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Machine Learning Model for Prediction of Smartphone Addiction

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Abstract: In this era of advancing technology, where smartphone addiction is becoming a growing concern, with an increasing number of people exhibiting symptoms such as excessive phone usage, reduced productivity, and potential physical and psychological health issues, the role of big data analytics is evolving in analysing the smartphone addiction. This study aimed to find the possibility of predicting smartphone addiction levels based on their use of smartphones. This research study has used the openly available dataset of smartphone usage by people and with a combination of machine learning algorithms such as Decision Tree, Logistic Regression, and Random Forest to analyse smartphone addiction level for effective decision making. According to the simulation results, the Random Forest algorithm achieved the best accuracy with a score of (0.89), the decision tree algorithm achieved the accuracy score of (0.86). The least performer was Logistic Regression which achieved an accuracy score of (0.74).

Keywords: Logistic Regression, Decision Tree, Random Forest

INTRODUCTION

The proliferation of smartphones has fundamentally transformed various aspects of modern society, with profound implications for individual behavior and well-being. In recent years, the phenomenon of smartphone addiction has garnered increasing attention, reflecting the growing recognition of its impact on mental health and social functioning.

Smartphones have become indispensable tools in our daily lives, facilitating communication, information access, and entertainment. However, the widespread use of smartphones has also given rise to concerns about excessive usage patterns and their associated consequences. Smartphone addiction, characterized by compulsive and dysfunctional smartphone usage, has emerged as a significant public health issue, affecting individuals of all ages.

Overcrowding in digital spaces, coupled with the constant influx of notifications and stimuli, can contribute to excessive smartphone usage and addictive behaviors. This, in turn, may lead to negative outcomes such as decreased productivity, social isolation, and psychological distress.

Recent research has utilized machine learning techniques [1] to predict smartphone addiction levels based on the data collected from people 15 to 25 years old. These studies [2] have compared the performance of various algorithms, including Decision Tree, Random Forest, XGBoost and evaluated them using metrics like accuracy.

The current study proposes a model that uses a dataset collected from [12] and performed data cleaning on it for more confident results. We have applied machine learning algorithms on the data to predict the results and get the prediction for smartphone addiction as yes or no. We evaluate our model using accuracy scores for the best machine learning technique which is able to predict the smartphone addiction. The paper is organized as follows: Section II discusses relevant literature, Section III describes the methodology, Section IV presents the results, Section V discusses the findings, and Section VI concludes the paper.

RELATED WORK

Research into smartphone addiction has adopted methodologies akin to those used in healthcare facility prediction to forecast addiction levels. Chen and Wu (2021) explored the reciprocal relationship between sleep problems and problematic smartphone use in Taiwan through a cross-lagged panel study. This research sheds light on how sleep issues and smartphone addiction interact over time, offering insights into potential intervention strategies [3].

Similarly, Lopez-Fernandez *et al.* (2017) conducted a European cross-cultural empirical survey on self- reported dependence on mobile phones among young adults. Their study delved into the prevalence and impact of mobile phone addiction, providing valuable data on the scope of the issue across diverse cultural contexts [4]. Goswami and Singh (2016) conducted a comprehensive literature review on the impact of mobile phone addiction on adolescents' lives. Their synthesis of existing research findings highlighted the multifaceted effects of excessive smartphone use on various aspects of adolescent behavior and well-being [5].

Furthermore, Seo *et al.* (2016) investigated the consequences of mobile phone dependency on adolescents' social and academic behaviors. Their study contributed insights into the relationship between smartphone addiction and its adverse outcomes, informing interventions aimed at mitigating negative consequences among adolescents [6]. Beyond smartphone addiction specifically, Bodker,Gimpel, and Hedman (2009) examined the user experience of smartphones from a consumption values perspective. Their research provided insights into individuals' perceptions of and value derived from smartphone usage, offering a nuanced understanding of the factors influencing smartphone adoption andusage patterns [8].

Additionally, Ahmed and Perji (2011) explored the relationship between mobile phones and youngsters, assessing whether mobile phones are viewed as a necessity or an addiction. Their study enhanced understanding of how mobile phone usage patterns among youngsters impact their daily lives and well-being [9]. These studies highlight diverse approaches to understanding smartphone addiction and its implications across various demographics and settings. By leveraging different methodologies and perspectives, researchers aim to develop effective intervention strategies and enhance healthcare delivery to address smartphone addiction and its associated negative outcomes.ion mechanism. Transformers are large and heavy and require a lot of space. There have been extensive studies to reducethe size and weight of transformers.

METHODOLOGY

The proposed implementation for our machine learning model in predicting smartphone addiction is asthe paper follows.

1. Dataset: In this research study, the predictive analysis is done using a dataset from the Dataworld dataset repository. The dataset contains 5000 records. The dataset is quite suitable for this research asthe dataset comprises 19 predictor factors:

- Timestamp
- full name
- gender
- Do you use your phone to click pictures of class notes?
- Do you buy books/access books from your mobile?
- Does your phone's battery last a day?
- When your phone's battery dies out, do you run for the charger?
- Do you worry about losing your cell phone?
- Do you take your phone to the bathroom?
- Do you use your phone in any social gathering (parties)?
- Do you check your phone just before going to sleep/just after waking up?
- Do you keep your phone right next to you while sleeping?
- Do you check emails, missed calls, texts during class time?
- Do you find yourself relying on your phone when things get awkward?
- Are you on your phone while watching TV or eating food?
- Do you have a panic attack if you leave your phone elsewhere?
- You don't mind responding to messages or checking your phone while on date?
- For how long do you use your phone for playing games?
- Can you live a day without phone?

The exploratory analysis shows that all of the 19 factors estimated the likelihood of target variable and acted as dependent variables, and there is a correlation between dependent and independent variables, while the independent target variable (whether you are addicted to phone) was defined with three possible values of whether you are addicted to phone? ‘addicted’ or ‘not addicted’ or 'may be addicted'. The data is split in the ratio of 70-30 with 70\% for training and 30\% for testing.

2. Data Cleaning: During the data cleaning procedure, managing missing and null values was the main priority. These missing values were visually represented via visualization. The interpolation technique was then used to substitute approximated values for the missing numerical data. With this method,which is frequently applied in Python dataset processing, the missing value is computed using known values. This method works especially well for adding missing data that are considered necessary. In addition, missing values in categorical variables were addressed using the forward fill approach. Using this tactic, a missing value is filled in with the most recent acceptable value that was noticed.

3. Experimental Setup: The Python PyCharm IDE is used in this research study for data management and processing. Essential Python packages like scikit-learn, PyTorch, and TensorFlow are included withPyCharm. Its graphical user interface (GUI) makes it easier to manage packages and libraries and run applications. The prediction model is created using three machine learning algorithms: logistic regression, decision trees, and random forest classifier. Microsoft Windows 10, 8, or 7 and a minimum of 8 GB of RAM (recommended) and 2 GB of hard disk space are needed for PyCharm, in addition to atleast 1 GB of cache space.

4. Exploratory Analysis: The subsequent stage is examining the data using exploratory analysis in order to obtain a deeper understanding. This entails using histograms, bar charts, and line graphs to analyzethe correlations between dependent variables as well as between dependent and independent (target) variables. To ascertain which variables are essential for forecasting the objective variable, a thorough investigation of the variables is the aim. Based on the predicted variables, this phase helps predict a smartphone's addiction.

5. Predictive Analysis: Using three machine learning algorithms for predictive analysis is the next stage.With values for addicted or not addicted, the predictive model will estimate the target variable "whether you are addicted to phone?" Based on the independent variable, three algorithms are constructed: Random Forest, Decision Tree, and Logistic Regression. Binary dependent variable prediction is appropriate for these algorithms. ROC and accuracy scores are used to measure the model's efficiency.

6. Evaluation: In this research study, we have utilized the accuracy score and AUROC score as a parameter to evaluate the performance of our model that we are using. The proposed predictive model's performance is presented and compared with the various other factors and the best performing algorithmin terms of accuracy score and AUROC.

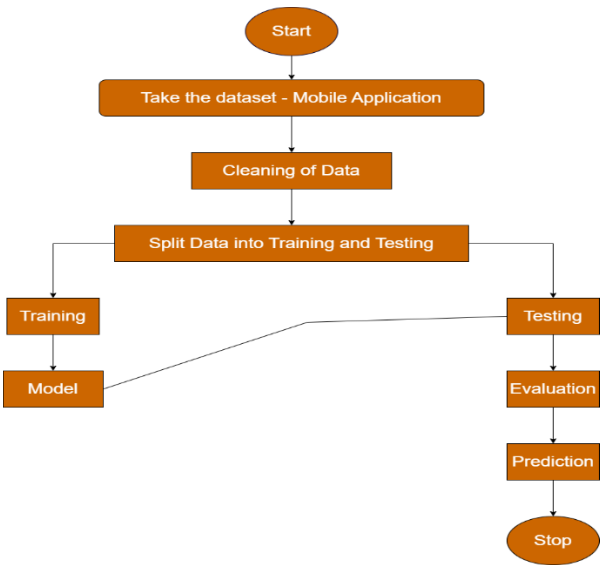

Figure 1. Data Flow Diagram

Figure 1 depicts the data flow diagram of the implemented methodology.

RESULTS

Table 1 summarizes the results of the best-performing algorithms based on accuracy score. The classification results of Logistic Regression, Random Forest, Decision Tree are presented in Tables. Thefigure 2 signifies the kernel density estimate plot of the smartphone addiction and the figure 3 compares the accuracy score of the different models between Random forest, Decision tree, Logistic Regressionby using a bar plot.

The table 1 shows that Random Forest has the highest prediction accuracy of 0.89. This means that the model using this algorithm will provide us the best prediction for smartphone prediction.

Table 1: Accuracy scores scores for Logistic Regression, Decision Tree and Random Forest

Algorithm	Accuracy
Logistic Regression	0.74
Decision Tree	0.86
Random Forest	0.89

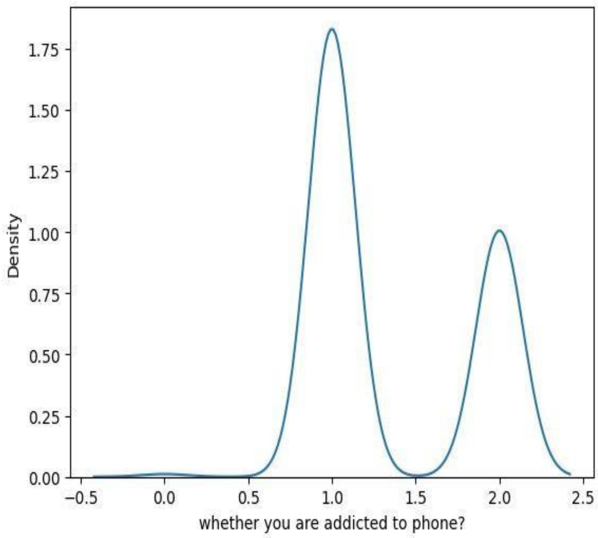

Figure 2: Kernel Density Plot

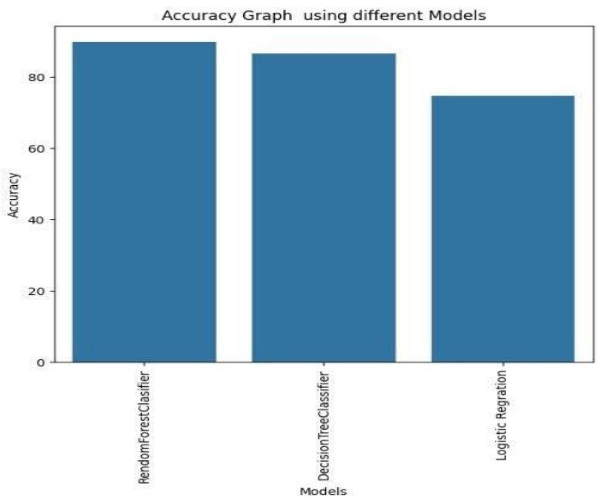

Figure 3: Accuracy score of different models

DISCUSSION

In the contemporary era marked by technological progress, the escalating concern surrounding mobile phone addiction warrants a comprehensive examination, facilitated by sophisticated

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big data analytics. This study endeavors to forecast levels of mobile phone addiction by scrutinizing user behaviors, employing machine learning algorithms such as Decision Tree, Logistic Regression, and Random Forest. Leveraging openly accessible datasets on mobile phone usage, the research aims to provide actionable insights for decision-makers grappling with the multifaceted challenges posed by excessive device dependency.

Results from simulated scenarios underscore the efficacy of machine learning algorithms in discerning levels of mobile phone addiction. Notably, the Random Forest algorithm emerges as the most adept, boasting an accuracy score of 0.89, followed closely by the decision tree algorithm at 0.86. Conversely, Logistic Regression lags behind with a comparatively modest accuracy score of 0.74. This study epitomizes a concerted effort to harness data-driven methodologies in combating the pervasive issue of mobile phone addiction, shedding light on potential intervention strategies and bolstering informed decision-making in healthcare and societal spheres.

CONCLUSION

The study provides evidence for the effectiveness of machine learning algorithms in predicting smartphone addiction. The study shows encouraging outcomes by utilizing multiple models, such as Random Forest, Logistic Regression, and Decision Tree. However, Random Forest's 0.89 accuracy was the highest. These results highlight the potential of machine learning models to accurately anticipate smartphone addiction, enabling well-informed decision-making to manage the smartphone's level of addiction and transform it into a non-addicted device.

FUTURE SCOPE

The future scope of the methodology, leveraging the LLaMA model, includes several promising directions. Key areas for advancement encompass enhancing the model to support multilingual processing, thereby broadening its global applicability. Additionally, integrating an automated quality assessment system would streamline the curation process by providing real-time feedback on content quality. Finally, addressing hardware dependency and optimizing the model for varying computational resources will also be crucial, ensuring wider accessibility and usability.

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