

MOBILE DEPENDENCY RISK ANALYSIS USING MACHINE LEARNING MODELS

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ABSTRACT: Excessive smart phone usage and mobile dependency have emerged as growing behavioral health concerns globally, impacting psychological well-being, cognitive focus, and sleep quality. This paper presents a machine learning-based risk analysis framework to detect, assess, and classify levels of mobile dependency among users. Leveraging behavioral and usage patterns such as daily screen time, app category distribution, pickup frequency, and self-reported psychological metrics we preprocessed and transformed the feature space to train multiple supervised classification algorithms. We evaluated model performance across standard machine learning classifiers, including Decision Trees, Random Forest, and Logistic Regression, to identify behavioral risk tiers (e.g., Low, High Risk) based on user addiction condition. The Random Forest model achieved the highest predictive accuracy and F1-score, successfully isolating key predictors of addiction such as late-night activity and notification responsiveness. The proposed system provides an automated, objective tool for early risk identification, paving the way for targeted digital wellness interventions.

Keywords: Machine learning classifiers, including Decision Trees, Random Forest, Logistic Regression, psychological well-being, cognitive focus, accuracy and F1-score

1. INTRODUCTION

Smartphones have become an integral part of our lives, and their usage has increased dramatically over the past decade. While smartphones offer numerous benefits, excessive smartphone usage can lead to addiction and have negative impacts on individuals' physical and mental health, social relationships, and productivity. Machine learning can be used to develop models that can predict smartphone addiction based on various features such as smartphone usage patterns, social media usage, demographic information, and psychological factors. These models can help identify individuals who are at risk of smartphone addiction and provide them with appropriate interventions and support.

In recent years, the widespread adoption of smartphones has transformed the way individuals communicate, learn, and interact with their environment. While mobile devices offer numerous benefits such as instant connectivity, access to information, and digital services, excessive smartphone usage has led to a growing concern known as mobile dependency or smartphone addiction. This behavioral phenomenon is increasingly being recognized as a significant public health issue, particularly among students and young adults.

Mobile dependency is associated with various adverse effects, including decreased academic or work performance, reduced cognitive focus, poor sleep quality, and psychological issues such as anxiety, stress, and depression. The constant engagement with mobile applications—especially social media, gaming, and messaging platforms can create compulsive usage patterns, making it difficult for individuals to regulate their screen time effectively.

Traditional methods of assessing mobile dependency rely heavily on self-reported surveys and psychological assessments, which may be subjective and prone to bias. With the advancement of data-

driven technologies, machine learning (ML) offers a promising approach for objectively analyzing user behavior and predicting dependency risk. By leveraging features such as screen time, app usage frequency, notification interactions, and behavioral patterns, ML models can identify hidden trends and classify users into different risk levels.

This study proposes a machine learning-based framework for mobile dependency risk analysis. The system aims to detect and classify users into risk categories (e.g., low risk and high risk) using supervised learning algorithms such as Decision Trees, Random Forest, and Logistic Regression. By automating the detection process, the proposed model enables early identification of at-risk individuals and supports the development of targeted digital wellness interventions.

2. LITERATURE REVIEW

Mobile dependency, often termed as Problematic Smartphone Usage (PSU), has gained increasing attention as a behavioral and psychological concern in the digital era. With the exponential growth in smartphone adoption, researchers have focused on analyzing usage patterns and identifying risk levels associated with excessive mobile usage. Recent studies emphasize the use of machine learning (ML) models to perform mobile dependency risk analysis, enabling early detection and preventive interventions.

Recent studies highlight the growing importance of mobile and smartphone-based technologies in influencing human behavior, health, and learning outcomes. Demir and Akpinar [1] demonstrated that mobile learning applications significantly improve students' academic achievement and motivation, indicating the positive role of smartphones in educational environments.

Abadiyan et al. [2] showed that integrating smartphone applications with physical therapy interventions can improve neck pain, posture, endurance, and quality of life, establishing a strong link between mobile usage and physical health outcomes. Similarly, Osailan [3] found that prolonged smartphone usage negatively affects musculoskeletal strength, particularly hand-grip and pinch-grip strength among young individuals.

In healthcare settings, Hitti et al. [4] observed that mobile devices enhance communication and coordination among professionals but may also introduce negative effects due to excessive personal usage, impacting workplace performance. Wilkerson et al. [5] further demonstrated that smartphone-based applications can reliably detect neurological and behavioral changes, highlighting their potential for health monitoring and assessment.

Joo et al. [6] emphasized issues related to user awareness, privacy, and persuasion in mobile health applications, indicating challenges in transparency and ethical data usage.

Overall, the literature confirms that Problematic Smartphone Usage (PSU) significantly impacts mental, physical, academic, and professional well-being. Machine learning techniques such as SVM, Decision Trees, Random Forest, and Neural Networks have been widely used for PSU detection and severity classification using behavioral and usage-based features. However, existing studies face limitations such as lack of large-scale datasets, limited real-time detection systems, and poor model interpretability. These gaps motivate further research in developing accurate, scalable, and interpretable ML-based PSU detection systems.

In conclusion, the literature demonstrates that mobile dependency is a multifaceted issue with significant implications for mental, physical, and social well-being. Machine learning models provide an effective framework for risk analysis and severity prediction, offering opportunities for proactive intervention. However, future research should focus on improving data quality, incorporating multimodal inputs, and developing standardized frameworks to enhance the accuracy and applicability of these models in real-world scenarios.

3. EXISTING SYSTEM

In the existing system, implementation of machine learning algorithms is bit complex to build due to the lack of information about the data visualization. Mathematical calculations are used in existing system for Logistic Regression model building this may takes the lot of time and complexity. To overcome all this, we use machine learning packages available in the scikit-learn library.

4. PROPOSED METHOD

Many machine learning algorithms are available for prediction of smartphone addiction Some of the machine learning algorithm are Decision Tree, Random Forest We used proposed and compute best method for diagnosis a comparative study of machine learning techniques for smartphone addiction detection In this stage we have first implement these dataset and the implement algorithm individual then we are combine these results and an compute the Accuracy.

Advantages of Proposed System:

- Requires less time
- Good score.
- Easy to handle

5. METHODOLOGY

The proposed study on mobile dependency risk analysis using machine learning follows a structured pipeline consisting of data collection, pre-processing, feature engineering, model development, and evaluation.

A. Data Collection:

Data is gathered from primary sources such as questionnaires (e.g., Smartphone Addiction Scale) and mobile usage logs including screen time, app usage, and unlock frequency. Secondary datasets may also be used to improve model reliability.

B. Data Pre-processing:

The dataset is cleaned and prepared by handling missing values, removing duplicates, encoding categorical variables, normalizing numerical features, and eliminating outliers to ensure data quality.

C. Feature Extraction & Selection:

Key behavioural and psychological features such as screen time, app usage patterns, sleep duration, and stress levels are extracted. Techniques like correlation analysis or PCA may be used for feature reduction.

D. Model Development:

The dataset is split into training and testing sets (70:30). Machine learning models such as Logistic Regression, Decision Tree and Random Forest are applied to classify PSU severity into Low and High risk levels.

E. Model Validation:

Models are evaluated using k-fold cross-validation to ensure generalization and reduce overfitting. Hyper parameter tuning is applied for performance optimization.

F. Performance Evaluation:

Model performance is measured using Accuracy, Precision, Recall and F1-score to identify the best-performing model for PSU detection.

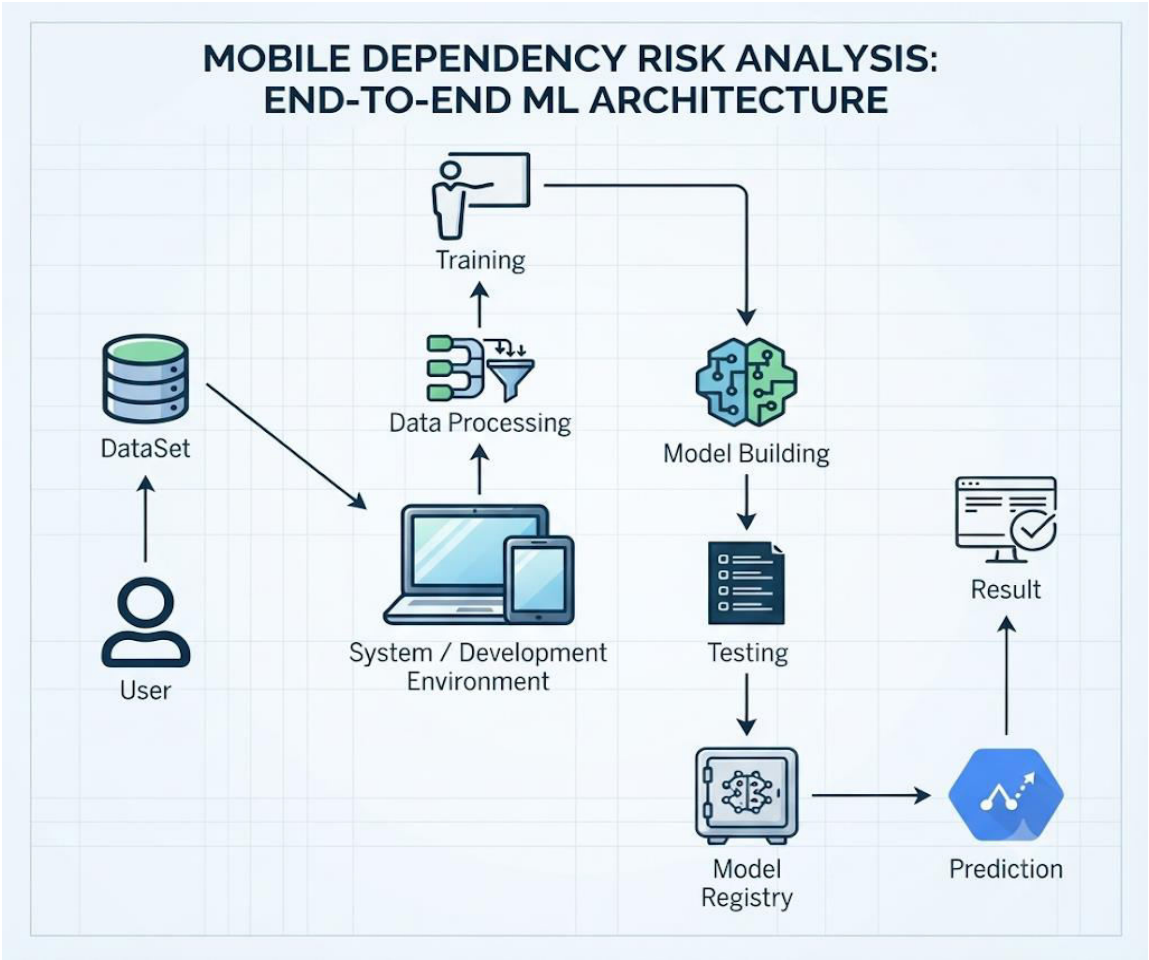


Figure 1: System Achitecture

6. RESULTS

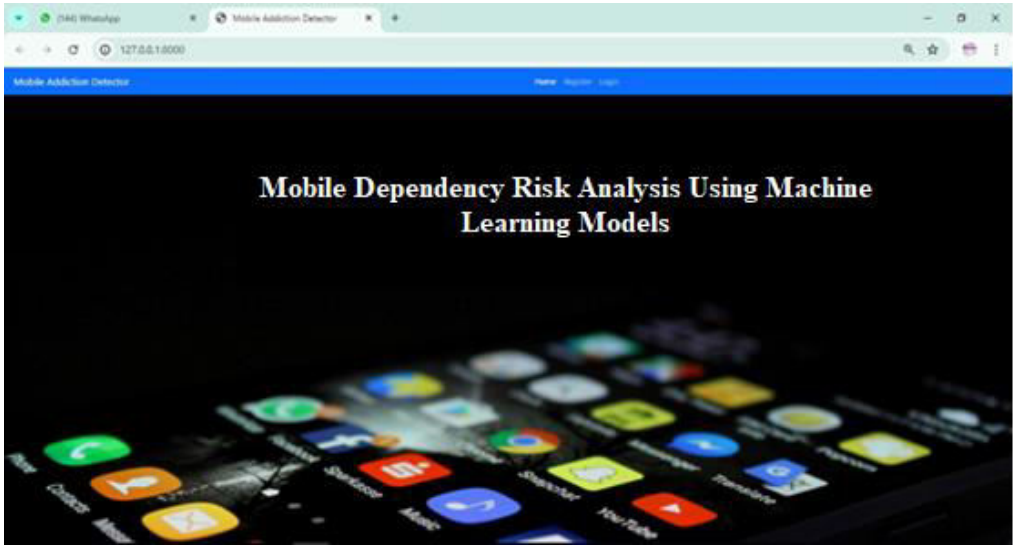
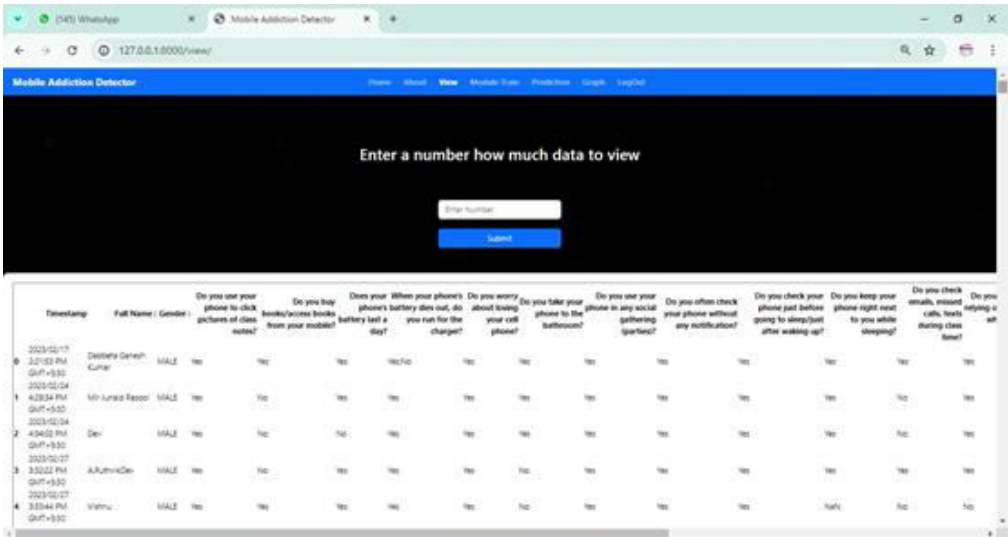


Figure2: Home Page



Mobile Addiction Detector

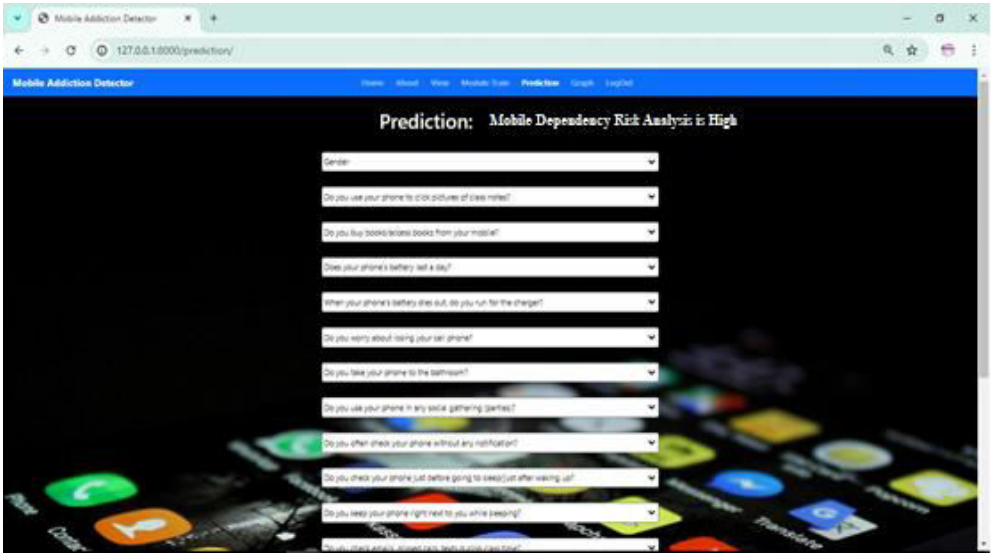
Enter a number how much data to view

Enter Number

Submit

Timestamp	Full Name	Gender	Do you use your phone to click pictures of class mates?	Do you buy books/access books from your mobile?	Does your phone's battery dies out, do you run for the charger?	When your phone's battery dies out, do you worry about losing your cell phone?	Do you take your phone to the bathroom?	Do you use your phone in any social gathering (parties)?	Do you often check your phone without any notification?	Do you check your phone just before going to sleep/just after waking up?	Do you keep your phone right next to you while sleeping?	Do you check emails, missed calls, texts during class hour?	Do you sleeping is not
2023-05-17 2:27:53 PM GMT+5:30	Dimple Gireesh Kumar	MALE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2023-05-04 4:28:34 PM GMT+5:30	Muhammad Razaq	MALE	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
2023-05-04 4:46:52 PM GMT+5:30	Dev	MALE	Yes	No	No	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes
2023-05-07 3:52:22 PM GMT+5:30	Akshita Devi	MALE	Yes	No	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
2023-05-07 3:53:44 PM GMT+5:30	Vishnu	MALE	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes	No	No

Figure 2: View Smart phone Addiction Dataset



Mobile Addiction Detector

Prediction: Mobile Dependency Risk Analysis is High

Gender

Do you use your phone to click pictures of class mates?

Do you buy books/access books from your mobile?

Does your phone's battery die a day?

When your phone's battery dies out, do you run for the charger?

Do you worry about losing your cell phone?

Do you take your phone to the bathroom?

Do you use your phone in any social gathering (parties)?

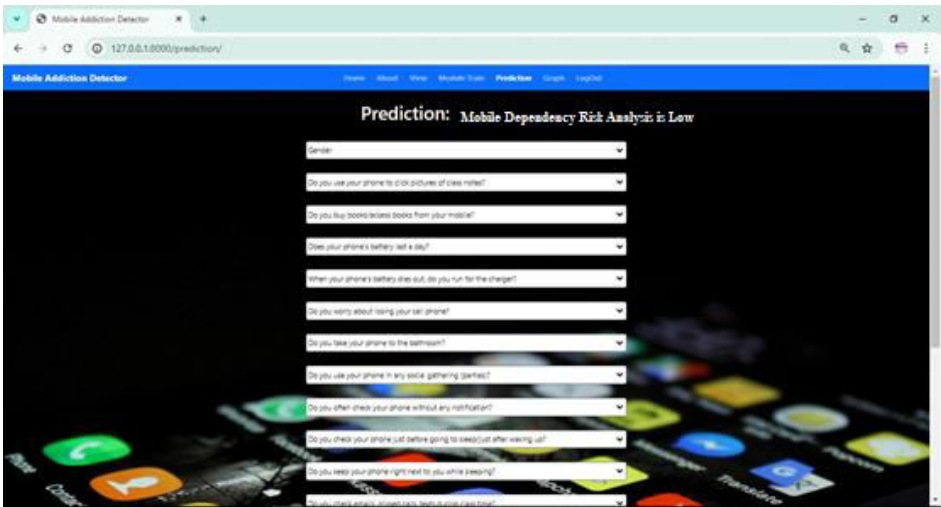
Do you often check your phone without any notification?

Do you check your phone just before going to sleep/just after waking up?

Do you keep your phone right next to you while sleeping?

Do you check emails, missed calls, texts during class hour?

Figure 3: Mobile Dependency Risk Analysis is High



Mobile Addiction Detector

Prediction: Mobile Dependency Risk Analysis is Low

Gender

Do you use your phone to click pictures of class mates?

Do you buy books/access books from your mobile?

Does your phone's battery die a day?

When your phone's battery dies out, do you run for the charger?

Do you worry about losing your cell phone?

Do you take your phone to the bathroom?

Do you use your phone in any social gathering (parties)?

Do you often check your phone without any notification?

Do you check your phone just before going to sleep/just after waking up?

Do you keep your phone right next to you while sleeping?

Do you check emails, missed calls, texts during class hour?

Figure 3: Mobile Dependency Risk Analysis is Low

Algorithm	Accuracy	Precision	Recall	F1-Score
Decision Tree	83.86	0.8460	0.8386	0.840
Random Forest	89.04	0.9131	0.8904	0.8925
Logistic Regression	83.86	0.8460	0.8386	0.8405

Figure 5: Algorithms Comparison Table

7. CONCLUSION

In this project, we have developed a user friendly application called prediction of smartphone addiction using Machine Learning Model techniques such as Decision tree, Random forest, Logistic Regression, We used the best techniques we found and its show the Addicted, not addicted are maybe addicted. The rapid proliferation of smartphones has brought unprecedented connectivity alongside growing concerns regarding Problematic Smartphone Use (PSU) and digital addiction. This study successfully developed and demonstrated a machine learning framework capable of accurately assessing mobile dependency risk based on behavioral metrics, screen-on time, unlock frequency, application categories, and psychological/sleep indicators.

In future research, the focus can be on developing more accurate prediction models for smartphone addiction using advanced classification techniques, such as deep learning algorithms. Additionally, investigating the impact of different demographic and psychological factors on smartphone addiction can provide valuable insights for prevention and intervention strategies.

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