



Predicting Smartphone Addiction

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ABSTRACT

Smartphone addiction has become a growing concern in today's digital era, where excessive mobile phone use impacts mental health, productivity, and social interactions. This project aims to identify individuals at risk of addiction based on their usage behaviors and psychological patterns. The project is developed with the objective of identifying individuals prone to smartphone addiction based on various behavioral, psychological, and usage patterns. The survey included questions about demographics, cell phone usage patterns, and various psychological conditions such as anxiety, depression, and stress. The system utilizes Python for backend, while the frontend is built using HTML, CSS, and Java Script. The data was pre-processed by coding the raw variables and adjusting the numerical variables to ensure that the model could be studied effectively. We train the model on some data and evaluate its performance on other data using some metric such as accuracy. Our results show that the model achieves high accuracy in predicting the smartphone addiction. The dataset used for this project comprises 200 records with 10 attributes, which include survey responses focused on phone usage patterns and addiction-related behaviors. These attributes range from questions about daily phone habits, such as taking the phone to social gatherings or frequently checking it without notifications, to more serious indicators of addiction like anxiety over losing the phone or relying on it in awkward situations. The target attribute classifies users into two categories: addicted and not addicted, providing a clear objective for the prediction models.

1 Introduction

Smartphones have become an integral part of our lives, and their use has increased dramatically over the past decade. Although smartphones have many benefits, excessive smartphone use can lead to addiction and have a negative impact on physical and mental health, social relationships, and personal productivity. Machine learning can be used to develop models to predict smartphone addiction based on different factors such as smartphone usage patterns, social media usage, demographics, and psychological characteristics.

These models can help identify people at risk of smartphone addiction and provide them with the right intervention and support. Developing machine learning models to predict smartphone addiction starts with collecting data from a large sample of people. The data includes information about their smartphone usage, social media usage, demographic information such as age and gender, as well as psychological factors such as anxiety, depression and stress.

Once data is collected, it is processed and cleaned to remove missing or irrelevant data points. Next, choose an appropriate machine learning algorithm, such as Random Forest and Logistic Regression based on the nature of the data and the problem at hand. The data is divided into



two groups: the training set and the test set.

The training set is used to train the machine learning model through the corresponding input and output labels. These students learn to recognize patterns in data and make connections between input features and output labels. Once the model is trained, it is tested on a test set to evaluate its performance.

Model performance is measured using various metrics such as accuracy. Improve the model by adjusting its parameters and choosing a different algorithm until good performance is obtained. Once the model is developed, a person's smartphone addiction can be predicted by including individual input parameters into the model. On this account, appropriate intervention and support can be offered to people at risk of developing addiction. In short, machine learning models can be a valuable tool for predicting smartphone addiction and identifying people at risk. These models can help individuals and health professionals take steps to prevent addiction and reduce its negative effects. However, it is important to collect high quality data and develop accurate and reliable models that can be used effectively in the real world.

2 Literature Survey

[1] Demir, K. & Akpinat, E. The effect of mobile learning applications on students' academic achievement and attitudes toward mobile learning. Malays. Online J. Educ. Technol. 6, 48–59 (2018). This study investigates the impact of mobile learning applications on academic performance, attitudes toward mobile learning, and the level of animation development in university departments. This study adopted a quasi-experimental design. The research participants were students of the Buca Faculty of Education, Dokuz Eylul University, Türkiye. The exam was conducted in the first semester of 2013- 2014. Attitude scales were used to measure students' attitudes toward mobile learning, and achievement tests were used to examine the impact of mobile learning applications on student performance. To evaluate the animation created by the students, a rubric is used. For research analysis, students were interviewed. Research results show that mobile learning can improve student achievement. Both groups scored on attitudes toward job learning.

[2] Abadiyan, F., Hadadnezhad, M., Khosrokiani, Z., Letafatkar, A. & Akhshik, H. Adding a smartphone app to global postural re-education to improve neck pain, posture, quality of life, and endurance in people with nonspecific neck pain. In this study, the effects of adding a smartphone application to 8 weeks of global rehabilitation (GPR) on neck pain, endurance, quality of life, and posture anterior head in patients with chronic neck pain and FHP assessed (FHP).

[3]. Osailan, A. The relationship between smartphone usage duration (using smartphone's ability to monitor screen time) with hand-grip and pinch-grip strength among young people: An observational study. BMC Musculoskelet. Disord. 22, 186 (2021). The study was aimed to investigate the association between smartphone usage duration and hand-grip, pinch-grip strength among young people. One hundred young males volunteered to participate in the study. Participants were briefly examined for height and weight using a portable stadiometer



and a digital scale. Hand-grip, pinch-grip strength measurement was performed using a hand-held dynamometer. Smartphones usage duration was obtained from the daily average screen time reported in the last seven days.

[4] Hitti, E., Hadid, D., Melki, J., Kaddoura, R. & Alameddine, M. Mobile device use among emergency department healthcare professionals: prevalence, utilization and attitudes. *Sci. Rep.* 11, 1917 (2021). Mobile device use for personal reasons was similar across all medical facilities, with medical students having the highest usage rate (81.3%) and physicians having the lowest usage rate (75.0%). Medication/drug referral requests were the most frequently used requests by service providers, followed by therapy/disease management requests at 84.4% and 69.5%. Most respondents believe that mobile devices will improve coordination of services between providers and improve patient care. The majority of respondents believe that using mobile devices can help solve personal problems quickly and reduce feelings of stress, but most do not believe that using personal devices can improve the job. According to the findings, although health care providers appreciate the benefits of mobility on care coordination, the impact of personal problems from moving to the workplace may have an impact on staff performance.

[5] Wilkerson, G. B. et al. Wellness survey responses and smartphone app response efficiency: Associations with remote history of sport-related concussion. *Percept. Mot. Skills* 128, 714–730 (2021). Current research findings strongly suggest that sports related concussions (SRCs) increase the risk of any type of subsequent injury and have long-term negative effects on mental health and mind. The primary objective of this study was to examine the reliability and discriminant validity of a clinical trial method for detecting the effects of ongoing SRC. We used a cross-sectional study design to evaluate self-reports of post-traumatic stress disorder and the impact of mental or physical activity on outcome measures. From a smartphone application designed to examine perceptual-motor feedback.

3 Existing System

In existing models for smartphone addiction prediction, all the user data are very particular and do not involve the overall wellbeing of the human being. This leads to a probability result that the user is affected over a physical imbalance due to the usage of smartphones. Overall, the existing system provided a strong foundation for predicting smartphone addiction, utilizing different classification techniques to model user behaviors effectively.

Disadvantages of Existing System

The existing system exhibited several technical disadvantages that impacted the system's overall efficacy and reliability.

Data Privacy Concerns: Sharing personal health data with individuals raises privacy issues and the risk of data breaches.

Accuracy of Self-Reported Data: The accuracy of data inputted by users can be variable, affecting the reliability of insights and recommendations.



Limited Personalization: Generic apps may not adequately address individual needs and preferences.

Potential for Misuse: Apps could be used to justify unhealthy behaviors or neglect professional medical advice.

4 Proposed System

The proposed system for "Predicting Smartphone Addiction Using Machine Learning" project introduces a more advanced approach by utilizing two machine learning models: Random Forest and Logistic Regression. These models are designed to improve the accuracy and robustness of smartphone addiction prediction by leveraging ensemble techniques which are well-suited to handle the complexity and nonlinearity inherent in behavioral data.

The Random Forest Algorithm is the key component of the proposed system. It has High Accuracy as it combines multiple decision trees, Random Forest often achieves high predictive results. The randomness in the tree creation process helps to prevent overfitting, a common issue in machine learning models. Random Forest can handle missing data effectively. It can identify the most important features in the dataset, aiding in feature selection and understanding the underlying pattern. It can be used for both classification and regression tasks.

Logistic regression is a powerful statistical method used in this project. The coefficients of the logistic regression model can be interpreted to understand the impact of each feature on the predicted outcome. It is computationally efficient and can handle large datasets. It can be extended to handle multi-class classification problems.

These attributes include a mix of categorical and continuous features such as the frequency of phone use in various scenarios, phone dependency, and behavioral responses to being without a phone. The target attribute classifies users into addicted and not addicted.

The proposed system is built using Python for the backend, with the frontend developed in HTML, CSS, and JavaScript. This framework allows the system to be deployed as a web application, making it accessible and easy to use for end-users.

Overall, the proposed system introduces a more sophisticated and robust machine learning pipeline. Combining advanced classification techniques and ensemble learning methods to enhance the accuracy and generalizability of smartphone addiction predictions.

Advantages of Proposed System

The proposed system for "Predicting Smartphone Addiction Using Machine Learning" offers several significant advantages over its predecessor, primarily due to the integration of advanced machine learning models and ensemble Techniques.

Improved Prediction Accuracy: The system achieves high accuracy, with the Random Forest and Logistic Regression algorithms ensuring reliable predictions of smartphone addiction.

Enhanced Generalization: By employing ensemble models, the system effectively reduces



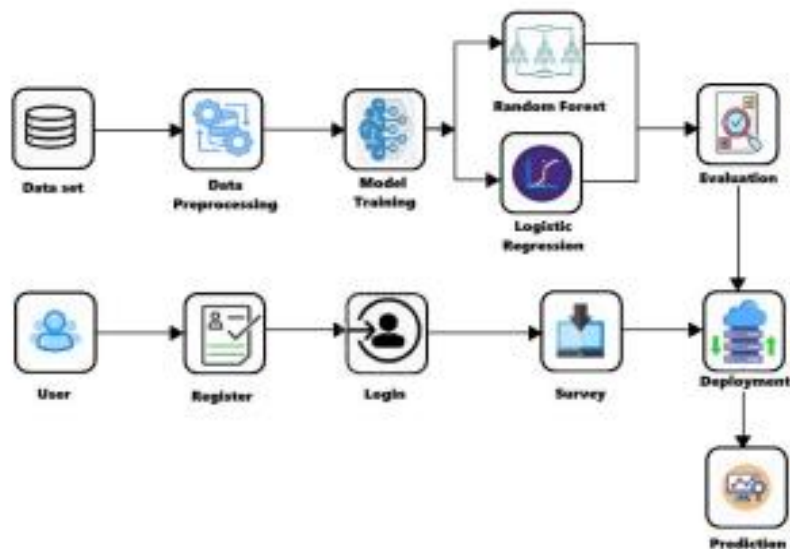
overfitting, resulting in predictions that perform well on diverse user inputs, improving its applicability in real-world scenarios.

Efficiency in Handling Categorical Data: Processing categorical variables efficiently, reducing the complexity of data preparation and enabling faster, more accurate predictions based on user behaviors.

Robust Web Integration: Utilizing this framework ensures seamless interaction between machine learning models and the user interface, allowing for instant predictions and a smooth user experience.

Alternate Activities: Provides suggestions to help users gradually reduce screen time.

Architecture Diagram



5 Methodology

Data Collection

The dataset used for this project consists of 200 records, each with 10 attributes gathered through surveys focused on phone usage and addiction-related behaviors. Attributes include daily habits, dependency indicators, and psychological factors.

Data Preprocessing

Data was cleaned to remove any missing or irrelevant data points. We ensured the quality and reliability of the dataset through rigorous preprocessing steps.

Model Training

Model is trained using two effective algorithms mentioned below:



Random Forest

It selects random samples from a given training set and this algorithm will construct a decision tree for every training data. Then voting will take place by averaging the decision tree. Finally, select the most voted prediction result as the final prediction result.

Logistic Regression

Logistic regression uses mathematics to analyse the relationship between two or more data factor. Then constructs a dividing hyper-plane between two data sets. Based on the data calculates the probability of a certain outcome given the input variables. Finally it uses the calculated probability to make predictions about the value of one of the data factors.

6 Result

The Random Forest achieved an accuracy of 77.97%. The Logistic Regression achieved an accuracy of 74.58%. These results indicate a substantial improvement in predictive performance compared to existing models.

Future Scope

Future research can expand the dataset to include a more diverse demographic profile, enhancing model robustness. Integrating additional behavioral metrics such as social media engagement, app usage patterns, and contextual factors could provide deeper insights into addiction drivers. Advanced modeling techniques, including deep learning and hybrid models, may be explored to capture more complex patterns within the data.

Additionally, the application of predictive models in real-world settings warrants further investigation. Collaborations with healthcare professionals and app developers could lead to the design of intervention programs tailored to individuals at risk, as well as the creation of applications that promote healthier usage habits. Real-time data collection through mobile applications could enable continuous monitoring of usage behaviors, allowing for timely interventions when signs of addiction emerge.

7 Conclusion

This study demonstrates the feasibility and effectiveness of utilizing machine learning models to predict smartphone addiction. By analyzing key factors such as usage patterns and psychological conditions, we successfully identified individuals at risk of developing problematic smartphone behaviors. The high accuracy achieved by the models highlights their potential as valuable tools for healthcare professionals and application developers. Continued research is essential to validate findings across broader datasets and explore innovative solutions for promoting healthier smartphone usage habits.



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