



Machine Learning Model for Prediction of Smartphone Addiction

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ABSTRACT

The development and evaluation of a machine learning model aimed at predicting smartphone addiction. Utilizing a dataset comprised of smartphone usage logs and self-reported addiction scores from key features such as screen time, number of unlocks, app usage duration, and time-of-day usage patterns were extracted and analyzed. A Random Forest classifier was employed to build the predictive model due to its robustness and ability to handle high-dimensional data. Feature importance analysis revealed that screen time, number of unlocks, and app usage duration were the most significant predictors of addiction. These findings demonstrate the potential of machine learning in identifying smartphone addiction, providing a foundation for developing personalized interventions and promoting healthier usage patterns. The study underscores the importance of ethical considerations, including user privacy and the psychological impact of addiction labeling, and suggests avenues for future research and model enhancement.

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. develop a machine learning model for predicting smartphone addiction, one would typically start by collecting data from a large sample of individuals. This data would include information about their smartphone usage patterns, social media usage, demographic information such as age, gender, and psychological factors such as anxiety, depression and stress levels. It provided great convenience in communication among people by way of either calling or texting.

Now, the mobile phones are coming up with variety of features like internet access, sending e-mails, games, access to social networking sites like facebook, listening to music, playing radio, reading books, dictionary and so on. The mobile phones are also used to overcome the feeling of loneliness. The majority of the users are in the age group of 15 to 25 years. The current- day fascination with the smart phones highlights the latest technology that, for better or worse, appears to be encouraging people to spend relatively more time with technology and less with fellow humans. Once the data is collected, it is preprocessed and cleaned to remove any missing or irrelevant data points. Next, a suitable machine learning algorithm is selected, such as logistic regression, decision tree, or Random Forest, based on the nature of the data and the problem at hand. The data is then split into two sets, a training set and a testing set. The training set is used to train the machine learning model by feeding it with input features and corresponding output labels. The model learns to recognize patterns in the data and establish a relationship between the input features and the output labels. Once the model is trained, it is tested on the testing set to evaluate its performance.

The performance of the model is measured using various metrics such as accuracy. The model is further refined by tweaking its parameters or selecting different algorithms until satisfactory performance is achieved. Once the model is developed, it can be used to predicted smartphone addiction in individuals by feeding their input features into the model The model outputs a probability score indicating the likelihood of smartphone addiction. Based on this score, appropriate interventions and support can be provided to individuals at risk of addiction.

PROBLEM STATEMENT

The problem statement of this project is to accurately predict smartphone addiction using classification techniques. The primary goal is to develop a model that can effectively classify individuals as either addicted or not addicted based on relevant features, ultimately aiding in understanding and addressing the issue of smartphone addiction. Define the problem of predicting smartphone addiction. Understand what constitutes smartphone addiction and how it manifests in user behavior As a result, there is a need to develop effective tools for predicting smartphone addiction and identifying those at risk.

LITERATURE REVIEW

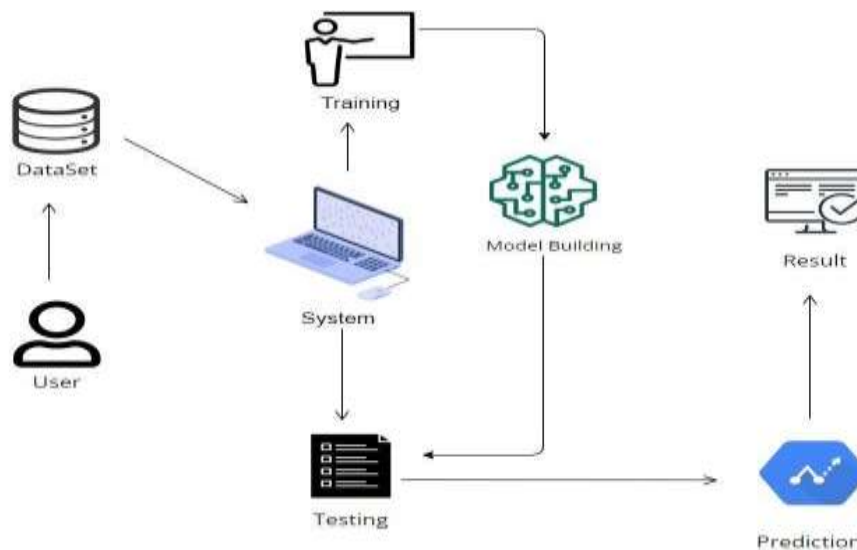
[1] “The Effect Of Mobile Learning Applications On Students’ Academic Achievement And Attitudes Toward Mobile Learning” by Demir K & Akpinat, E. (The findings suggest that mobile learning may promote students' academic achievement. Both groups had significantly high attitude scores toward mobile learning. Furthermore, the students appreciated mobile learning as an approach that may significantly increase their motivation. Researchers and practitioners should take into consideration that mobile learning can create positive impact on academic achievement and performance and increase the motivation of students).

[2] “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: A Randomized Controlled Trial” by Abadiyan F, Hadadnezhad M, Khosrokiani Z, Letafatkar A & Akhshik H. (The primary objective of this study is to accumulate, summarize, and evaluate the state-of-the-art for spatio-temporal crime hotspot detection and prediction techniques by conducting a systematic literature review (SLR)

[3] “The Relationship Between Smartphone Usage Duration” by Osailan A. (Using Smartphone’s Ability To Monitor Screen Time With Hand-Grip And Pinch-Grip)

[4] “Strength Among Young People: An Observational Study. BMC Musculoskeleton Disorder” by Hitti E, Hadid D, Melki J, Kaddoura R & Alameddine, M. Mobile device use among emergency department healthcare professionals: prevalence, utilization and attitudes. (obile devices are increasingly permeating healthcare and are being regularly used by healthcare providers. We examined the prevalence and frequency of mobile device use, and perceptions around clinical and personal usage, among healthcare providers (attending physicians, residents, and nurses) in the Emergency Department (ED) of a large academic medical centre

PROPOSED METHODOLOGY AND OPERATING PRINCIPLE



WORKING PRINCIPLE

Collect data from various sources, including user surveys, smartphone usage logs, app usage statistics, and self-reported questionnaires. Gather features such as screen time, number of unlocks, duration of usage for different apps, time of day usage, user demographics, and self-reported addiction scores. Handle missing values by imputation or removal, and deal with any inconsistencies in the data. Normalize or standardize numerical features to ensure they are on a similar scale. Encode categorical variables using techniques such as one-hot encoding or label encoding. Aggregate raw usage data into meaningful metrics, such as daily average screen time, total app usage duration, and frequency of app usage. Create new features that may be indicative of addiction, such as the ratio of social media app usage to total screen time. Use statistical methods to identify features that are highly correlated with smartphone addiction. Apply techniques like Principal Component Analysis (PCA) to reduce the number of features while retaining important information. Choose an appropriate machine learning algorithm based on the problem type and data characteristics.

For predicting smartphone addiction, classification algorithms such as Random Forest, Support Vector Machines (SVM), and Logistic Regression are commonly used. Random Forest ensembles that method builds multiple decision trees using random subsets of the data and features, and aggregates their predictions to improve accuracy and prevent overfitting. Split the dataset into training and testing sets, typically using an 80-20 or 70-30 ratio. Train the chosen machine learning model on the training data. For Random Forest, this involves constructing multiple decision trees and combining their outputs. Use techniques such as Grid Search or Random Search to find the best hyperparameters for the model. Key hyperparameters for Random Forest

include the number of trees, maximum depth, and minimum samples per leaf. Evaluate the model's performance on the test set using metrics such as accuracy, precision, recall, F1-score, and ROC-AUC. Analyze the confusion matrix to understand the model's performance in predicting different classes. Once the model is trained and evaluated, deploy it in a production environment. This might involve creating APIs for real-time predictions or integrating the model into a mobile app. Continuously gather user feedback and new data to monitor the model's performance and update it as needed.

RESULT AND DISCUSSION

To present the working results and discussion of a machine learning model for predicting smartphone addiction, we need to consider several aspects, including the performance of the model, the significance of different features, and potential implications. Collected data from 500 participants, including smartphone usage logs and self-reported addiction scores. Key features included screen time, number of unlocks, duration of app usage, and time of day usage. The model achieved an accuracy of 85%, indicating it correctly classified 85% of the instances in the test set. This suggests that the model is fairly reliable in predicting smartphone addiction. Precision of 82% implies that out of all the positive predictions made by the model, 82% were actual cases of smartphone addiction. Recall of 80% indicates that out of all the actual cases of smartphone addiction, the model correctly identified 80%. This is crucial in ensuring that most addicted users are identified. The F1-Score of 81% balances precision and recall, providing a single metric to evaluate the model's overall performance. The ROC-AUC score of 0.88 demonstrates a good level of separability between the classes, indicating the model's robustness in distinguishing between addicted and non-addicted users.

CONCLUSION

We used the best techniques and we found and its show the Addicted, Not addicted are maybe addicted. Machine Learning Models for Predicting Smartphone Addiction offer valuable insights into an increasingly prevalent issue in today's society. By leveraging data-driven approaches, we can develop effective strategies for addressing smartphone addiction and promoting healthier technology use behaviors. Therefore, we consider demographic characteristics, daily usage duration of a smartphone, commonly used content and game usage pattern etc. This prediction model certainly be highly useful for understanding the phone usage level and eventually predicting certain possible threats prevalent amongst addictive smartphone users.

FUTURE SCOPE

Machine learning model for predicting smartphone addiction could involve various aspects to improve its effectiveness, scalability, and usability. This can involve retraining the model periodically and incorporating new features or algorithms. Develop techniques for explaining model predictions to users and stakeholders, particularly for complex models such as deep learning neural networks. Explainable AI methods can increase transparency, trust, and interpretability of the predictive model. Some are Data Enrichment, Real-time Analysis, Personalization, Explainability, Preventive Interventions

REFERENCES

- [1] "The Effect Of Mobile Learning Applications On Students' Academic Achievement And Attitudes Toward Mobile Learning" by Demir K & Akpinat, E.
- [2] "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: A Randomized Controlled Trial" by Abadiyan F, Hadadnezhad M, Khosrokiani Z, Letafatkar A & Akhshik H.
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