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Research Article

Impact of Mobile Device Usage on User Behaviour: Predictive Analytics and Digital Health Perspectives

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ABSTRACT

Mobile devices have transformed communication, information access, and consumer behavior, but excessive usage raises concerns about smartphone addiction. Despite extensive research, challenges persist in accurately predicting and mitigating the negative effects of excessive smartphone use. Traditional methods often struggle with biases, small sample sizes, and the inability to capture real-time behavioral patterns. This paper analyzes mobile usage patterns and employs machine learning models, including Random Forest Classifier and Multilayer Perceptron, to predict addiction levels with high accuracy. Using ANOVA for feature selection, the research enhances prediction reliability. A web application, developed with Streamlit and Python, provides real-time feedback and recommendations for healthier usage. These insights help businesses, policymakers, and health professionals promote digital well-being in an increasingly mobile-centric world.

Keywords: *Smartphone Addiction, Behavioral Analytics, Machine Learning, Random Forest Classifier, Multilayer Perceptron, Screen time management*

INTRODUCTION

Mobile devices have become an indispensable part of modern life, shaping communication, entertainment, work, and education. The rapid advancements in mobile technology, particularly after the introduction of smartphones, have led to widespread dependency, raising concerns about excessive usage and its impact on mental health, productivity, and social interactions [1]. Smartphone addiction is increasingly recognized as a public health concern, contributing to issues such as reduced concentration, academic underperformance, physical strain, and emotional stress. Despite the growing awareness of these negative consequences, there remains a lack of accessible and reliable tools to assess and mitigate smartphone addiction effectively.

One of the major challenges faced by mobile users is the difficulty in self-regulating screen time and balancing mobile engagement with daily responsibilities. The instant accessibility of social media, gaming, and entertainment platforms fuels multitasking behaviour and a preference for instant gratification, making it harder for users to recognize unhealthy usage patterns. Additionally, existing smartphone addiction assessment methods rely heavily on self-reported data, which may introduce biases and reduce accuracy in predicting actual addiction levels. There is a need for an objective, data-driven approach that can provide accurate insights into user behaviour and offer personalized recommendations for healthier usage habits [2]. To address this gap, Machine learning models are essential to provide an automated, data-driven approach for identifying smartphone addiction patterns with high accuracy [3], [4]. This study leverages machine learning techniques, specifically the Random Forest (RF) Classifier and Multilayer Perceptron (MLP), to predict smartphone addiction levels with high accuracy. The Random Forest Classifier, known for its robustness and ability to handle complex data relationships, enables precise feature selection and classification of user behavior patterns. On the other hand, the MLP model, a deep learning approach, enhances prediction accuracy by identifying intricate patterns in user engagement data.

By integrating advanced machine learning models with an interactive web-based tool, this study aims to bridge the gap in smartphone addiction assessment and provide users with a practical solution for monitoring and managing

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their digital habits. The findings will offer valuable insights for businesses, policymakers, and healthcare professionals seeking to promote digital well-being and create strategies for responsible mobile usage in an increasingly technology-driven world. The paper is structured as follows: Section II presents the related works. Section III details the proposed methodology for hybrid RF and MLP methods. Section IV provides a detailed discussion of the experimental results. Finally, the conclusion is given in Section V.

LITERATURE REVIEW

Several studies have explored the impact of mobile usage on various aspects of life, including mental health, communication, academic engagement, and technological dependence. Different methodologies have been employed to analyze these effects, each presenting unique advantages, limitations, and performance metrics. Table 1 provides the summary of the existing methodologies. A study examined the impact of internet usage on mental health, utilizing multiple regression analysis combined with propensity score matching to assess its effects on older adults [5]. Depression levels were measured using the CES-D index, and regression results were validated for robustness. The findings indicated that while internet usage could positively influence mental health by reducing isolation, potential biases remained despite propensity score matching, and causality could not be fully established.

Another study conducted a pilot analysis with 32 participants to assess depression severity through smartphone-based communication logs, GPS data, and continuous audio recordings [6]. The study provided real-world behavioral insights into depressive symptoms, capturing patterns in free-living conditions. However, the small sample size limited the generalizability of the findings, and privacy concerns were raised regarding continuous audio recordings. A large-scale study investigated mobile phone addiction and its relationship with self-injury in adolescents diagnosed with Major Depressive Disorder (MDD). The research included 2,343 patients from psychiatric hospitals, using structured clinical interviews for diagnosis [7]. It was found that mobile phone usage restrictions were largely ineffective in reducing addiction-related behaviors. While the study‘s large sample size enhanced reliability, the non-systematic recruitment process introduced selection bias, and the absence of participation rate measurement reduced representativeness.

TABLE 1. Comparison of Existing Methodologies

References	Methodology	Performance Metrics	Limitations
[4]	Multiple regression analysis combined with propensity score matching	Depression index measurement using CES-D; validated regression	Potential biases despite matching; causality cannot be fully established
[5]	Smartphone-based communication logs, GPS data, audio recordings	Depression severity via call/text logs, location data, and audio	Small sample size; privacy concerns with continuous audio recording
[6]	Adolescent patients diagnosed with MDD (SCID)	Patient demographics, mobile usage restrictions	Selection bias; lack of participation rate
[7]	Structured questionnaire survey (employees)	Minimum sample size determined via G*Power;	Possible response bias; reducing generalizability
[8]	Pearson's correlation, regression, and ANOVA	Validated psychological scales; statistical modeling	Self-report bias; limited demographic scope; lacks longitudinal data
[9]	Structured questionnaire survey (mobile users)	Descriptive statistics, inferential analysis, CFA, Cronbach's alpha	Convenience sampling; self-reported data introduces bias; lacks longitudinal insights
[10]	Quantitative study analyzing 224 survey responses	Reliability via Cronbach's α (>0.7); mediation/moderation analysis	Convenience sampling limits generalizability; potential self-report bias
[11]	Monitoring apps, network operators, app stores	Data granularity, response rate, accuracy, sampling bias analysis	Surveys have self-report bias; monitoring apps need consent; lacks offline usage insights
[12]	Qualitative study with in-depth interviews	Thematic analysis for recurring patterns, qualitative insights	Subjective responses introduce bias; limited generalizability; time-consuming analysis

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The effects of smartphone use in the workplace were examined in a study that distributed structured questionnaires to employees of a telecommunications company [8]. A minimum sample size was determined using G*Power calculations, and statistical relationships were analyzed. The study provided reliable insights into smartphone usage and work performance, but potential response bias and limited generalizability were noted due to the focus on a single organization. An investigation into mobile game usage analyzed its impact on mental health, academic engagement, and aggression among high school students [9]. The study applied statistical methods such as Pearson's correlation coefficient, regression analysis, and ANOVA. It was revealed that excessive mobile gaming was linked to increased aggression and decreased academic engagement. The study employed validated psychological scales with strong reliability, but self-report bias and the lack of longitudinal data limited causal interpretations.

Mobile network usage patterns and customer satisfaction were analyzed through a structured questionnaire survey involving mobile consumers [10]. The study used descriptive and inferential statistics, Confirmatory Factor Analysis (CFA), and Cronbach's alpha for reliability. The results highlighted key determinants of social media usage across demographic characteristics, ensuring statistical rigor. However, the convenience sampling method restricted generalizability, and self-reported data introduced potential bias. Methods for smartphone app usage analysis were explored, including surveys, monitoring apps, network operators, and app stores [11]. The study evaluated factors such as data granularity, sampling bias, and accuracy. While in-app surveys reached a broad user base, and monitoring apps captured real-time usage, challenges such as self-report bias, user consent requirements, and the exclusion of offline app usage were noted. A qualitative study explored smartphone usage behaviors using existential phenomenology and in-depth interviews [12]. Thematic analysis was performed to identify recurring patterns and user perspectives. The study provided rich qualitative insights into personal smartphone experiences, which could inform future survey development. However, subjective responses introduced bias, and the findings had limited generalizability due to the nature of qualitative research.

METHODOLOGY

This research presents a systematic approach to predicting smartphone addiction and analyzing user behavior using machine learning techniques. The methodology consists of multiple stages, including data collection, preprocessing, feature selection, model training, integration into a web application, and deployment. The primary objective is to develop a predictive model that effectively classifies users based on their smartphone addiction levels and provides actionable insights.

A. Data Collection and Preprocessing

The first phase of the methodology involves collecting user data through a structured questionnaire. This questionnaire captures various attributes related to smartphone usage, including: Device type and operating system, Daily screen time and app usage duration, Total data consumption and Number of installed applications. Behavioral indicators are late-night usage, distractions during work/study, physical symptoms like headaches, etc. Once the data is collected, preprocessing is performed to clean and prepare it for analysis. This includes:

- **Handling Missing Values:** Numerical data is imputed using mean values, while categorical data is imputed using the most frequent value.
- **Outlier Detection and Removal:** Statistical techniques such as Z-scores are used to identify and handle outliers.
- **Feature Normalization:** Data is scaled to ensure that all input features are within a comparable range, which is essential for models that rely on distance-based learning.

B. Feature Selection Using ANOVA

The features are carefully selected to ensure that the model effectively captures behavioral patterns associated with smartphone addiction. To enhance model performance and reduce computational complexity, Analysis of Variance (ANOVA) is used for feature selection. ANOVA determines the statistical significance of each feature in relation to

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the target variable (smartphone addiction probability). The most significant features, such as screen time, app usage patterns, and late-night usage, are retained for model training, while less relevant features are excluded.

C. Model Training and Evaluation

Two machine learning models are employed to classify smartphone addiction level. They are Random Forest Classifier and Multilayer Perceptron (MLP). An ensemble learning technique that constructs multiple decision trees and aggregates their outputs for improved accuracy and reduced overfitting is called as Random Forest Classifier. Multilayer Perceptron is a type of artificial neural network that captures complex, non-linear relationships within the data, enhancing behavioral pattern recognition.

Training Process:

- The pre-processed and selected dataset is split into training and testing subsets (e.g., 80:20 ratio).
- Models are trained using Python-based machine learning libraries such as Scikit-learn and TensorFlow.
- Hyperparameter tuning is conducted using grid search and cross-validation to optimize performance.

The models are evaluated using standard performance metrics:

- Accuracy (overall correctness of predictions)
- Precision (ability to avoid false positives)
- Recall (ability to detect actual addicted users)
- F1-score (balance between precision and recall)

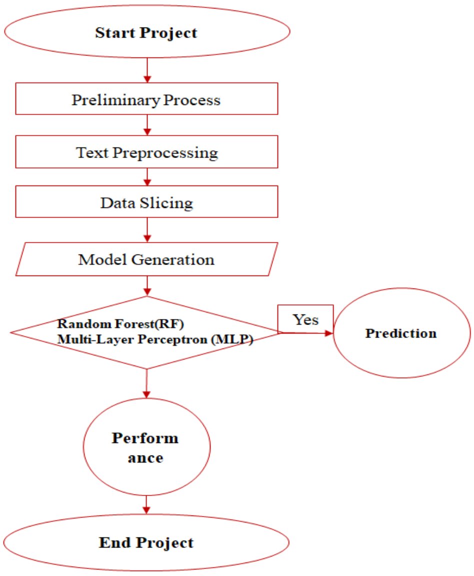

Figure 1. Flowchart of the Smartphone Addiction Prediction Process

Figure 2. Visualization of User Behaviour Prediction in Web Portal

D. Web Application Integration

To make the model accessible to users, a web-based application is developed. The web-based system designed is shown in figure 6.

- Frontend: Built using HTML, CSS, and Streamlit for an interactive user interface.
- Backend: Developed in Python, integrating trained models to process user inputs and generate real-time addiction predictions.
- User Interaction: Users provide details through a form, and the system predicts addiction probability with actionable suggestions to reduce excessive smartphone use.

The application serves as a practical tool for predicting and managing smartphone addiction, contributing to

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improved digital well-being. The figure 1 illustrates the step-by-step methodology for predicting smartphone addiction using machine learning models. The process starts with preliminary steps such as data collection and preprocessing, followed by feature selection and model generation. The two machine learning models used—Random Forest (RF) and Multilayer Perceptron (MLP)—analyze the processed data to make predictions. The system then evaluates the model's performance, ensuring accuracy and reliability before providing real-time addiction predictions and recommendations.

RESULTS AND DISCUSSIONS

This section provides a detailed analysis of the performance of the hybrid Random Forest and MLP method. The figure 3 and 4 provides a classification report for a hybrid Random Forest (RF) and Multi-Layer Perceptron (MLP) and random forest classifier across different classes respectively. It visualizes three key classification metrics Precision, Recall, and F1-score. The right y-axis (black dotted line with markers) represents the number of samples (support) for each class, which varies across different categories. Class 3 shows the highest scores, suggesting that the model performs best in this category. Class 4 has relatively lower recall, indicating potential misclassification or difficulty in identifying true positive cases. The variation in support (number of samples per class) suggests an imbalance in dataset distribution, which may affect model performance. Figure 5 shows the confusion matrix that depicts the classification performance of a binary classifier. The two classes are represented as 0 and 1, where:

- True Positives (TP) = 72: The model correctly predicted class 1 when it was actually 1.
- True Negatives (TN) = 146: The model correctly predicted class 0 when it was actually 0.
- False Positives (FP) = 0: The model did not incorrectly predict class 1 when it was actually 0.
- False Negatives (FN) = 0: The model did not incorrectly predict class 0 when it was actually 1.

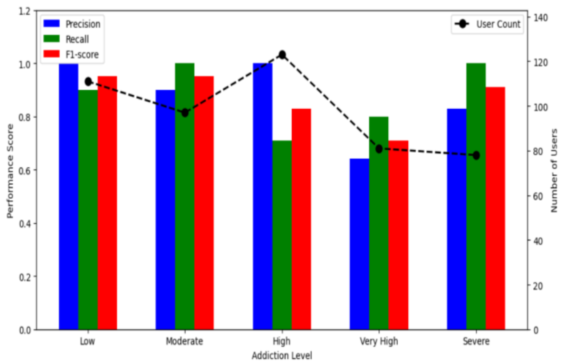

Figure 3.Classification Performance of Hybrid Random Forest & MLP Classifier

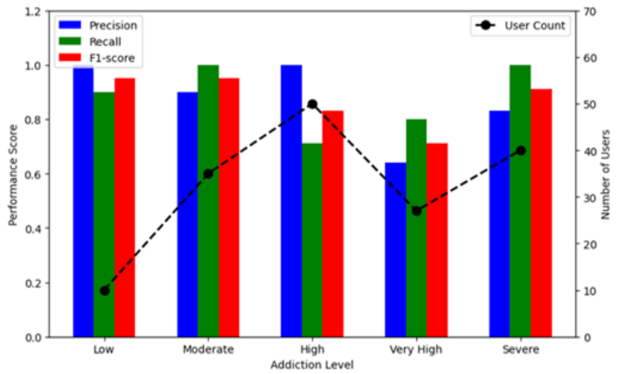

Figure 4.Classification Performance of Random Forest

Perfect Classification: Since both FP and FN are zero, the model achieved 100% accuracy on this dataset, meaning there were no misclassifications. Accuracy Comparison of RF and MLP is shown in Figure 6. RF consistently outperforms MLP across all frequency categories, achieving higher accuracy. MLP, while still performing well, has slightly lower accuracy, indicating it may struggle in certain cases compared to RF. The difference in accuracy suggests that Random Forest might be the preferred model for this classification task, but further tuning could improve MLP's performance.

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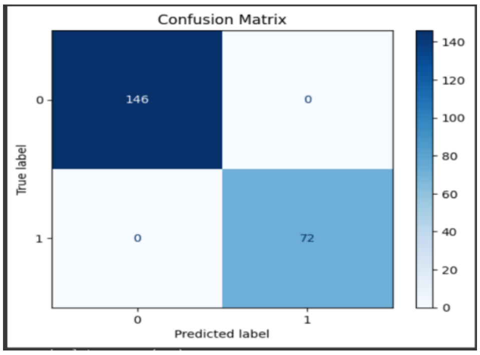

Figure 5. Confusion Matrix of Prediction

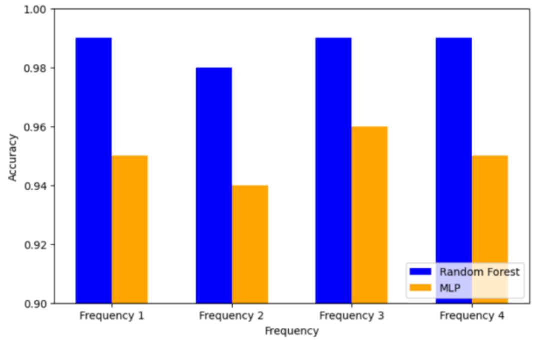

Figure 6. Performance metrics of Prediction Accuracy

The web-based system shown in figure 2 enables to analyze user behavior and predict smartphone addiction levels using machine learning models. The portal collects user inputs regarding behavioral patterns and device usage to provide real-time addiction classification and personalized recommendations. The system utilizes a trained Random Forest (RF) and Multi- Layer Perceptron (MLP) model to classify the user as: Addicted and Not Addicted. The result is displayed dynamically on the screen.

CONCLUSION

With the increasing reliance on smartphones for communication, entertainment, and work, excessive usage has become a growing concern, leading to potential addiction. Smartphone addiction can negatively impact mental health, productivity, and social interactions. The paper successfully implements a systematic methodology to predict smartphone addiction using machine learning models. By leveraging structured data collection, feature selection through ANOVA, and robust classification models like Random Forest and Multilayer Perceptron (MLP), the approach ensures accurate addiction detection. Utilizing the Random Forest(RF) and Multi-Layer Perceptron (MLP) models, the system achieved an impressive 99% accuracy in classifying addiction levels, highlighting the efficiency of machine learning in identifying potential addictive behavior. Notably, the Random Forest Classifier (RF) outperformed the Multilayer Perceptron (MLP), achieving higher accuracy in addiction prediction. The integration of these models into a user-friendly web application enables real-time predictions and personalized recommendations, empowering users to manage their smartphone usage effectively.

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