MACHINE LEARNING MODEL FOR PREDICTION OF SMARTPHONE ADDICTION

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ABSTRACT

Smartphone addiction has become a growing concern in recent years, with increasing numbers of people exhibiting symptoms such as excessive phone use, loss of productivity, and even physical and psychological health problems. As a result, there is a need to develop effective tools for predicting smartphone addiction and identifying those at risk. In this study, we built a ML model used for predicting smartphone addiction using data collected from a survey of smartphone users. Demographics, phone usage habits, and a range of psychological issues like stress, anxiety, and depression were all covered in the poll. A popular and effective machine learning method, to build our model. In this study, the data is preprocessed by encoding categorical variables and normalizing numerical variables to ensure that the model could learn effectively. Further, the model is trained on some percentage of the data and evaluated its accuracy and its performance on the remaining percentage of the data using several metrics such as accuracy. The results showed that the model has achieved a high accuracy in predicting smartphone addiction. The most important features for predicting addiction were mobile phone usage patterns such as the frequency of checking notifications, the number of hours spent on the phone each day, and the types of apps used most frequently. Other important factors included age, gender, and stress levels. The model developed has several potential applications. It could be used by healthcare professionals to identify individuals who are at risk of developing smartphone addiction and provide appropriate interventions. It could also be used by app developers to design apps those are less addictive and promote healthier phone usage habits. In a brief, this study illustrates both the practicality and efficacy of using machine learning models for predicting smartphone addiction. Further research is needed to validate our findings on larger and more diverse datasets and to explore the potential applications of this model in different contexts.

I. INTRODUCTION

Over the past years, there has been a continuous growth in the usage of smartphones, which have become an essential part of our lives. Even while mobile phones have many advantages, using them excessively can cause addiction and have a detrimental effect on a person's productivity, social connections, physical and mental health, and relationships. Models that predict smartphone addiction based on a variety of parameters, including social media usage, usage patterns of smartphones, demographic data, and psychological aspects, may be created using machine learning. These models can be used to detect people who may become addicted to

smartphones and to help them receive the right assistance and therapies. Usually, the first step in creating a machine learning model to forecast smartphone addiction is gathering data from a sizable sample of people. Information on their social media and smartphone usage habits, as well as demographic details like age and gender and psychological characteristics like stress, anxiety, and depression, would all be included in this data. After the data is gathered, it is cleaned and preprocessed to eliminate any unnecessary or missing data points. During the preprocessing of the data, it is required to replace imputations and label encoding. Replacing imputations means it can handle all the null values and replace them as 0 or 1 by considering the particular value as an outlier. Label Encoding modifies the categorical data into numerical values. Then the data will be preprocessed and it will be split into training data and testing data.

Next, based on the type of data and the problem at hand, an appropriate machine learning method is chosen. After that, the data is divided into two sets: a testing set and a training set. By providing the machine learning model with input characteristics and matching output labels, the training set is utilized to train the model. By identifying patterns in the data, the model is able to determine a correlation between the input characteristics and the output labels. The model is tested on the testing set once it has been trained in order to assess its performance. Accuracy is one of the measures used to gauge the model's performance. Until the model performs well enough, it is further improved by adjusting its parameters or using other methods. Once the model is created, user input features may be fed into it to forecast a person's likelihood of developing a smartphone addiction. A probability score showing the chance of developing a smartphone addiction is produced by the model. People who are at risk of addiction can receive the proper interventions and assistance based on their score. To sum up, machine learning models can be a useful tool for identifying those who are at risk of smartphone addiction and forecasting the likelihood of addiction. These models can assist people in preventing addiction and lessening its harmful impacts, as well as healthcare professionals. Nonetheless, gathering high-quality data and creating precise, trustworthy models that work well in practical situations are crucial.

II. LITERATURE SURVEY

A quick synopsis of all the research conducted up to this point is provided in this chapter. Additionally, it summarizes all of the research studies that have been done up to this point on the prediction of smartphone addiction, including advancements in prior technology as well as the challenges that users face. As a result, this develops the project's problem statement, which explains bot development and performance challenges and suggests a recommended architecture to address them.

In a study by Demir and Akpinat (2018), the impact of mobile learning applications on students' academic performance and their perception of mobile learning was investigated.

This study looks at how undergraduate students' academic performance, attitudes toward mobile learning, and animation development levels are affected by mobile learning applications. The study's design was quasi experimental. Students from Dokuz Eylul University in Turkey's Buca Faculty of Education participated in the study. The 2013–2014 school year's first semester saw the execution of the experiment. The experimental group (n = 15) employed a mobile learning technique, whereas the control group (n = 26) attended a lecture-based classroom. Students' attitudes toward mobile learning were gauged using an attitude scale, and the impact of mobile learning applications on students' academic performance was investigated using an achievement test. A criteria was utilized to assess the animations that the students had created. The students thought that mobile learning was a useful tactic that may significantly increase their motivation. It is imperative that scholars and professionals acknowledge that mobile learning has the potential to enhance students' motivation and positively performance and achievements. impact their academic

In a randomized controlled trial, Abadiyan et al. (2021) investigated the effectiveness of combining a smartphone application with global postural re-education to improve outcomes for people with nonspecific neck pain, including posture improvement, improved quality of life, and endurance.

This study examined the effects of integrating a smartphone app into an 8-week global postural reeducation (GPR) program on neck pain, endurance, quality of life, and forward head posture (FHP) in people with chronic neck pain and FHP. Thirty office workers with persistent neck pain (38.5 ± 9.1 years), twenty of whom were male and twenty of whom were female, were randomly assigned to one of three groups: group 1 (GPR with a smartphone app, n = 20); group 2 (GPR alone, n = 20); and group 3 (the control group, n = 20). The primary outcome was pain, followed by disability, quality of life, posture, and endurance in second and third place. Pain, disability, endurance, quality of life, and posture were measured pre- and post-8-week interventions using the visual analog scale (VAS), neck disability index (NDI), progressive iso-inertial lifting evaluation (PILE) test, quality of life questionnaire (SF-36), and photogrammetry, respectively. The data have been statistically examined using a one-way analysis of covariance (ANCOVA).

In an observational research , Osailan(2021) investigated the relationship between young people's hand-grip and pinch grip strength and the amount of time they spent using their smartphones, as tracked by the device's screen time function.

Smartphone use has grown significantly, particularly among youth, for a variety of uses outside of communication, such as online gaming and surfing. One of the primary issues linked to the growing usage of cellphones is wrist and hand weakness. Flexion and extension of the wrist, thumb, and fingers causes this weakening and serious musculoskeletal disease. The association between hand and pinch grip strength and the length of time spent using a smartphone to track screen time is not well

understood. Thus, the aim of the research was to look into the relationship between young people's hand and their pinch grip strengths and the length of time they spend using smart phones. One hundred teenage boys offered their time to take part in the research. A digital scale and a portable stadiometer were used to quickly measure each participant's height and weight. A handheld dynamometer was used to assess the strength of the hand and pinch grips. The amount of time spent on smartphones was calculated using the average daily screen time over the previous seven days.

III. EXISTING SYSTEM

Currently, smartphone addiction is predominantly identified through subjective methods, including self-reported surveys and psychological evaluations conducted by healthcare professionals. These assessments often rely on individuals to accurately report their behaviors and emotions, which can lead to inconsistencies due to factors like mood, self-perception, or misunderstanding of survey questions. These methods may include standard questionnaires such as the Smartphone Addiction Scale (SAS), which evaluates addiction levels based on self-reported data on phone usage and associated feelings. However, this reliance on subjective responses introduces a substantial margin for error, as people may underreport or inaccurately gauge their usage habits. Additionally, there is no universally adopted scale to measure smartphone addiction, meaning that different studies or healthcare providers might use varying benchmarks, which affects the comparability and reliability of results. Existing smartphone monitoring applications, though helpful in tracking metrics like screen time or specific app usage, fall short in offering a holistic view of addiction risk. They often overlook crucial psychological and demographic factors that influence addiction and lack predictive power, providing only descriptive summaries of behavior without insight into future risk. Consequently, the current system is limited in its capacity to proactively identify individuals at risk of developing smartphone addiction, and intervention often occurs after negative impacts on productivity, social interactions, and mental well-being have already materialized.

Algorithms used :

Descriptive Statistics and Correlation

Psychometric Scales

Cluster Analysis

Disadvantages :

The traditional approaches for identifying smartphone addiction have several notable disadvantages. Since they rely on self-reported data, there is a high possibility of inaccurate or biased responses, as individuals might not fully recognize or honestly report their usage patterns. This makes it difficult for professionals to reliably gauge addiction severity. Furthermore, traditional psychological assessments are typically time-consuming and often require skilled interpretation, which can make them costly and inaccessible for the general population. In addition, the absence of standardized measures to consistently identify addiction makes it challenging to apply these methods broadly across different demographics or contexts. Smartphone monitoring apps,

while somewhat informative, lack comprehensive data analysis capabilities, as they primarily focus on screen time or app usage rather than psychological factors like stress, anxiety, or depression, which are often strongly associated with addiction. This reactive approach to intervention means that issues are only addressed once symptoms are evident, often too late to prevent significant adverse effects on mental health, productivity, or social relationships. Therefore, there is a pressing need for a more objective, data-driven system that enables early detection of addiction risk and supports timely intervention.

IV. PROPOSED SYSTEM

The proposed system aims to address the limitations of traditional approaches by employing machine learning to predict smartphone addiction risk based on a range of data inputs, including demographic information, smartphone usage patterns, and psychological factors. Data collected from a survey of smartphone users, covering variables like age, gender, phone usage habits, and mental health indicators such as stress and anxiety, are preprocessed to ensure accuracy and consistency. This preprocessing includes encoding categorical variables and normalizing numerical data, which enhances model performance and enables meaningful comparisons across diverse data points. After preprocessing, the data is split into training and testing sets, allowing the model to learn correlations between input features and addiction risk. The machine learning model is then trained using methods such as decision trees, random forests, and logistic regression, chosen for their ability to capture complex patterns in the data. After training, the model evaluates its predictive performance using metrics like accuracy and recall, providing an objective assessment of addiction risk. With this model, healthcare providers can identify individuals at high risk for addiction based on real-time data inputs and recommend timely interventions.

Advantages:

This machine learning-based system offers several advantages that improve upon traditional approaches. Firstly, it provides an objective, data-driven assessment of smartphone addiction risk, reducing reliance on subjective self-reporting. The model's ability to incorporate a wide range of features, including screen time, notification-checking frequency, and psychological factors like stress, allows for a comprehensive understanding of addiction risk. This approach enables early identification of at-risk individuals, making proactive intervention possible before negative effects escalate. The model's predictive accuracy can also be valuable for app developers, who can use these insights to design applications that encourage healthier usage patterns, potentially reducing addictive tendencies in their user base. Additionally, by automating data collection and analysis, the system is scalable and can be easily applied to large, diverse populations, offering valuable insights across different demographics. Overall, this system supports better mental health outcomes and promotes balanced smartphone use, making it a valuable tool for both healthcare providers and technology developers in the pursuit of healthier digital habits.

V. BLOCK DIAGRAM

System Architecture:

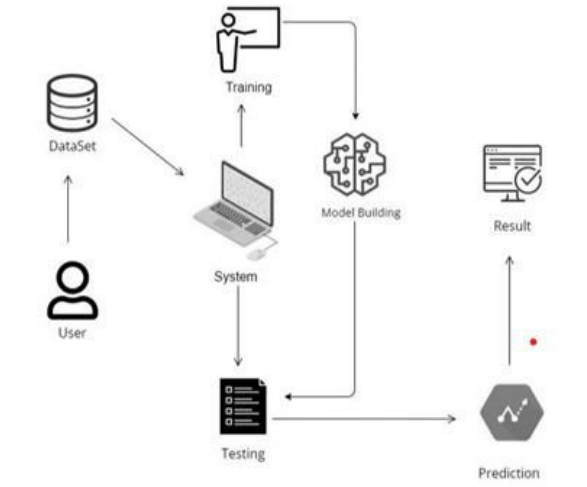


Fig 2. Architecture Diagram

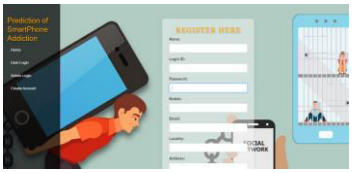
VI. IMPLEMENTATION

Landing Page / Main Interface:

User Login Screen:

Admin Login Screen:

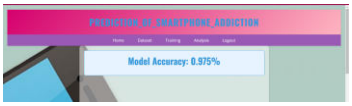
User Registration Page:



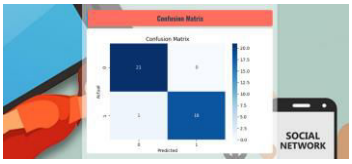
User Home Dashboard:

Dataset Viewer Interface:

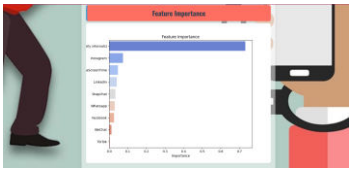
Model Accuracy & Confusion Matrix:



Feature Importance Plot:

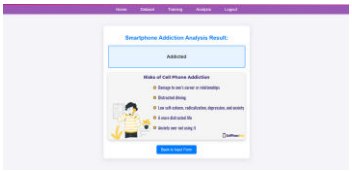


Model Evaluation Classification Report:



Smartphone Addiction Predictive Analytics:

Final Prediction Result Dashboard:



VII. CONCLUSION

For this project, we used machine learning model approaches such decision trees, random forests, logistic regression, Multi-Layer-Perceptron (MLP) and Adam (Adaptive Moment Estimation) to create a user-friendly application named prediction of smartphone addiction. Using the finest methods we could find, we were able to demonstrate that while some people are not addicted, they may be. We have successfully developed a user-friendly application in this project that uses Machine Learning Model approaches to predict smartphone addiction. The goal was to provide a workable way to identify those who could be at risk of developing a smartphone addiction. For the most accurate forecasts, this study has carefully selected and adjusted these machine learning algorithms and developed a strong prediction model by utilizing a broad dataset that included several variables including screen time, app usage, and self-reported behaviors. This approach offers important insights into consumers' smartphone usage behaviors by classifying them into three groups: possibly addicted, not addicted, and addicted.

VIII. FUTURE SCOPE

Integration with Real-Time Usage Data:

Instead of relying solely on survey data, future models could incorporate real-time smartphone usage data, such as screen time, app usage statistics, and notification frequency, through app-based monitoring. This would improve model accuracy and provide insights into real-time behavioral patterns.

Incorporating More Behavioral and Environmental Features:

Expanding the dataset to include environmental factors such as location data, time of day, and social interactions could offer more context to phone usage patterns. Additionally, features like in-app behavior, notification responses, and social media activity can further enhance prediction accuracy.

Adding More Advanced Deep Learning Models:

While current models are effective, exploring more complex architectures like recurrent neural networks (RNNs) and transformer-based models might capture temporal patterns in usage data, offering more dynamic predictions of addiction trends over time.

Developing a Self-Monitoring App with Feedback Mechanisms:

An interactive app could be created to give users feedback on their phone usage patterns and provide suggestions or reminders for healthier usage. Users could set goals for reducing screen time, track their progress, and receive tips for managing smartphone addiction based on their personalized usage.

Building a Multi-Language and Cross-Cultural Model:

Expanding the dataset to include data from diverse linguistic and cultural backgrounds would help build a model with global applicability, enabling more accurate predictions across varied populations. It would make the model more inclusive and applicable to a broader range of users.

Including Mental Health Assessments and Recommendations:

By integrating mental health resources, the app could assess related mental health factors (e.g., stress, anxiety, and depression) and provide

users with recommendations for mental health resources or suggest mindfulness practices to help manage addiction tendencies.

Predictive Modeling with Temporal Analysis:

Future iterations could involve temporal analysis, where the model not only predicts addiction risk but also identifies trends over time. This could help in understanding how addiction develops and fluctuates, aiding in early intervention and relapse prevention.

Exploring Additional Machine Learning Techniques:

Exploring ensemble methods or hybrid approaches (such as combining traditional ML with deep learning) could further enhance accuracy. Techniques like meta-learning, where the model learns from multiple model outputs, may also improve robustness.

Collaboration with Healthcare Providers for Intervention:

Developing partnerships with mental health professionals could allow the model to serve as an early screening tool. This could assist healthcare providers in identifying at-risk individuals and offering tailored interventions or counseling sessions based on the addiction prediction scores.

Personalization of Prediction Models:

By adding personalization features, the model could adjust based on individual baseline behaviors, thus improving the model's predictive capacity by recognizing unique usage patterns rather than general usage statistics.

IX. 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. A randomised controlled trial aimed at improving neck pain, posture, quality of life, and endurance in individuals with nonspecific neck pain by incorporating a smartphone app into global postural re-education.Trials 22, 274 (2021).

[3] Osorio-Molina, C. et al. A systematic review and meta-analysis of smartphone addiction among nursing students, risk variables, and its detrimental impacts. Nurse Educ. Today 98, 104741 (2021).R. Nicole, "Title of paper with only first word capitalized," J. Name Stand. Abbrev., in press.

[4] Osailan, A. B An observational study examined the association between young people's hand and pinch grip strength and the length of time they used their smartphones to track screen time. MC Musculoskelet. Disord. 22, 186 (2021). M. Young, The Technical Writer's Handbook. Mill Valley, CA: University Science, 1989.

[5] Hitti, E., Hadid, D., Melki, J., Kaddoura, R. & Alameddine, M The prevalence, use, and attitudes of mobile device use among emergency department healthcare personnel.. Sci. Rep. 11, 1917 (2021).

[6] Shaygan, M. & Jaberi, A. The impact of a smartphone-based pain management software on teenagers with chronic pain's quality of life and level of discomfort. Sci. Rep. 11, 6588 (2021).

[7] 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).

[8] 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).

[9] Thornton, L. et al. A multiple health behavior change, self-monitoring mobile app for adolescents: Development and usability study of the Health4Life App. JMIR Format. Res. 5, e25513 (2021).

[10] 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).