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MACHINE LEARNING MODEL FOR PREDICTION OF SMARTPHONE ADDICTION

[1]D.Srinivasa Rao, [2]Kamireddy Vaishnavi
[1]Associate Professor,[2]PG Scholar, Department of CSE
[1,2]N.B.K.R Institute of Science & Technology (Autonomous), Vidyanagar

ABSTRACT

There has been a growing concern about smartphone addiction in recent years, with more and more people experiencing symptoms such as excessive phone use, decreased productivity, and more. to physical and mental health problems. Therefore, there is a need to develop effective tools to predict smartphone addiction and identify those at risk. Cell phone addiction. The survey included questions about demographics, cell phone usage patterns, and various psychological conditions such as anxiety, depression, and stress. It is a popular and effective machine learning technique for building our models. 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 most important thing Factors that predict addiction include phone usage patterns, such as how often you check for notifications, how many hours you spend on your phone each day, and the types of apps you use it. Other important factors are age, gender and stress. Health professionals can use it to identify people at risk of smartphone addiction and provide appropriate intervention. Application developers can also use it to design less complex apps and promote healthier cell phone usage habits. In conclusion, our study demonstrates the feasibility and effectiveness of using machine learning models to predict smartphone addiction. Further research is needed to validate our findings on larger and more diverse data sets and to explore the potential application of this model in different contexts.

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

I. 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 logistic regression, decision trees, or random forests, 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. The model produces a probability score that indicates the risk of smartphone addiction. 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..

II.LITERATURE REVIEW

[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. The experimental group used hands-on learning strategies (n=15), while the control group took lecture-based classes (n=26). 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. In addition, the students felt that work-based learning was a method that significantly increased their motivation. Researchers and practitioners should consider that action learning can have an effect on academic achievement and performance and increase student motivation.

[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).

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). Sixty male and female office workers (38.5 ± 9.1 years) with chronic neck pain were divided into three groups: Group 1 (GPR + smartphone application, n = 20), Group 2 (GPR only, n = 20) and Group 2 (GPR only, n = 20). The primary outcome was pain, and the secondary outcomes were disability, quality of life, endurance, and posture. Pain, disability, endurance, quality of life and posture were assessed using a visual analog scale (VAS), Neck Disability Index (NDI), Progressive Isoinertial Lift Evaluation (PILE) test, Quality of Life Questionnaire (SF-36) and photogrammetry. each before and 8 weeks after the intervention. One-way analysis of covariance (ANCOVA) was performed to analyze the data statistically

[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 use of smartphones has become widely popular, especially among young people, for multiple purposes other than communication, including gaming and internet browsing. The hand and wrist weakness is one of the main complications associated with the increased use of smartphones. This weakness occurs due to the repetitive flexion and extension of the wrist, thumb, and fingers, leading to a significant musculoskeletal pathology. Little is known about the relationship between smartphone usage duration (using the phones ability to monitor screen time) and hand-grip, pinch-grip strength. Therefore, 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 devices are becoming increasingly popular in the world of healthcare and are used by healthcare providers. We examined the extent and frequency of mobile device use, and perceptions of clinical and personal use, among healthcare providers (physicians, residents, and nurses) in the emergency department (ED).) at a major health center in Lebanon. Half of the target population (N=236) completed the electronic questionnaire. 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. Among 30 regularly active college students, 15 participants reported SRC occurrence prior to testing (M time since injury = 4.0 years, SD = 3.1, range = 5 months to 11 years). We found good test-retest accuracy (ICC $\leq$ 0.70) for the primary measures derived from the smartphone app; Internal consistency was good (Cronbach's $\alpha \leq 0.80$). The power-walking test showed a significant difference in strength in response to exercise between participants with a history of SRC (HxSRC) and those without a history of SRC (No SRC), which is best determined by the inverse efficiency index (IEI:X Group). Interaction test p = 0.055). Our findings suggest that the effects of long-term SRC development can be seen through an easy-to-administer screening program that can identify individual athletes who would benefit from intervention to return to their best performance. and health.

III.EXISTING METHOD:

In the existing system, implementation of machine learning algorithms is bit complex to builddue to the lack of information about the data visualization. Mathematical calculations are used in existing system for Logistic Regression model building this may takes the lot of time and complexity. To overcome all this, we use machine learning packages available in the scikit-learn library.

Disadvantages:

1. Requires more time
2. Difficult to handle

IV.PROPOSED SYSTEM

Several machine learning algorithms can be used to predict smartphone addiction. Some machine learning algorithms are decision trees or random forests. A comparative study of machine learning methods used to propose and calculate the best analysis methods for smartphone attachment detection is presented in this section, we first implement this set data and individual implementation changes, then combine these results and calculate their accuracy..

Advantages:

1. Requires less time
2. Good score
3. Easy to handle

Block Diagram:

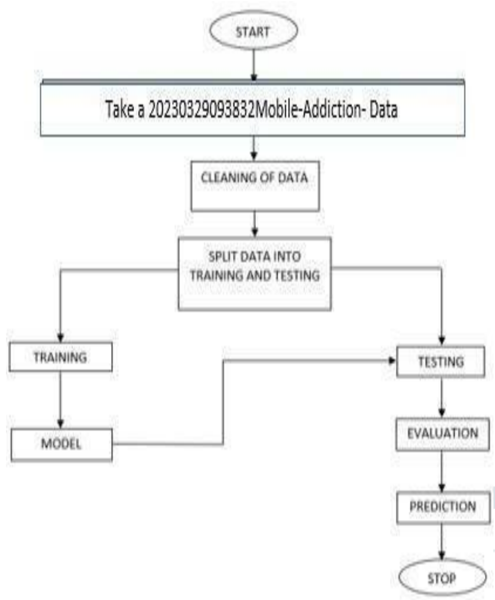

Fig 1. Block Diagram of Proposed System

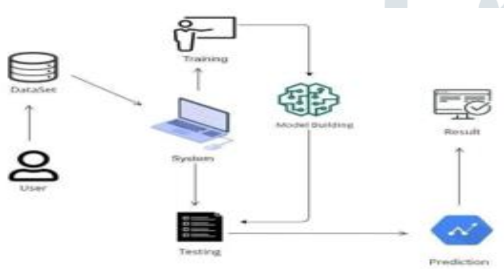

Fig 2: Architecture diagram

V.MODULE DESCRIPTION

User:

Register:

Users can register for the Mobile web application here.

Login:

After registering, the user can access his portal.

View Data:

View data What are the Data There in dataset (cleaned dataset)

Input:

User will give the input values.

Result History:

After giving the inputs, model will predict the result which it was set according toperformance, it will predict that the Mobile Addiction.

Take Dataset:

The dataset for the 20230329093832Mobile-Addiction Data is collected from the kagglewebsite (kaggle.com).

The size of overall dataset is 80.0 KB (81,920 bytes).

Pre-processing:

- In preprocessing first of all we will check whether there is any Nan values.
- If any Nan values is present we will fill the Nan values with different fillna techniqueslike bfill, ffill, mode, and mean.
- Here we used the ffill (front fill) technique on our project.

Training the data:

Irrespective of the algorithm we select the training is the same for every algorithm**.**

Given a dataset we split the data into two parts training and testing, the reason behind doing this is to test our model/algorithm performance just like the exams for a student the testing is also exam for the model.

We can split data into anything we want but it is just good practice to split the data such that the training has more data than the testing data, we generally split the data.

And for training and testing there are two variables X and Y in each of them, the X is the features that we use to predict the Y target and same for the testing also.

Then we call the .fit ( ) method on any given algorithm which takes two parameters i.e., X and Y for calculating the math and after that when we call the .predict ( ) giving our testing X as parameter and checking it with the accuracy score giving the testing Y and predicted X as the two parameters will get our accuracy score and same steps , these are just checking for how good our model performed on a given dataset.

VI.OUTPUT RESULTS

Fig 3: Home Page

Fig 4: About Page.

VII.CONCLUSION

In this project, we developed a user-friendly app called Smartphone Addiction Prediction using machine learning modeling techniques such as decision trees, random forests, logistic regression, and we used the best method we found, showing addiction, non-addiction, and risk of addiction. .

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