REST Journal on Data Analytics and Artificial Intelligence
Vol: 4(4), December 2025
REST Publisher; ISSN: 2583-5564
Website: http://restpublisher.com/journals/jdaai/
DOI: https://doi.org/10.46632/jdaai/4/4/9

Predicting Mobile Phone Addiction through Machine Learning

R. Monisha, C. Prakash Narayanan M.E, K. Sharmila, *Tejaswini S L
P.S.V College of Engineering and Technology, Krishnagiri, Tamil Nadu, India.
*Corresponding Author Email: tejaswinisl151@gmail.com

Abstract: *As more and more people exhibit the symptoms of smartphone addiction like obsessive mobile device usage, reduced efficiency, and impacts on both physical and psychological well-being issues- concern over smart phone addiction has escalated in recent years. Therefore, it is necessary to create efficient technique for predicting smart phone addiction and identifying people who are at risk. In this study, we developed a Machine Learning model able to forecast the danger of smart phone addiction using data collected from a survey of smart phone users. The study covered a wide range of psychological traits such as stress, anxiety and depression in addition to demographics and phone use patterns. Our model using popular and effective machine learning method. We employed a number of metrics like accuracy for assessing the model's performance after training it on a subset of the data. The results demonstrated that the model was highly precise in forecasting smartphone addiction. Our built model has several potential applications. It could be used by medical professionals to identify the individuals who are most at risk of developing a smart phone addiction and to provide the appropriate support. It might be used by app developers to make less addictive apps that promote wiser phone usage habits. In conclusion, our study shows that it is both possible and successful to predict smart phone addiction using machine learning models. To confirm our results and investigate the possible uses of this model in various settings, further research is necessary involving larger and more diverse datasets.*

1. INTRODUCTION

The rise of smartphone addiction has emerged as a significant worry in contemporary society, impacting individuals of all ages. Excessive use of smartphones leads to negative consequences in daily life such as reduced productivity, poor social interactions, and psychological problems like anxiety and depression. The dependence of smartphone is a result of various activities including social media, gaming, instant messaging, and the constant necessity for digital validation. This article explores the mechanisms behind smartphone addiction, its impact on social behavior, and the potential risks to physical health, including eye strain and sleep disturbances. Also, it discusses the role of app developers and social media companies in designing engaging, often addictive, interfaces that encourage extended usage.

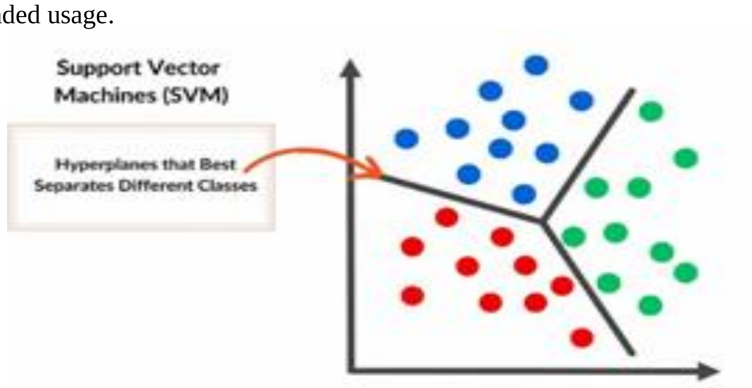

FIGURE 1. Support vector machine

The prediction is done by using various models like Logistic regression, decision tree models, and support vector machines identification of the most precise method to be considered. The study concludes by emphasizing the need of a balanced approach for the usage of technology in a proper way, promoting healthier digital habits while responsibly exploiting the benefits of smartphones in a responsible manner. The usage of smart phones has increased dramatically over the last 10 years, becoming a necessary component of our everyday life. While using a smart phone excessively may result in addiction and adversely affect a person's physical and mental health, social connections, and productivity, it also has many positive effects. Based on a variety of characteristics, including social media usage, smart phone usage patterns, demographic data, and psychological aspects, machine learning can help in developing models that predict smart phone addiction. With the use of these models, people who run the risk of developing a smart phone addiction can be identified and given the right assistance and interventions. In order to develop a machine learning model capable of predicting smartphone addiction first step would typically be to collect rephrasing data collected from a large population. This information would encompass specifics regarding how they use social media and smart phones, as well as demographic data like age and gender and psychological characteristics like stress, anxiety, and depression. Following collection, the data is cleaned and preprocessed to eliminate data points that are either missing or superfluous. Afterward, a machine-learning approach that is deemed appropriate is chosen, taking into account the problem at hand, the data type, and logistics Regression, Entscheidungsbaum Oder Random Forest Subsequently, a training data set and a testing data set are generated.

2. LITERATURE REVIEW

1. BOGOAN KIM, SEOK-WON LEE “Automated Time Manager: Effectiveness of Self-Regulation on Time Management”

We examined the effectiveness of a self-regulated time-management approach that utilizes smartphone features, grounded in a theoretical framework comprising four key elements of self-regulation. The four elements are: 1) establishing objectives; 2) applying task strategies; 3) self-evaluation and reflection; and 4) confidence in one’s abilities coupled with internal motivation.

2. ANDRÉS GARCíA-UMAÑA, VAGNER BESERRA “Gratifications Associated with the Use of Smartphone and Internet in Students”

The research Using the Uses and Gratifications framework, the study collected data through a survey administered to school students in Ecuador (n = 355), Spain (n = 263), and Colombia (n = 241 quota sampling method. This analysis identifies the main gratifications in using smartphones to access the internet through four study Variables: achievement (ACH), social interaction (SI), self-representation (SP) und entertainment (EN). We present a confirmatory factor analysis (CFA) as well as an exploratory factor analysis (EFA). Moreover, a multi-group analysis is conducted to highlight statistically significant differences linked to cultural context and associated traits each country. The growing integration of technology into all aspects of society, the prevalence of connectivity, and the ease of accessing the network from any device are prompting the scientific community to determine user motivations and improve various aspects surrounding them.

3. METHODOLOGY

A. Existing system: There were many studies and researches that took place for detecting the addiction of smartphones from various perspectives. The surveys which were taken during the commencing of the research were dependent primarily on psychological factors and were mostly self-reported. Kwon et al. demonstrated that smartphone usage has identified symptoms of stress, tolerance and psychological imbalance which resulted in addiction. Though these techniques gave a clear understanding of dealing with this problem, it lacked subjectivity, recall bias and inconsistencies. Many researchers through their research, have identified certain factors that hold an important role in predicting the addiction of smartphone. Elchaig et al., have conducted research on smartphone addiction and its relationship with mental health challenges like anxiety, stress, and depression, as well as on excessive screen time and frequent phone unlocking. Social media overuse leading to compulsive behavior was identified by Andreessen et al., Lin et al. (2017) have done research on identifying the effects of smartphone usage on sleep schedule and psychological well-being. Leola et al., studied disrupted sleep patterns due to late-night smartphone use. Kiss and Griffith’s research resulted in a conclusion that extreme use of smartphones can decline communication between individuals, poor academics and mainly effect the relationships in a very bad way where two people may not even have time to interact with each other. In short, it can be said that balancing the usage of smartphone plays a significant role in every individual’s life.

B. Advantage: In a digitally globalized environment, the variety of cultural contexts serves to modulate the incentives that drive students to access the Internet via smartphones. The research was conducted in three different contexts, employing a non-probabilistic quota sampling that allows for the selection of target groups according to the study's needs. However, it is encouraged to replicate the study with a broader scope, applying probabilistic sampling to reduce selection bias and minimize the margin of error within the population. Furthermore, the use of qualitative instruments in focus groups is recommended to better understand the realities of each study group. Additionally, the inclusion of analyses in multicultural groups across more than three Spanish-speaking countries, with similar characteristics and based on the same study variables, could be of significant scientific interest.

C. Proposed system: This study primarily aims to detect smartphone addiction by using a machine learning-based predictive model that depends on the data collected. Many studies have observed that teenagers and young adults are at-risk which makes this prediction of smartphone addiction in various demographics an essential aspect. The psychological, technological social, elements—such and as personality traits, the influence of social media, and smartphone design elements— that lead to addictive behaviors are also being investigated by researchers. This research aims to provide an overview of how individuals of the same age are dependent on smartphone and their usage patterns by considering the answers given by them to a common questionnaire. It also evaluates the diverse impacts of smartphone addictions on academic and professional performance, on various relationships, how it affects mental and physical health and many such areas is another crucial objective. Additionally, this study proposes establishing guidelines to help individuals identify and treat this condition effectively.

D. Disadvantages: The model was developed and evaluated using survey-derived data gathered from a limited number of participants, which may restrict its generalizability to larger populations. Since the data was obtained through self-reported surveys, responses may be affected by personal bias, inaccurate recall, or social desirability, impacting the model's accuracy. The study relies on static survey data rather than real-time smartphone usage data, which may not fully capture actual user behavior. The dataset may not represent diverse age groups, cultural backgrounds, or socioeconomic conditions, limiting the applicability of the model across different populations.

E. Design of the system: The file design is a key feature that largely relies on the system's performance. The design of the file addresses the two crucial components. Their dimensions are the data redundancy and the file sizes. Concurrently, all files are structured to include all pertinent information about each module. An information database containing details about every module will render the system complex. Conversely, a relational database contains several tables and provides means for these tables to interact. Relationships among the data in tables can be collected, combined, and presented in the format of most relational databases provide mechanisms that allow data to be shared across different users and applications:

- Through networks
- Via the Internet
- Using laptops and various other electronic devices, like palm pilots
- Alongside other software solutions

Thus, relational database file is implemented in the Predicting mobile phone addiction through machine learning. The design base files are the most important of the mechanism. The system's performance depends on how the system is design. It has been given at most attention to reduce the size of files and redundancy. Concurrently, all files are designed to include all pertinent information about each entity. A unified database containing data on all entities will enhance the system more complicated. Each database tables will be related with one another which will be shown in the table structure and normalization process in upcoming chapters.

4. TESTING

A. Data testing (data validation phase)
This phase ensures the dataset's correctness and quality prior to training the model.

- Verifying for absent values and outliers
- Verifying data consistency and correctness
- Normalization and encoding validation
- Ensuring balanced class distribution

B. Unit testing
Each component of the system is tested independently.

- Data pre-processing module testing
- Feature extraction and selection testing

- Individual model testing (Logistic Regression, Decision Tree, Random Forest)

C. Performance testing
This phase evaluates the efficiency of the system.
- Accuracy comparison across models
- Training and prediction time analysis
- Memory usage evaluation

D. Acceptance testing
Final testing to verify system readiness.
- Validating results against project objectives
- Confirming stakeholder requirements

5. ARCHITECTURE

This study of predicting the addiction of smartphone is based on machine learning approach using the data collected from different people. This data is usually a mix of different methods and designs. It is based on patterns which were followed by people who were observed for a very long period. The collection of data includes standardized surveys and questionnaires. By combining all these methods, researchers have generated a thorough understanding of smartphone addiction that will assist them in creating effective treatments and principles for dealing with this diverse issue. There are many machine learning methods available for predicting smartphone addiction. A few machine learning algorithms include Random Forest and others. After comparing multiple machine learning algorithms for smartphone addiction detection, we employed the suggested approach to identify the most effective diagnosis method. We need to apply the different algorithms and datasets first in order to calculate the accuracy. Next, we integrate the results.

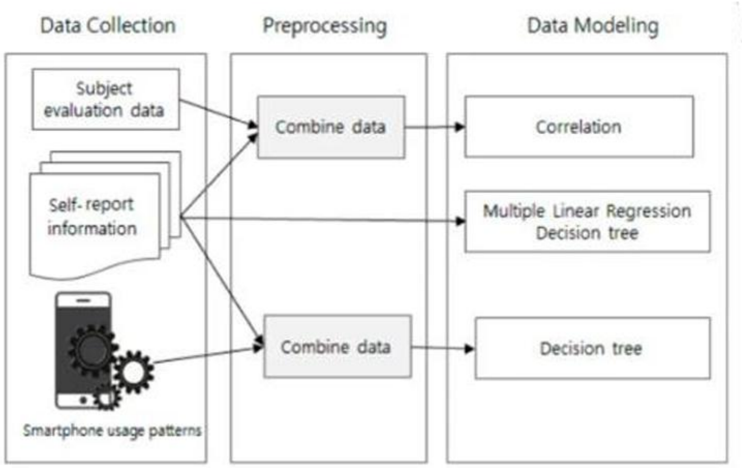

FIGURE 2. System architecture

Feature Selection to have better accuracy, the selection of proper and relevant features is a must. The questionnaire consists of several questions that are to be considered which facilitate in getting accurate results. Some of the important factors based on which the dataset is built are listed below:
- Age, Gender
- Battery life and Screen time
- Time spent on playing games
- Concern about losing phone
- Time spent on social media applications
- Constant unlocking of the phone
- Carrying phone to the bathroom
- Usage of the phone in social gathering
- Checking of phone before and after sleep
- How long one can stay away from the phone
- Constant checking of notifications

- Sleep pattern/sleep schedule
- Placing of the phone while sleeping

All these factors are considered to reach a conclusion in this study based on which we get accuracy. These factors differ from person to person that shows whether they are addicted to smartphones or not. Pre-processing it is the next important step for guaranteeing data provision for the machine learning models is of high quality. Pre-processing of data must be done correctly without any error to prepare data for meaningful examination that helps researchers in finding patterns, impacts and causes of addiction of smartphone. The dataset, if it is collected manually, must undergo various pre-processing steps that are mentioned below:

Data cleaning: There may be some irrelevant information. In such cases duplicate values must be removed and also formats must be standardized.

Management of missing data: There may be some missing data occurring frequently in the dataset which are handled using mean/mode/median computation.

Data normalisation: Here, when data from various sources is merged together, it guarantees that all variables are measured on a comparable scale.

Encoding: In this section, demographic data which is frequently categorical is transformed into numerical expressions.

Splitting the dataset: To evaluate the model, the data is separated into training and testing subsets.

6. IMPLEMENTATION

Module description

1. Decisions tree: The Decision Tree is a supervised machine learning algorithm used for both classification and regression tasks purposes. The method operates by It works by recursively partitioning the dataset into subsets based on feature values that best distinguish the target classes. An internal node indicates a decision based on a feature, a branch represents the result of that decision, and a leaf node signifies the final outcome represents an entity used to identify patterns in psychological factors and smartphone usage behaviors that contribute to smartphone addiction. The model is easy to interpret and helps in understanding how different features influence addiction risk. However, it may suffer from over fitting when trained on limited data.

2. Logistics Regression: Logistic Regression serves as a statistical classification technique that is widely applied to binary classification issues. It calculates the likelihood of a target variable being part of a specific class by employing a logistic (sigmoid) function. The model analyzes the relationship between independent variables such as stress, anxiety, depression, and smartphone usage patterns and the dependent variable indicating addiction risk. Logistic Regression is characterized by its computational efficiency, straightforward implementation, and results that are easy to interpret. It does, however, assume it assumes a linear relationship between the input features and the output, which can limit its ability to model complex patterns in the data.

3. Random Forest: Random Forest is an ensemble learning technique that integrates multiple Decision Trees to enhance predictive performance and reduce over fitting. Each tree is trained using a randomly selected subset of the data and features, and the final output is obtained by aggregating the predictions of all trees, typically through majority voting. This study utilized the Random Forest model for capturing intricate nonlinear relationships among psychological traits, demographic factors, and smartphone usage patterns. Due to its robustness and high accuracy, Random Forest performed better compared to individual models. However, it requires more computational resources and is less interpretable than a single Decision Tree.

7. RESULT

The suggested smartphone addiction prediction system was assessed using three machine learning algorithms are considered: Logistic Regression, Decision Tree, and Random Forest. To guarantee an unbiased assessment of the models, the dataset was split into training and testing subsets effectiveness of each model was assessed with the help of Traditional performance metrics, including accuracy, precision, recall, and F1-score Logistic Regression method served as a baseline performance for smartphone addiction prediction. It demonstrated stable and consistent results, indicating its suitability for problems with relatively straight-line correlations among the input features and the target variable. However, its prediction accuracy was comparatively lower when handling complex and nonlinear patterns in the information. The Decision Tree model outperformed Logistic Regression by effectively capturing nonlinear relationships among psychological factors and smartphone usage behaviours. The tree structure enabled clear decision-making paths, making the model interpretable. However, the model showed signs of over fitting, particularly when trained on limited data. The Random Forest algorithm generated the most accurate prediction accuracy and overall performance. By combining multiple decision trees, Random Forest effectively reduced over fitting and improved generalization on unseen data. It demonstrated superior performance on all assessment metrics, confirming it as the most reliable model for forecasting smartphone addiction risk. To sum up, the experiments show that ensemble models like Random Forest are more successful in forecasting smartphone addiction than individual classifiers. The results confirm that it is feasible to use machine learning techniques for early identification of individuals at risk of smartphone addiction.

8. CONCLUSION

For this project, we developed an application called prediction of smart phone addiction, utilizing different methods of Machine learning models like logistic regression, decision trees, and random forests. The application is designed to be easy to use. Our most effective techniques show how people who are not addicted but could still be addicted. To present the results and discussion of a machine learning model designed to predict smartphone addiction, several aspects must be considered, including the model's performance, the importance of different features, and potential implications. Data was collected from 500 participants, including smartphone usage logs and self-reported addiction scores. Key features included screen time, number of unlocks, app usage time, and time of use. The model achieved an accuracy of 85%, indicating that it correctly classified 85% of the instances in the test set. This suggests that the model is reasonably reliable in predicting smartphone addiction. A precision of 82% means that of all the positive predictions made by the model, 82% were true instances of smartphone addiction. A recall of 80% shows that of the actual smartphone addiction instances, the model correctly identified 80% of them. 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 discriminative ability between classes, indicating the model's strength in differentiating between addicted and non-addicted users.

Future Work: Although the proposed machine learning model demonstrates effective performance in predicting smartphone addiction, several directions can be explored to enhance and extend this research. Future studies can focus on collecting larger and more diverse datasets that include participants from different age groups, professions, and cultural backgrounds to improve the generalizability of the model. Incorporating real-time smartphone usage screen time, app usage logs, and notification frequency are examples of data that can offer more precise and dynamic insights into user behaviour. Advanced machine learning and methods of deep learning, like hybrid ensemble models and neural networks, can be explored to capture complex behavioural patterns more effectively. Feature selection and optimization methods may also be applied to identify the most influential factors contributing to smartphone addiction. Additionally, integrating techniques of explainable AI could enhance the transparency of models and aid medical professionals in comprehending the decision-making process of the prediction system. Future work may also involve deploying the model as a mobile or web application for immediate addiction risk monitoring and early intervention. Ensuring data privacy, ethical compliance, and secure handling of sensitive psychological information will be essential for practical implementation. Overall, these enhancements can help transform the proposed model into a scalable and impactful tool for promoting healthier smartphone usage behaviours.

REFERENCES

[1]. 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: A randomized controlled trial. Trials 22, 274 (2021).

[2]. 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).

[3]. 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).

[4]. Osorio-Molina, C. et al. Smartphone addiction, risk factors and its adverse effects in nursing students: A systematic review and meta-analysis. Nurse Educ. Today 98, 104741 (2021).

[5]. 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).

[6]. Sohn, S. Y., Krasnoff, L., Rees, P., Kalk, N. J. & Carter, B. The association between smartphone addiction and sleep: A UK cross-sectional study of young adults. Front. Psych. 12, 629407 (2021).

[7]. 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).

