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Intelligent Model for Smartphone Addiction Assessment in University Students using Android Application and Smartphone Addiction Scale

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Abstract: Smartphones have been owned and used ubiquitously in all facets of society utilized for a wide number of tasks such as calling and messaging, social media, surfing as well as for entertainment. Spending a large amount of time on smartphone might lead to a dependence on it for a variety of purposes. This study uses objective measures of real time smartphone usage features to assess smartphone addiction. A purpose built android application to collect real time smartphone usage has been developed and linear classification models namely Support Vector Machine and Logistic Regression are used to predict smartphone addiction among university students. Furthermore, correlation and information gain measures are used to identify most vital features of smartphone usage which contribute maximum in assessment of smartphone addiction. It has been observed that both the linear models give worthy performance with more than 80% of accuracy. Also, the most important technical features impacting smartphone addiction are longest session spent for entertainment, total time used for communication, longest session spent for communication, longest session spent for work, total time used for entertainment, longest session for news and surfing, and data usage in other activities.

Index Terms: Smartphone addiction, machine learning, linear classification, android application.

1. Introduction

Smartphone usage has become inevitable with phones becoming an integral part of lifestyle serving multiple purposes such as communications, social networking, media streaming, information retrieval, etc. Spending significant amounts of time using smartphones for numerous activities potentially develop dependency on them for numerous purposes which may lead to addictive usage and development of associated psychological disorders [1,2]. There are many impairments associated with excessive and addictive used of smartphones such as increase in the risk of sleeping disturbance and stress, sensation of being less physically active, fall in mental health and even depression [3]. Novel psychological variables such as nomophobia and Fear of Missing Out (FOMO) arising from smartphone addiction have also been studied [2,4]. Researchers suggest that smartphone use can be detrimental if it forms an addiction via abuse of technology.

Smartphone addiction is conventionally assessed via smartphone addiction scales, most of which rely on self-reported data obtained through questionnaires [5]. However, a research restriction is that self-report based smartphone addiction scales cannot reliably measure the actual phone usage. [5]. Moreover, this pairs with other shortcomings of these type of scales such as unconscientious or missing responses, and wrong interpretations of questions which lead to inaccurate information. Furthermore, filling of questionnaires is a cumbersome task for participants due to a large number of questions. Purpose-built smartphone applications that can track phone usage attributes in order to provide accurate measures of real-time usage patterns can provide an intervention for this. Subjective data from questionnaires can be replaced by application extracted objective measures of smartphone usage features.

Motivated by this, the objective of this study is to use real time smartphone usage data to predict smartphone addiction using supervised machine learning. A purpose built android application namely "UsageStats" has been developed with the capability to track real time smartphone usage patterns among multiple attributes such as duration of smartphone use and internet data used over the past 30 days. The applications installed in the smartphone are categorized into nine types namely Social Media, Communication, Entertainment, Productivity, News & Surfing, Gaming, Work, Photos & Camera, and Others. Patterns of usage of various categories of applications are attributed in features such as category total time used, category sessions, category longest session, and data used in that category. Smartphone addiction is labeled using the measures of most commonly used smartphone addiction scale, i.e. Smartphone Addiction Scale-Short Version (SAS-SV) designed by Known et al. [6]. Linear classifiers including Support Vector Machine (SVM) and Logistic Regression (LR) are used to predict smartphone addiction. Also, the most contributing attributes of smartphone usage are identified using correlation attribute evaluator and Information Gain (IG) attribute evaluator using predefined thresholds.

2. Related Work

The conventional approach for assessment of smartphone addiction is based on questionnaire based smartphone addiction scales which have been discussed in existing studies [2,5]. Soft computing techniques have been applied to these self-reported data by a number of researchers to provide a technically sophisticated diagnosis of smartphone addiction. Shin et al. [7] used a variety of mobile phone usage data to discover a number of variables in order to build machine learning methods for automated prediction of problematic smartphone use, such as Nave Bayes, Support Vector Machine, and AdaBoost. Supervised machine learning models based on K-Nearest Neighbour, Decision Tree, Nave Bayes, and Support Vector Machine were proposed for smartphone addiction evaluation [8]. However the accuracy and reliability of these results is subject to biasness in information filled.

Recent studies have suggested successful interventions of real time smartphone usage tracking for analysis of behavioral patterns and assessment of problematic use [1,9]. Soft computing methodologies are being used on these real-time smartphone extracted data to provide an accurate diagnosis of smartphone addiction. Ellis et al. [10] implemented an unsupervised machine learning algorithm, i.e. K-Means clustering to group the users with similar smartphone usage patterns. They used the usage behavior pattern retrieved from Apple's Screen Time application which logs a series of behavioral screen time metrics. Other psychological variables arising from smartphone addiction have also been assessed by researchers using real time smartphone extracted usage patterns and soft computing techniques. Arora et al. [2] utilized Gaussian mixture clustering algorithm to identify nomophobic behavior in users with similar smartphone usage pattern retrieved via smartphone application. In another study, Arora et al. [11] extracted real time smartphone data via an android application for prediction of nomophobia severity using supervised machine learning algorithms such as Random Forest, Decision Tree, Support Vector Machines, Naïve Bayes And K-Nearest Neighbor. Elhai et al. [12] implemented supervised machine learning algorithms in order to detect problematic smartphone use severity among undergraduate students in China.

3. Materials and Methods

The materials and methods used in this study are described in the following subsections.

3.1 Android Application: UsageStats

In order to collect real time smartphone usage data of participants, an android application namely "UsageStats" has been developed which automatically collects data from the smartphones of user. Fig. 1 presents the UsageStats screen.

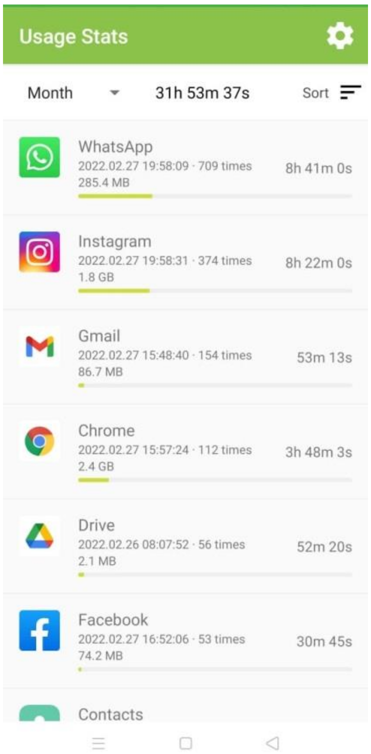

Fig. 1. Smartphone usage during the month

The application tracks overall smartphone usage as well as usage of various smartphone applications including the in-built applications and third party applications. The features of smartphone usage directly collected by UsgeStats are listed in Table 1.

Table 1. Features Extracted by Smartphone Application

S. No.	Attribute	Description
1.	Total_time	Total duration of smartphone use for the last 30 days
2.	Total_data_used	Sum of internet data used by all apps during the smartphone use in last 30 days
	For each application	
1.	Time_used	Total duration of the application usage for last 30 days
2.	Times_open (sessions)	Total number of sessions of the application in last 30 days
3.	Longest_session	Longest duration in last 30 days for which the application is used in one launch
4.	Data_used	Sum of mobile and Wi-Fi internet data that has been used during the application usage in last 30 days
5.	Tag	Category to which the application belongs

The application is sent to undergraduate students of Netaji Subhas University of Technology and the records are maintained in an online database.

3.1.1 Smartphone Usage Attribute Set

After data collection using the UsageStats, the applications are categorized into nine tags viz. Social Meida, Communication, Entertainment, Productivity, News & Surfing, Gaming, Work, Photos & Camera, and Others. These tags are created by sorting and modifying the default tags extracted by the developed application. Applications are categorized as follows:

1. *Social Media* includes applications such as Twitter, Tumblr, Facebook, Instagram, Reddit.
2. *Communication* includes messaging applications and call applications like Snapchat, WhatsApp, Telegram, Truecaller, messenger, Discord and system applications such as contacts, phone, messaging, contacts and dialer etc.
3. *Entertainment* combines system applications such as movies & videos and music & audio as well as the third party video and music applications like Youtube, Netflix, Sonyliv, Prime video, Hotstar, Spotify, FM Radio Gaana, etc.
4. *Productivity* includes the applications like Paytm, Gpay, Docs, Sheets, etc.
5. *News & Surfing* includes various browsers such as Google, Chrome, Browser, Mi Browser, Internet and others as well as news and magazine applications like Inshorts, Quora, Google news, etc.
6. *Gaming* tag includes third party gaming applications like Battleground.

7. *Work* tag is maintained for all the work and study related applications including Gmail, Mail, LinkedIn, Classroom, Zoom, Unacademy, Udemy Meet, etc.
8. *Photos & Camera* include system applications like Albums, Camera, Photos, Gallery and third party applications like Picsart.
9. *Others* is the tag for applications belonging to none of the abovementioned categories. It includes applications like Files, numerous shopping applications, drive and maps applications and various food delivery applications.

After categorizing and sorting the applications into their respective tags, a dataset is created which for each user contains attributes of overall smartphone usage such as total_time in hours and total_data_used in GB and attributes for every tag including time_used in minutes, times_open (sessions), longest_session in minutes, and data_used in MB.

3.1.2 Normalization

The smartphone usage attribute set is normalized using the Min-Max normalization. For each attribute it transforms its values to a decimal between 0 and 1 which works as given in equation 1.

$$x'_a = \frac{x_a - min_a}{max_a - min_a} \tag{1}$$

where, x_a is a instance value belonging to attribute a,
min_a is the minimum value over attribute a
max_a is the maximum value over attribute a.

3.2 Labeling using SAS-SV

SAS-SV designed by by Known et al. [6] is the most commonly used scale for assessment of smartphone addiction [13]. This study uses SAS-SV to collect responses from students about their perception on their dependence on smartphones. SAS-SV contains 10 questions each of which has to be answered on a 6-point Likert scale. The sum of the answers is the indicator of presence of smartphone addiction with a cut off value of 33 for girls and 31 for boys. This is used for labeling students with smartphone addiction.

3.3 Classification

The dataset containing real time smartphone usage features with labels derived from SAS-SV is fed as input to two linear classification models namely, SVM and Logistic Regression. These models are chosen as they are the most suitable model for small datasets [14]. The performances of classification models are evaluated with accuracy and F1-score.

3.4 Identification of Most Contributing Smartphone Usage Attributes

This study uses statistical attribute evaluator methods which evaluate the relationship between each input variable and the target variable in order to use scoring measures as a basis to filter those input variables which contribute maximum for classification [15]. The methods used are Correlation attribute evaluator and Information Gain attribute evaluator. Correlation attribute evaluator evaluates the worth of an attribute by measuring the Pearson's correlation between it and the class [16,17]. IG attribute evaluator evaluates the worth of an attribute by measuring the information gain with respect to the class [16,18]. For each attribute evaluator, top 5 smartphone usage features are identified which contribute the most in assessment of smartphone addiction.

4. Results

The dataset is labeled using SAS-SV and evaluated using the real time attributes extracted via android application. Linear classification performance is evaluated using 5-fold cross validation.

Table 2. Classification Performance

	Accuracy	**F1 Score**
Linear SVM	81.33	0.810
Logistic Regression	82.67	0.827

The most important smartphone usage attributes contributing maximum in assessment of smartphone addiction are identified using correlation and information gain. Table 3 and Table 4 present the top five attributes extracted using the correlation evaluator and the information gain evaluator respectively.

Table 3. Top 5 Attributes Identified Using Correlation Evaluator

S. No.	Attributes	Correlation Score
1.	Entertainment Longest Session	0.4129
2.	Communication Total Time	0.3987
3.	Communication Longest Session	0.3496
4.	Work Longest Session	0.348
5.	Entertainment Total Time	0.3475

Table 4. Top 5 Attributes Identified Using Information Gain Evaluator

S. No.	Attributes	IG Score
1.	News and Surfing Longest Session	0.4129
2.	Communication Total Time	0.3987
3.	Communication Longest Session	0.3496
4.	Entertainment Longest Session	0.348
5.	Others Data Usage	0.3475

5. Conclusion

This study proposes a model for assessment of smartphone addiction in university students using the objective measures of real time smartphone usage and supervised machine learning. An android application is developed to collect real time smartphone usage features and linear classification models namely Support Vector Machine and Logistic regression are used to predict smartphone addiction among university students. Smartphone Addiction Scale-Short Version is used to label smartphone addiction among university students. Support Vector Machine predicts smartphone addiction with a superlative accuracy of 81.33% while Logistic Regression gives accuracy of 82.67%. Most contributing features of real time smartphone usage for assessment of smartphone addiction have also been identified using correlation and information gain measures.

The easy availability of smartphones and the Internet and the flexible schedules of millennials including students are leading them to have addictive smartphone usage behaviors [11]. Online education which involves use of digital technologies including smartphones has become useful, yet stressful practice for university students after the COVID-19 pandemic. However, overuse of smartphones and other digital technologies are known to cause fatigue [19] and affect academic performance of students [20]. Therefore, universities should make judicious use of these technologies.

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