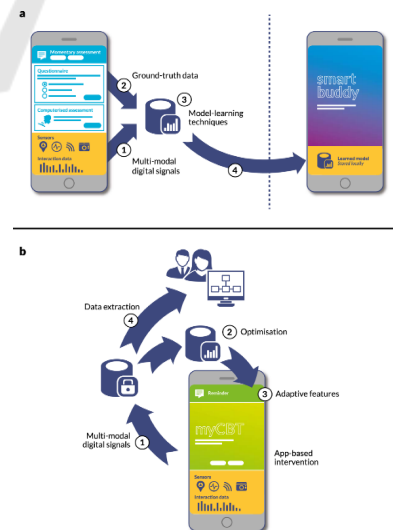


Figure 1: Schematic flow of theoretical structure.

## 3.2 Perceived Features

### 3.2.1 Data Collection and Processing

Data is collected through smartphone monitoring apps and validated psychological scales such as the Smartphone Addiction Scale (SAS). The dataset undergoes preprocessing, including data cleaning, feature selection, and encoding. Feature engineering is applied to extract the most relevant attributes for addiction prediction.

### 3.2.2 Machine Learning Model Development

Various supervised learning models are implemented, including Decision Trees, SVM, Random Forest, and Artificial Neural Networks. The dataset is split into training and testing sets, with hyperparameter tuning and cross-validation performed to enhance accuracy. Model performance is evaluated using Accuracy, Precision, Recall, F1-score, and ROC-AUC.

### 3.2.3 Statistical Analysis

Structural Equation Modeling (SEM) is used to assess the relationship between smartphone usage behaviors and addiction severity. Pearson's correlation analysis identifies the strongest predictors of addiction. The final model is selected based on its predictive accuracy and generalization capability.

## 4 PURPOSE

The proposed system aims to develop an intelligent, data-driven, and automated model for the prediction of smartphone addiction using machine learning techniques. Unlike traditional systems that rely heavily on self-reported data and static assessments, this system leverages real-time smartphone usage patterns and behavioral metrics to assess addiction risk. By collecting and analyzing data such as screen time, app usage frequency, unlock count, call duration, and notifications, the system can detect early signs of addiction without user intervention. A core element of the proposed system is the integration of machine learning algorithms to accurately classify and predict smartphone addiction levels. Additionally, the proposed system is designed to be adaptive and personalized. It monitors behavioral trends over time and adjusts risk prediction based on a user's changing habits. Users receive feedback in the form of addiction risk levels (low, moderate, or high) along with actionable suggestions such as

screen-time reduction tips, app usage control, and wellness prompts. This feedback mechanism helps users stay aware of their usage patterns and motivates them to adopt healthier digital behaviors proactively.

Ultimately, the proposed system addresses the limitations of existing solutions by providing an intelligent, real-time, and scalable framework for smartphone addiction prediction. It can be deployed in mobile applications, institutional wellness programs, or digital therapy platforms to support individuals, students, and employees in maintaining digital well-being. By identifying at-risk users early, the system can contribute to preventive mental healthcare and reduce the long-term impact of smartphone addiction.

## 5 RESULT

The performance of the prediction model is evaluated by comparing real and predicted mobile phone addiction levels among students (Figure 2). Furthermore, the effectiveness of different machine learning techniques is assessed using  $R^2$  values across three model variants (Figure 3).

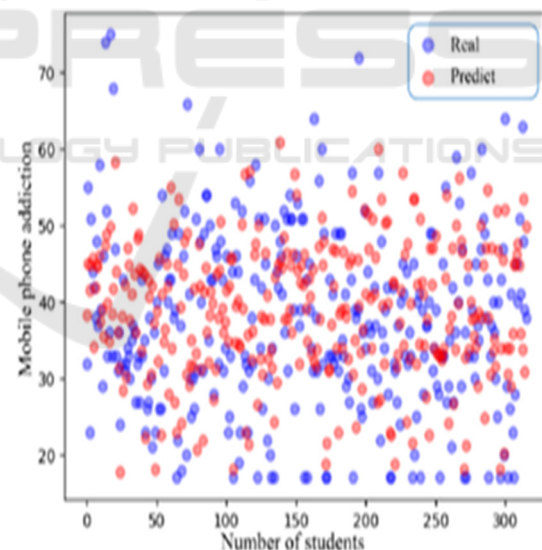


Figure 2: Comparison of real and predicted mobile phone addiction levels among students.

The scatter plot presented in the image visualizes the performance of a Multi-Layer Perceptron (MLP) model in predicting smartphone addiction levels among students. The X-axis represents the number of students, while the Y-axis indicates their respective smartphone addiction levels.

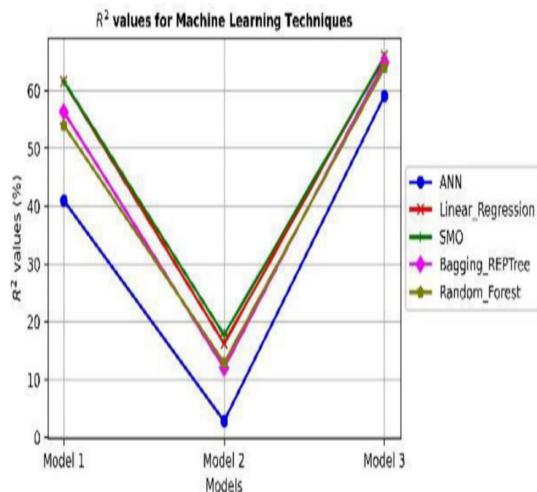


Figure 3:  $R^2$  value comparison of various machine learning models across three model variants.

## 6 CONCLUSIONS

In today's technology-driven world, smartphone addiction has become a significant concern affecting the mental health, productivity, and social well-being of individuals, especially among youth. Traditional methods of identifying addiction are limited by their dependency on subjective responses and delayed interventions. This project presents a modern solution by utilizing machine learning techniques to automate and enhance the accuracy of addiction prediction, thus enabling timely awareness and preventive actions.

The proposed system leverages real-time smartphone usage data and psychological inputs to build intelligent models capable of predicting addiction levels effectively. By integrating various supervised machine learning algorithms and analyzing key behavioral features such as screen time, app usage, and unlock frequency, the model offers a more comprehensive and accurate assessment of smartphone addiction risk.

Moreover, the system is designed to be adaptive, scalable, and user-centric. It not only identifies high-risk individuals but also provides personalized suggestions and insights to help users regain control over their smartphone usage. The use of hybrid data—combining behavioral and psychological parameters—enhances the depth of analysis, making the system a powerful tool for digital wellness and mental health awareness.

In conclusion, this machine learning-based approach to smartphone addiction prediction marks a

significant step forward in addressing the growing challenges of digital dependency. With further development and real-world implementation, this system has the potential to support individuals, institutions, and healthcare professionals in promoting healthier digital habits and improving overall quality of life.

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