DMPedia Lecture Notes in Multidisciplinary Research,
Volume 1, pp.48-53, 2026

International Conference on Multidisciplinary Perspectives in Advanced Computing and Technology (IMPACT 2026)
G. B. Pant University of Agriculture and Technology, Uttarakhand, India. Jan. 10-11, 2026

Smart Phone Addiction Prediction and Analysis

Vishakha Vijay Kadam, H.A.Akarte

Department Of Computer Engineering,DR. BATU, LONERE, BATU University, India

Vishakha.kadam84@gmail.com[1], haakarte@dbatu.ac.in

ABSTRACT

The role of big data analytics in analysing smart phone addiction is changing in this age of rapidly advancing technology, as more and more people show signs of smartphone addiction, including overuse of phones, a decline in productivity, and potential issues with one's physical and emotional well-being. The aim of this study was to identify the main arguments for the need for prediction analysis as well as if smartphone use might be utilized to forecast levels of smartphone addiction. wherein we will investigate the health issues that are expected to impact the individual. This research study has used the openly available dataset of smartphone usage by people and with a combination of machine learning algorithms as cat BOOST smartphone addiction level for effective decision making. According to the simulation results, cat boost algorithm achieved the best accuracy with a score 97.3

Keywords: *Smartphone addiction, Mobile learning, Academic performance, Posture analysis, Neck pain, Screen time, Mental health, Machine learning*

1. Introduction

The concern about smartphone addiction has been on the rise lately, as more and more individuals exhibit signs of this addiction, such as distracting activities in their daily lives, excessive phone use, decreased productivity, and even a number of physical and mental health problems. These highlight the need for efficient methods to forecast smartphone addiction and spot potential danger signs. While smartphones are invaluable in enhancing human-machine interactions and come with numerous benefits, their increasing usage has also led to cases of overuse and addiction. To address this, we've developed a model to predict smartphone addiction. This model is based on data from a study of smartphone users. Demographics, phone usage patterns, and psychological variables including stress, anxiety, and depression were all covered in the study. Sleep patterns, frustration, and anger management [1]. We collected data from a wide variety of sectors, asking questions about individuals' daily lives, which will help us make accurate predictions about a person's situation. Addiction to smart phones can have a number of detrimental impacts on one's physical and emotional well-being. Long-term screen use often causes headaches, eye strain, and irregular sleep patterns, particularly because blue light suppresses melatonin production. Excessive smartphone use can raise the risk of obesity and associated health problems by causing bad posture, neck pain (often referred to as "text neck"), and decreased physical activity [2]. Mentally, smartphone addiction is associated with higher levels of stress, worry, and depression, especially in young people who may experience FOMO or social media pressure. This dependence can eventually shorten attention spans, decrease in-person social connections, and have a detrimental effect on performance at work or in school. These are the primary justifications for the necessity of predic tion analysis. wherein we will investigate the health issues that are expected to impact the individual. The data is divided into two categories: the training set and the test set. Through the matching input and output labels, the machine learning model is trained using the training set. These pupils gain the ability to identify trends in data and draw links between output labels and input attributes. Following training, A test set is used to evaluate how well the model performs. Among the various metrics used to evaluate the model's performance is accuracy. Modify the model's parameters and use a different algorithm until good performance is attained. Once developed, the model can be adjusted to predict an individual's smartphone addiction based on specific input characteristics. The model generates a probability score that indicates the possibility of smartphone addiction. As a result, those who are at danger of addiction can receive the proper assistance and intervention. In summary, machine learning models can be a helpful tool for predicting smartphone addiction and identifying people who may be at risk. These models can assist people and medical professionals in taking action to lessen the harmful impacts of addiction and prevent it altogether. Nonetheless, it is critical to gather high quality data and create precise, trustworthy models that have practical applications.

The rest of the paper is organised as follows: Section 2 discusses the research methodology, and Section 3 discusses the literature survey. Sections 4 and 5 present the working principle and the result discussion, respectively. Finally, section 6concludese the work.

2. Research Methodology

We're excited to utilize the well-known and effective Cat Boost algorithm for our machine learning model! This approach naturally handles categorical variables, meaning there's no need for one-hot encoding or label encoding. Plus, it boasts high accuracy across many real-world datasets, is fast and robust with optimized training speed and GPU support, and is less prone to overfitting than traditional GBM methods. It even works well with imbalanced data by allowing class weights. After we preprocess the data, To make sure the model is learning well, we train it and assess its performance using accuracy. Our results clearly demonstrated how effective the recommended treatment is at curbing smartphone addiction. The key features for predicting addiction included various phone usage patterns, such as how often users check notifications, the number of hours spent on their phones each day, and responses to questions about their daily routines. Additionally, factors such as age, gender, and stress levels played important roles. Our model has a wide range of potential applications! It can be used by medical experts to identify those who are at risk of becoming addicted to smartphones and to provide appropriate therapies. App developers could also leverage the model to create apps that are less addictive and encourage healthier phone usage habits.

3. Literature Survey

Schou Andreassen C, Billieux J, Demetrovics Z, Mazzoni E, Griffiths MD, and Pallesen S talked about [4] a comprehensive cross-sectional study examining the connection between signs of psychiatric diseases and compulsive social media and video game use An online cross-sectional survey was completed by 23,533 adults (mean age 35.8 years, ranging from 16 to 88 years) in order to determine whether demographic factors, symptoms of OCD, ADHD, anxiety, and depression could account for variance in the addictive use (i.e., compulsive and excessive use linked to negative outcomes) of two contempo rary online technologies: video games and social media. Even though there was only a modest correlation between the two addicted technological behaviors, there were positive and sub stantial correlations between the symptoms of mental disorders and the symptoms of addictive technology use. The addictive usage of these technologies seemed to be inversely correlated with age. Video game addiction was highly correlated with male gender, while social media addiction was significantly correlated with female gender. Video gaming and compulsive social networking were positively correlated with being single. According to hierarchical regression analysis, demographic characteristics accounted for 11–12Between 7 and 15 II) Mike Rennoldson, Mark D. Griffiths, and Melina A. Throuvala talked on school-based prevention for teenage in ternet addiction: prevention is the key. By leveraging the recommendations of these studies, the systematic literature review aims to (i) identify school-based prevention programs or protocols for Internet addiction that target adolescents within the school context and examine the effectiveness of the programs; and (ii) highlight best practices, limitations, and strengths to inform the design of new initiatives. The results of the research that have been analyzed thus far have yielded inconsistent conclusions and require additional empir ical support. In order to: (i) more precisely define the clinical status of Internet addiction (IA); (ii) build methodologically sound evidence-based prevention programs; (v) concentrate on skill enhancement and the use of protective and harm reducing factors; (vi) include IA as one of the risk behaviors in multi-risk behavior interventions; (iii) use more recent psychometrically robust assessment tools for the measurement of effectiveness (based on the most recent empirical devel opments); and (iii) reconsider the main outcome of Internet time reduction as it appears to be problematic. These seem to be important considerations for future research plans and the development of new preventive programs. In a comprehensive analysis of epidemiological studies conducted over the past ten years on internet addiction, L. Karila and J. Billieux noted that internet use has increased dramatically worldwide over the past ten years. As Internet use grows in popularity and frequency, more and more papers are pointing out the possible drawbacks of excessive use. Research on Internet addiction has increased dramatically in the past ten years [3]. IV) Hadadnezhad M, Khosrokiani Z, Letafatkar A, & Akhshik H. [7] 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 Randomised Controlled Trial. (This study’s main goal is to conduct a systematic literature review (SLR) to compile, synthesize, and assess the state-of-the-art for spatiotemporal crime hotspot identification and prediction methodologies.) Osailan A.’s [5], The Relationship Between Smartphone Usage Duration” (using the smartphone’s hand-grip and pinch-grip capabilities to monitor screen time) Young People’s Strength: An Observational Study. ”BMC Musculoskeletal Disorder” by Melki J, Hadid D, and Hitti E [6] VI) Alameddine, M. and Kaddoura, R [7]. The frequency, use, and attitudes of mobile devices among emergency department medical staff. Healthcare providers are increasingly using mobile devices, and their use is becoming more widespread. In the Emergency Department (ED) of a major academic medical center, we looked at the frequency and prevalence of mobile device use as well as the attitudes of healthcare professionals (attending physicians, residents, and nurses) about clinical and personal use

4. WORKING PRINCIPLE

Let’s collect data from a range of sources, including self-reported questionnaires, app statistics, smartphone usage logs, and user surveys. We record information about user demo graphics, screen time, the quantity of unlocks, the duration of use of certain apps, and precise times of day. In addition to addressing any missing numbers, we can also resolve any discrepancies in the data by either adding them or deleting them. Normalization is necessary to make sure that our numerical features are scaled similarly. To efficiently process categorical data, we can use methods such as label and one-hot encoding. The raw usage data will subsequently be combined into useful measures, such include the average daily screen time, the overall amount of time spent using apps, and how often they are used. We can also design additional features that may indicate addiction, such as the percentage of screen time devoted to social networking applications or how gaming apps affect sleep. Additionally, we can look for traits that show how screen time and stress levels are related. To ascertain which traits are most closely linked to smartphone addiction.

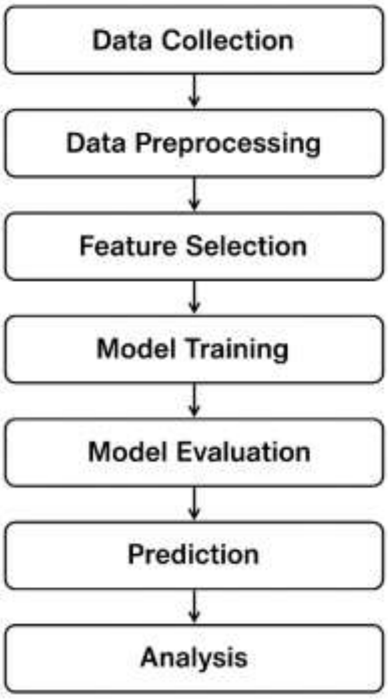

Figure 1: Flow for Predicting smartphone addictiom

5. Results and Discussion

Predicting Troublesome Smartphone Use Using Machine Learning This work employed decision trees, Random Forest (accuracy 82.6 percent), and CatBoost to analyze survey and usage data from indian people to estimate addiction risk using 16 characteristics, such as demographics and content utilization.

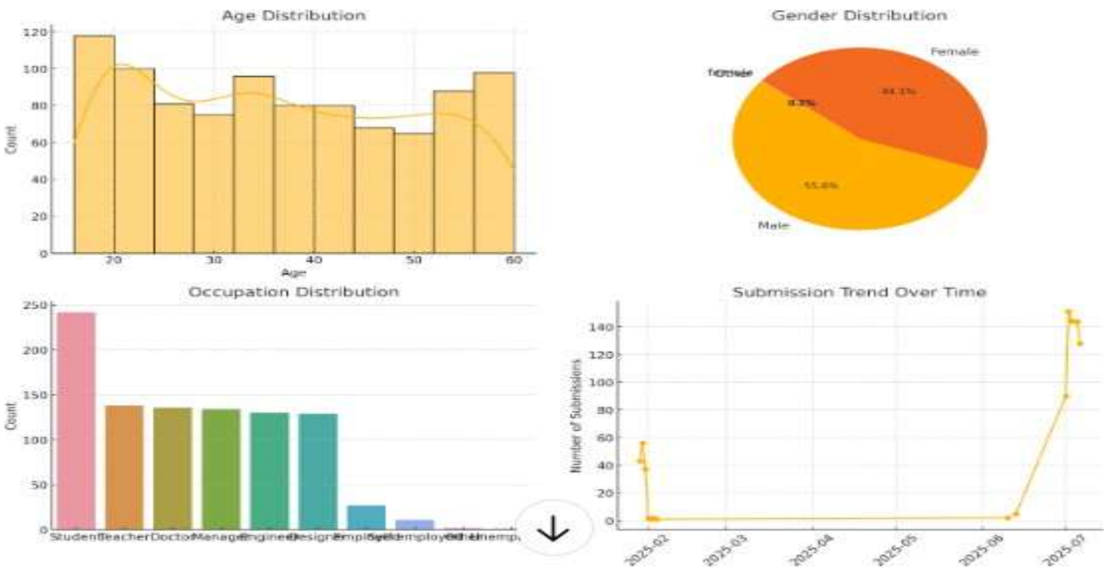

Figure 2: Pie chart ,Bar chart ,trend lines for Occupation Distribution, Age Distribution, Gender Distribution, Submission Trend over Time

Graphs generated After analysis Metric CatBoost Accuracy (Training Time (s) : 45 Inference Speed : High Memory Usage (MB) : 320 Inference Speed (CPU) : 50K–100K predictions/sec Results from the data collected • Count: 949 • Mean Age: 36.66 years • Median (50• Min Age: 16 years • Max Age: 60 years • Standard Deviation: 13.30

```
bestTest = 1
bestIteration = 18

Shrink model to first 19 iterations.
✅ Accuracy: 1.0

Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         4
           1       1.00      1.00      1.00       188

    accuracy                           1.00       192
   macro avg       1.00      1.00      1.00       192
weighted avg       1.00      1.00      1.00       192


Confusion Matrix:
 [[  4   0]
 [  0 188]]
📦 Model saved successfully!
```

Figure 3: Output of training dataset after applying cat boost algorithm

6. Conclusions

Based on user behaviour and usage patterns, the" Smart phone Addiction Prediction and analysis" project demonstrates the amazing potential of cutting-edge machine learning approaches to detect patterns of smartphone addiction. The system achieves exceptional prediction accuracy by utilizing a range of complex models, including the Extra Trees Classifier, Cat Boost Classifier, and Stacking Classifier. Its robustness and utility in predicting smartphone addiction tendencies are truly shown by its capacity to handle categorical data effectively and manage nonlinear connections. The method is a reliable tool for determining whether a person is at danger of smartphone addiction since the models produce reliable classifications based on a dataset that covers a wide variety of factors related to phone usage behaviour. In conclusion, by combining state of-the-art machine learning algorithms with an intuitive user interface, our project provides a comprehensive answer to the problem of smartphone addiction prediction. It turns out to be a useful tool for people and researchers who want to comprehend and address the growing issue of smartphone reliance

Acknowledgements

I would like to express my sincere gratitude to my Guide, Harishchandra A. Akarte, for their valuable guidance, continuous support, and encouragement throughout the course of this research. Their insightful feedback and suggestions were instrumental in shaping the direction and quality of this work.I also extend my heartfelt thanks to all the faculty members of the Department Of Computer Engineering, Dr. BATU,Lonere, for their support, encouragement, and for providing a stimulating academic environment. Their knowledge and expertise have greatly contributed to the development of this research. Finally, I am grateful to everyone who directly or indirectly contributed to the successful completion of this project.

Funding source

No funding was received for this study.

Conflict of Interest

I declare no conflict of interest.

References

[1]. Singh, P., & Shariff, M. A. U. (2023, July). An Unobtrusive Approach for Detecting Smartphone Addiction. In 2023 IEEE International Conference on Electronics, Computing and Communication Technologies (CONECCT) (pp. 1-6). IEEE.

[2]. Demir, K. Akpinat, E. The effect of mobile learning applications on students' academical achievement and attitudes toward mobile learning. Malays. Online J. Educ. Technol. 6, 48–59 (2018).

[3]. 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).

[4]. Osorio-Molina, C., Martos-Cabrera, M. B., Membrive-Jiménez, M. J., Vargas-Roman, K., Suleiman-Martos, N., Ortega-Campos, E., & Gómez-Urquiza, J. L. (2021). Smartphone addiction, risk factors and its adverse effects in nursing students: A systematic review and meta-analysis. Nurse education today, 98, 104741.

[5]. Osailan, A. (2021). 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 musculoskeletal disorders, 22(1), 186.

[6]. Hitti, E., Hadid, D., Melki, J., Kaddoura, R.Alameddine, M. Mo bile device use among emergency department healthcare professionals: prevalence, utilization and attitudes. Sci. Rep. 11, 1917 (2021). addiction and sleep: A UK cross-sectional study of young adults. Front. Psych. 12, 629407 (2021).

[7]. Yorozu, T., Hirano, M., Oka, K., & Tagawa, Y. (2008). Electron spectroscopy studies on magneto-optical media and plastic substrate interface. IEEE translation journal on magnetics in Japan, 2(8), 740-741.