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Smart Phones Compulsive Usage Predicted By Machine Learning Models

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Abstract:

As more and more people exhibit the symptoms of smartphone addiction such as obsessive phone use, lower productivity and even physical and mental health 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 that can predict the risk 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, anixity and depression in addition to demographics and phone use patterns. Our model with the help of popular and effective machine learning method. By preprocessing the data, which included encoding categorical categories and normalizing numerical variables, we made sure the model could train successfully. We employed a number of metrics, such as accuracy, to evaluate the model's performance after using a portion of the data to train it. Our results showed that the model was very accurate in predicting smart phone 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. Further research is needed to validate our findings on larger and more diverse datasets and explore the potential applications of this model in different contexts.

Keywords: Decision tree, Random Forest, Logistic Regression and Machine learning techniques

I.INTRODUCTION

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 can lead to addiction and have detrimental effects on one's physical and mental health, social relationships, 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 be used to create models that forecast 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 create a machine learning model that can forecast smartphone addiction, one would normally begin by gathering information from a sizable sample of people. This data would include details about 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 any missing or superfluous data points. Subsequently, a machine learning method that is deemed appropriate is chosen, taking into account the problem at hand, the data type, and logistic regression, decision tree, or Random Forest Following that, a training set and a testing set of data are produced. The model is tested on the testing set following training to evaluate its performance. A number of indicators, including accuracy, are used to gauge the model's performance. Up until an acceptable level of performance is attained, the model is further improved by adjusting its parameters or choosing other algorithms. After the model is created, users can use it to forecast their likelihood of developing a smartphone addiction by feeding the model their input features. The probability score that the model produces indicates the chance of developing a smartphone addiction. A person at risk of addiction can receive the proper support and therapies based on their score. Lastly, machine learning models may prove to be a valuable resource for predicting smart phone addiction and identifying people who are at-risk.

II LITERATURE SURVEY

Demir, K., and Akpinat The impact of mobile learning apps on undergraduate students' academic performance is investigated in this study. The purpose of this research is to investigate the potential effects of these mobile learning resources on various aspects of students' academic performance. Through our investigation of the correlation between academic performance and the use of mobile learning applications, we hope to make a substantial contribution to the ongoing conversation about the integration of technology in higher education. Our goal is to shed light on the intricate dynamics and implications of incorporating mobile learning into undergraduate education through empirical investigation and analysis.

Hadadnezhad and F. Abadiyan This study intends to assess whether adding a smartphone app to an 8-week Global Postural Reeducation (GPR) program can lessen patients' neck pain. The project aims to ascertain whether incorporating a smartphone application into the GPR program enhances or modifies its outcomes, with a particular focus on treating neck pain. By examining the relationship between changes in patients' neck discomfort levels and app use, the research seeks to shed light on the potential benefits and implications of technology-assisted therapies in the field of postural reeducation. The research attempts to further knowledge of how smartphone applications may be successfully incorporated into rehabilitation programs to maximize patient results in resolving rehab issues through empirical analysis.

Musculoskeletal Disorders BMC The primary goal of this study was to examine the various ways that young people use cellphones, with an emphasis on non-traditional forms of communication. In the modern world, there has been a noticeable rise in the younger generation's usage of cell phones for a range of purposes, including web browsing and entertainment. The goal was to examine the different ways that smart phones are integrated into the daily lives of young people in order to obtain a comprehensive understanding of the nature and extent of this shift. By examining usage patterns beyond basic communication, the study sought to shed light on the increasing impact of cell phones on the preferences and lifestyles of youth. The aim of the project was to provide through analysis and empirical research.

Melki, J.; Hadid, D.; Hitti, E. This study highlights how mobile devices are increasingly being incorporated into the healthcare industry and looks at how frequently healthcare professionals use them. Using mobile technology has become an essential part of the daily work routine for healthcare professionals. These portable gadgets serve multiple purposes in the healthcare delivery process, from patient care and communication to mobile access to essential data. The seamless integration of mobile devices into the healthcare industry is indicative of a broader trend in the industry towards technological advancement and digitization. In order to shed light on how mobile devices are used by healthcare professionals in the course of their work, this study intends to investigate the extent and implications of this integration. Through analysis and empirical investigation, the work aims to make important contributions.

III. EXISTING SYSTEM

The current system's ignorance of data visualization makes machine learning algorithms difficult to implement. The current approach builds Logistic Regression models are created via mathematical operations, which can be laborious and intricate. We use machine learning components from the scikit-learn library to get around all of this.

IV. PROPOSED SYSTEM

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.

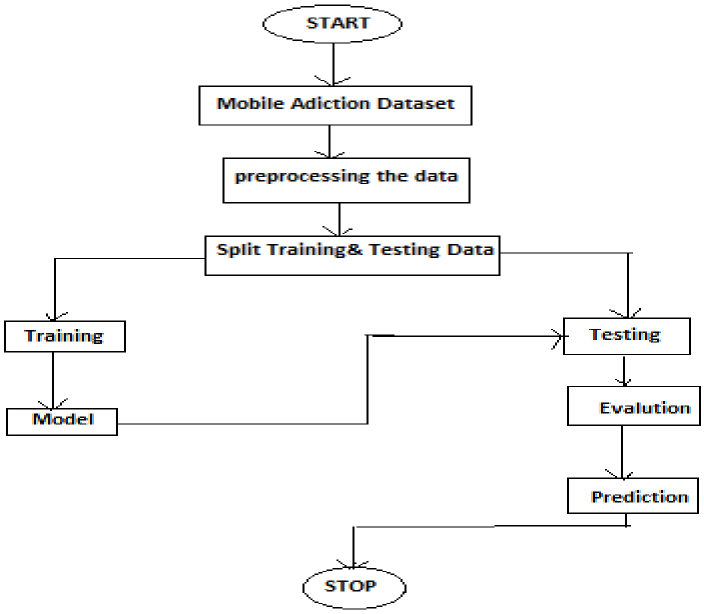

Fig:1 Block diagram of proposed System

V. RELATED WORK

A. Decision Tree

The decision tree algorithm is crucial for creating a prediction model for smartphone addiction. Initially, a dataset is put together with a variety of features related to smartphone usage, such as screen time, app usage, self-reported behavior, and demographic information. After preprocessing the data, the algorithm assesses multiple variables to see how well they contribute to classifying users as hooked or not, and thus determine their significance in predicting smartphone addiction. The method uses these characteristics to segment the dataset recursively according to the selected attributes, so creating a decision tree. The optimal depth and node size of the tree are ensured by continuing this process until specific stopping points are reached. The model's performance is then assessed using common metrics, such as recall, accuracy, precision, and F1-score. An illustration of a decision tree is shown with its root at the top and inverted. Each bolded word in black in the figure on the left represents an internal node or condition that controls how the tree splits into branches and edges. Whether or if the branch that no longer splits is the decision, or leaf, in this case.

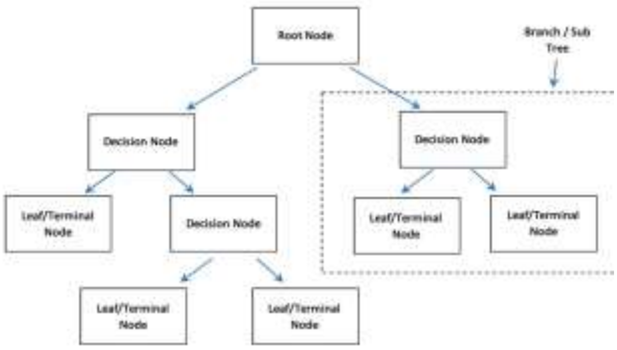

Fig.2.Working of Decision Tree

B. Random Forest

The Random Forest algorithm is crucial for developing a smartphone addiction prediction model. Initially, a sizable dataset is gathered that comprises a variety of attributes connected to smartphone use habits, such as screen time, app usage, self-reported habits, and demographic information. The system preprocesses the data and then uses an ensemble learning technique to mix multiple decision trees to increase prediction accuracy. Each Random Forest decision tree is trained using a randomized subset of the attributes and data instances from the original dataset. Because of its unpredictable nature, generalization performance is improved by reducing overfitting. During the training phase, each tree in the forest generates a separate forecast; the final prediction is obtained by summing up the guesses made by all the trees, typically using a majority voting system.

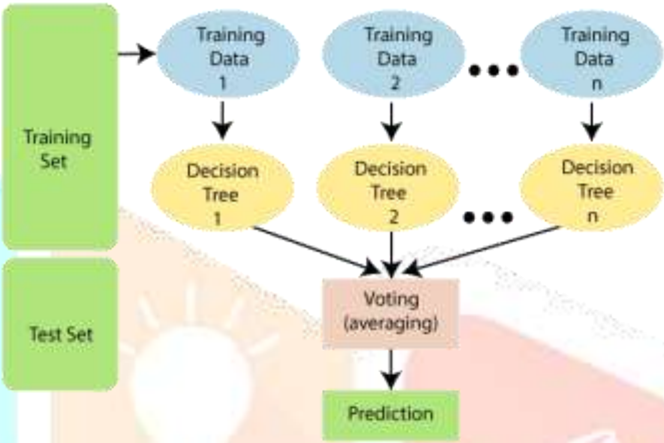

Fig.3.Implementation of Random Forest

Applications of the Random Forest algorithm are necessary when building a prediction model for smartphone addiction. First, a dataset with numerous variables linked to smartphone use behavior is collected, including screen time, app usage, self-reported behavior, and demographic data. After preprocessing the data, the method combines multiple decision trees to enhance prediction accuracy through ensemble learning. Using a different subset of the features and data instances from the original dataset, the Random Forest technique trains each decision tree. Its unpredictable nature helps prevent overfitting and improves the model's ability to generalize. During training, each tree generates its own predictions; the final prediction is determined by adding together all of the trees' forecasts through a majority voting process. The Random Forest model is subjected to a performance evaluation.

C. Logistic Regression

Developing a prediction model for smartphone addiction requires the use of the Logistic Regression technique. Initially, a dataset comprising various aspects of smartphone usage behavior is gathered, such as screen time, application usage, self-reported behavior, and demographic information. The dataset is put through a number of data pretreatment procedures before being subjected to the logistic regression method. Logistic regression can be used to assess whether an individual is likely to develop a smartphone addiction or not because it is more appropriate for binary classification tasks than linear regression, which predicts continuous outcomes. The algorithm models the probability of addiction based on the input data by converting the input features to a value between 0 and 1, using a logistic function. Next, this likelihood is utilized to categorize people as either addicted or not addicted.

VI . SIMULATION RESULTS

The study involved applying classification techniques such as decision trees, random forests, and logistic regression to construct a machine learning model to predict smartphone addiction. A dataset gathered from a survey of smartphone users, which asked questions about psychological variables, usage patterns, and demographics, was used to train the model. Preprocessing the data involved normalizing numerical variables and encoding categorical variables. The model was trained using some of the data, and it was evaluated using the remaining data. When it came to forecasting smartphone addiction, the model performed quite well. Frequency of checking notifications, daily phone hours, types of apps used, age, gender, and stress levels were the most predictive factors. The approach may be used to detect people who are susceptible to smartphone addiction so that medical experts can take appropriate action, as well as to assist app developers in creating less addictive programs that encourage responsible usage. The study comes to the conclusion that machine learning models may accurately predict smartphone addiction, but more work with more varied and larger datasets is required to confirm the results and investigate practical uses.

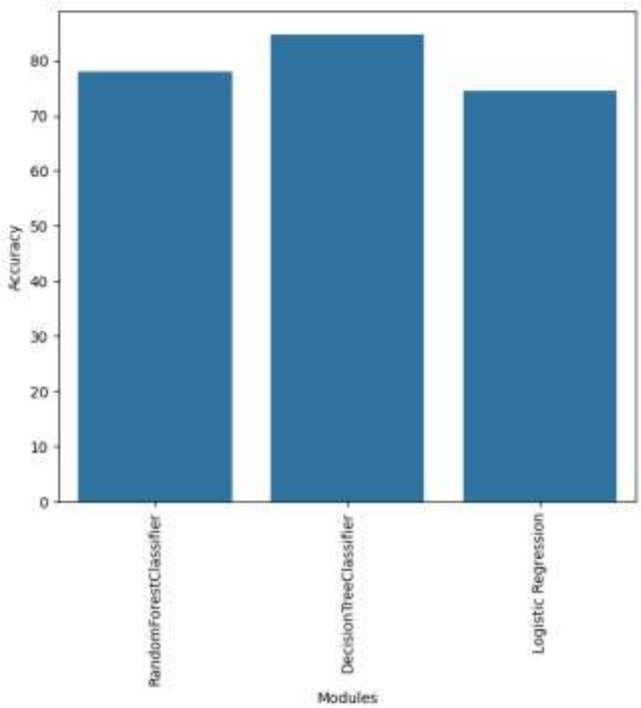

Fig.4. Accuracy result

VII. CONCLUSION

For this paper, we developed an application called prediction of smart phone addiction, utilizing various machine learning model techniques such as logistic regression, random forests, and decision trees. 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.

VIII.REFERENCES

[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).

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

[3] 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).

[4] 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).

[5] 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).

[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).

[8] Joo, E., Kononova, A., Kanthawala, S., Peng, W. & Cotten, S. Smartphone users' persuasion knowledge in the context of consumer mHealth apps: Qualitative study. JMIR Mhealth Uhealth 9, e16518 (2021).

[9]. Treede RD, Rief W, Barke A, Aziz Q, Bennett MI, Benoliel R, Cohen M, Evers S, Finnerup NB, First MB, Giamberardino MA, Kaasa S, Kosek E, Lavand'homme P, Nicholas M, Perrot S, Scholz J, Schug S, Smith BH, Svensson P, Vlaeyen JWS, Wang SJ. A classification of chronic pain for ICD-11. Pain. 2015 Jun; 156(6): 1003–1007.doi: 10.1097/j.pain. 0000000000000160. https://europepmc.org/abstract/MED/25844555 00006396-201506000-00006 - DOI - PMC - PubMed

[10].Miaskowski C, Blyth F, Nicosia F, Haan M, Keefe F, Smith A, Ritchie C. A biopsychosocial model of chronic pain for older adults. Pain Med. 2020 Oct 01;21(9):1793–1805. doi: 10.1093/pm/pnz329. 5679926 - DOI - PubMed

[11]. Cheatle MD. Biopsychosocial approach to assessing and managing patients with chronic pain. Med Clin North Am. 2016 Jan;100(1):43–53. doi: 10.1016/j.mcna.2015.08.007.S0025-7125(15)00145-5 - DOI - PubMed

[12]. Ampiah PK, Hendrick P, Moffatt F, Ahenkorah J. Operationalisation of a biopsychosocial approach for the non-pharmacological management of patients with chronic musculoskeletal pain in low- and middle-income countries: a systematic review. Musculoskeletal Care. 2020 Oct;18(3):227–244. doi: 10.1002/msc.1462. - DOI - PubMed

[13]. Right to pain relief. International Association for the Study of Pain. 2004.[2024-07-31].