

Real Time Smartphone Data for Prediction of Nomophobia Severity using Supervised Machine Learning

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doi: <https://doi.org/10.21467/proceedings.114.11>

Abstract

Excessive use of smartphones throughout the day having dependency on them for social interaction, entertainment and information retrieval may lead users to develop nomophobia. This makes them feel anxious during non-availability of smartphones. This study describes the usefulness of real time smartphone usage data for prediction of nomophobia severity using machine learning. Data is collected from 141 undergraduate students analyzing their perception about their smartphone using the Nomophobia Questionnaire (NMP-Q) and their real time smartphone usage patterns using a purpose-built android application. Supervised machine learning models including Random Forest, Decision Tree, Support Vector Machines, Naïve Bayes and K-Nearest Neighbor are trained using two features sets where the first feature set comprises only the NMP-Q features and the other comprises real time smartphone usage features along with the NMP-Q features. Performance of these models is evaluated using f-measure and area under ROC and It is observed that all the models perform better when provided with smartphone usage features along with the NMP-Q features. Naïve Bayes outperforms other models in prediction of nomophobia achieving a f-measure value of 0.891 and ROC area value of 0.933.

Keywords: machine learning, nomophobia, smartphone addiction, real time data

1 Introduction

Smartphones usage has grown to an extent where the phones have become an integral part of everyone's lives. Today smartphones are used throughout the day for multiple purposes including communication, productivity, utilities, and even entertainment, social networking, and gaming. The easy availability of smartphones and the Internet and the flexible schedules of millennials is leading them to excessive and addictive smartphone usage behaviors. Smartphone addiction is a shifting technological addiction as the mobile phones have evolved to smartphones encompassing varied Internet features and applications [1]. Smartphone addiction refers to overuse of smartphones with corresponding functional impairments. Strong evidences of smartphone addiction on adverse effects on academic performance of university students has been studied [1]. Recent investigations have explored novel psychological disorder associated with smartphone addiction which is termed as nomophobia.

Nomophobia is the abbreviation of No Mobile Phone Phobia which is defined as a disorder of millennials which includes nervousness, distress and/or anxiety caused by the non-availability of smartphone [2, 3, 4]. Nomophobia is an outcome of excessive use of smartphones leading to its dependency for social networking and information retrieval. It arises from fear of losing connection with people, losing internet connectivity and access to social networking, and losing access to online information [5] leading to nomophobic people being anxious in such situations. Such people tend to keep their phone switched on 24 hours a day and even take their phone to bed contributing to night time usage and causing sleep disorders. Nomophobia has been studied to impact psychological, social, academic, and professional lives of smartphone users [1, 6].

Recently many researchers have attempted to assess nomophobia and to study its various aspects and dimensions using different methods [2-5, 7-15]. Arora and Chakraborty [16] reviewed the existing studies on



nomophobia to identify the techniques used to detect nomophobia. It was found in their review that the most of the studies used self-reporting-based techniques for diagnosis of nomophobia with Nomophobia Questionnaire (NMP-Q) devised by Yildirim and Correia [5] being the most commonly used instrument. NMP-Q is a 20-item questionnaire where NMP-Q score is calculated as a sum of all items which indicates the severity of nomophobia. However, it has been suggested by most of the experts in psychological research and diagnosis that self-report data should not be used alone as it tends to be biased results [17]. Experts believe that combining individuals' behavior or psychological data with self-report data is best for research. Hence, we propose assessment of nomophobia severity utilizing real-time smartphone usage data in addition to self-report NMP-Q data using machine learning for reliable and accurate diagnosis. Five baseline classifiers are trained with and without real time smartphone features. The machine learning models implemented are Random Forest (RF), Decision Tree (DT), Support Vector Machines (SVM), Naïve Bayes (NB), and K-Nearest Neighbor (K-NN). The performance of these classifiers is evaluated using performance metrics such as f-measure and area under ROC value.

This paper is organised as follows: Section II presents the work done by researchers in the domain of assessment of smartphone addiction and nomophobia using machine learning. Section III presents the proposed methodology of the study. Section IV presents the results of implemented machine learning models. Section V provides the conclusion of the study.

2 Related Work

Recent studies employ machine learning and intelligent data mining techniques for analysis of smartphone addiction. Shin et al. [18] use a range of mobile phone usage data and identify a number of features in order to develop a machine learning based model for prediction of smartphone addiction. The algorithms used by them include Naïve Bayes, Support Vector Machines and AdaBoost and their model achieved an accuracy of 89.6% for detection of smartphone addiction. Lawanont et al. [19] built a smartphone addiction recognition system based on smartphone usage data. Based on this data, they implement a classification model utilizing Naïve Bayes, Decision Tree, K-Nearest Neighbor, and Support Vector Machines for recognition of likelihood of having smartphone addiction. In a recent study, Ellis et al. [20] utilize k-means clustering algorithm to cluster the users with similar smartphone usage behavior using the data retrieved from Apple's Screen Time application which automatically logs a series of behavioral metrics related to screen time over a period of seven days. In another more recent study, Elhai et al. [21] utilize supervised machine learning algorithms for detection of smartphone addiction severity among Chinese undergraduate students. They also correlated Fear of Missing Out (FOMO), depression and anxiety symptoms with smartphone addiction severity using the data from responses to smartphone addiction scale, Depression Anxiety Stress Scale-21, FOMO Scale, and Ruminative Responses Scale and concluded that FOMO had the largest relative contribution in modelling smartphone addiction severity. Kim et al. [22] propose a model based on Deep Belief Networks, K-Nearest Neighbor, and Support Vector Machines for prediction of smartphone addiction levels in individuals.

The use of intelligent data analysis approaches for assessment of nomophobia has not been explored by many researchers. Nusawat and Kwangsawad [23] utilize Decision Tree and Naïve Bayes to identify the risk level of nomophobia from smartphone usage behavior of participants acquired through a questionnaire.

Smartphone usage pattern data has been utilized for assessment of smartphone addiction using machine learning by a number of studies. However, no study has been reported utilizing smartphone usage data for assessment of nomophobia. This study aims to assess nomophobia severity among students utilizing supervised machine learning techniques using real time smartphone usage data along with the NMP-Q features.

3 Methodology

This study assesses nomophobia severity among adolescents using the NMP-Q and smartphone usage data. Fig. 1 describes the framework of the proposed work. The NMP-Q and the smartphone usage data of 141 undergraduate students has been collected and machine learning algorithms are implemented to detect the nomophobia level of these students. Machine learning techniques are trained with two datasets where one dataset comprises only the features obtained from the NMP-Q and the other dataset comprises smartphone extracted features with the NMP-Q features. Comparison of the performance of algorithms with these two datasets is done. Following subsections describe the materials and methods used in this work.

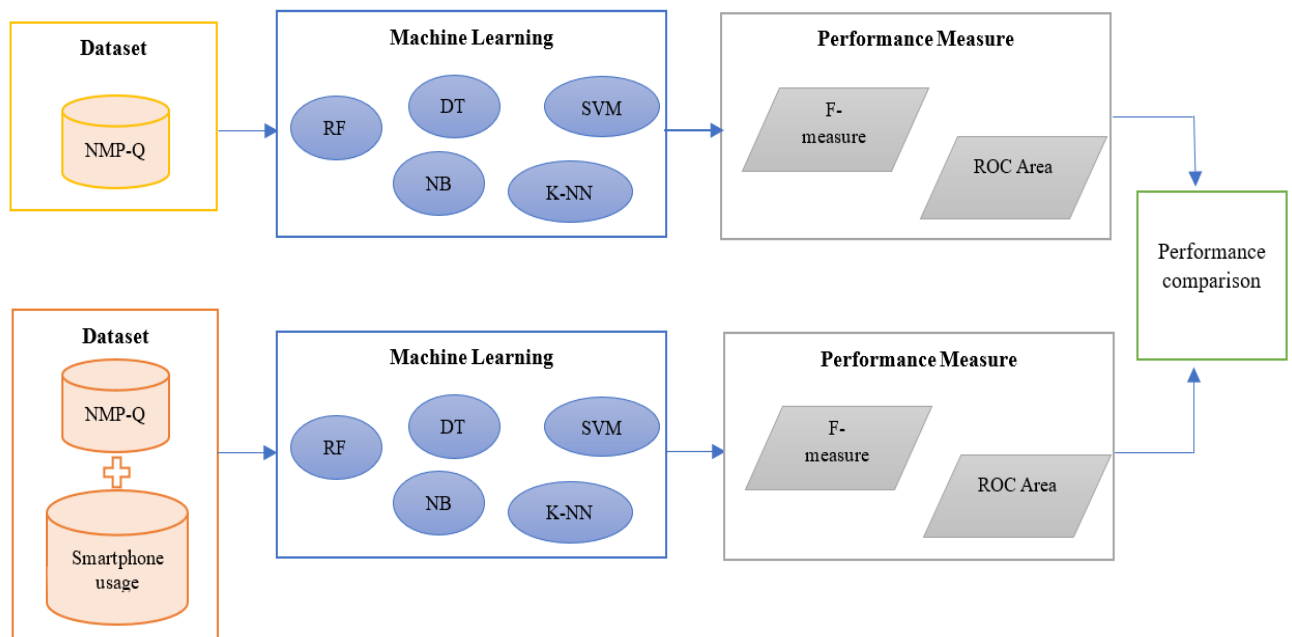


Fig. 1. Model Framework

3.1 Nomophobia Questionnaire (NMP-Q)

The nomophobia questionnaire (NMP-Q) [5] is used in this study in order to collect data from students on their dependence on smartphones. NMP-Q contains 20 questions each of which has to be answered on a 7-point Likert scale. The sum of answers is a measure of nomophobic behavior where a score less than or equal to 20 denotes absence of nomophobia. A score above 20 but less than 60 corresponds to mild nomophobia. A score above 60 and less than 100 corresponds to moderate nomophobia while a score above 100 is an indication of severe nomophobia.

3.2 Smartphone Application (Activity Tracker)

An android smartphone application named as “Activity-Tracker” is developed to automatically collect usage data from the smartphones of users. The application extracts how much the phone has been used in total, how much it has been used in night time (11 PM to 7 AM) and how many times it has been unlocked in the last 7 days. The application saves the extracted data in an online database from where it is accessed.

3.3 Machine Learning

Machine learning is a branch of artificial intelligence which provides computers the capability to automatically learn and improve through experience without human intervention or assistance via observations of data patterns and make decisions in the future. Data is labelled with four classes corresponding to four levels of nomophobia severity based on the NMP-Q value. Five supervised machine learning algorithms are implemented. The machine learning algorithms are Random Forest [24], Decision Tree [25], Support Vector Machines [26], Naïve Bayes [27], and K-Nearest Neighbor [28].

4 Results

Five supervised machine learning algorithms are implemented and performance of machine learning algorithms is evaluated using two performance measures i.e., f-measure and value of area under ROC. Performance is compared using the two feature sets (only NMP-Q features and NMP-Q + smartphone extracted features). Fig. 2 and fig. 3 show the f-measure and ROC area respectively of the machine learning models with the two feature sets.

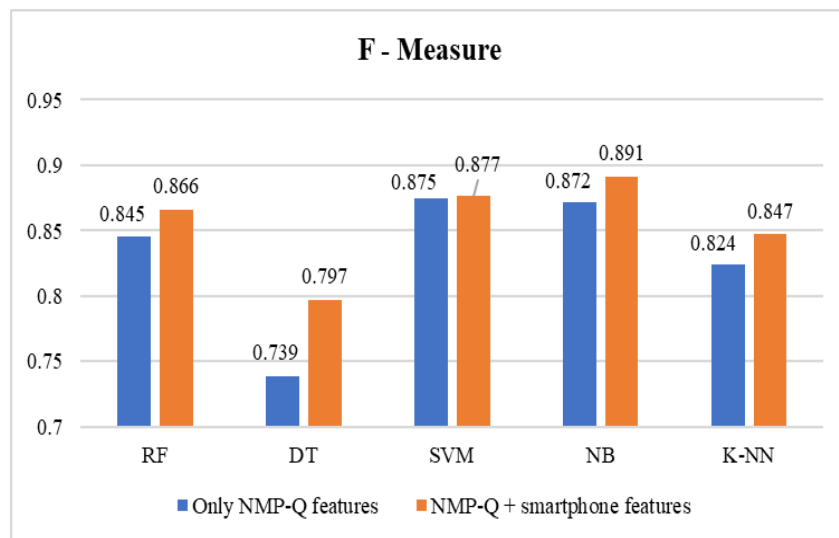


Fig. 2. F-measure

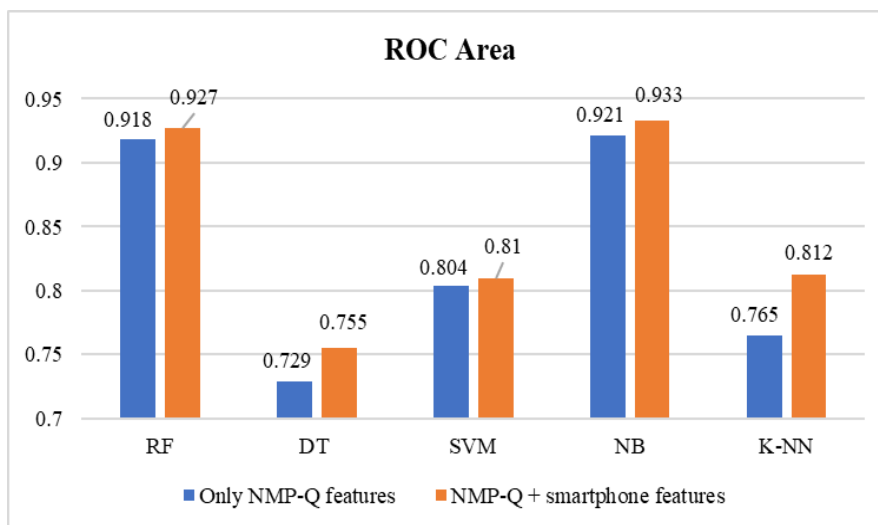


Fig. 3. Area under ROC

It can be observed that all the machine learning models perform better when real time smartphone usage features are added to the NMP-Q features. Maximum comparative difference of performance can be seen by DT and K-NN with two feature sets. DT performs with f-measure value of 0.739 and 0.797 without and with real time smartphone usage features respectively. It gives area under ROC value of 0.729 and 0.755 without and with smartphone usage features respectively. K-NN gives f-measure value of 0.824 and 0.847 without and with smartphone usage features respectively. It gives area under ROC value of 0.765 and 0.812 without and with smartphone usage features respectively. Naïve Bayes performs best in terms of both f-measure (0.891) and area under ROC value (0.933) when trained with both NMP-Q and real time smartphone usage features.

5 Conclusion and Future work

This paper proposes assessment of nomophobia severity using machine learning with real time smartphone usage data along with the nomophobia questionnaire (NMP-Q). Five baseline classification models namely random forest, decision tree, support vector machines, naïve bayes, and k-nearest neighbor are trained using two datasets. One dataset comprises only the NMP-Q features while the other comprises real time smartphone usage features along with the NMP-Q features. It has been observed that all the models perform better when trained with the smartphone usage features with the NMP-Q features. Decision tree and K-nearest neighbor show major performance difference when compared between the two feature sets. Naïve Bayes gives the highest value of f-measure (0.891) and area under ROC (0.933) with the smartphone usage features along with the NMP-Q features. Hence, the study concludes that real time smartphone usage features extracted from the smartphones of students are effective for prediction of nomophobia among students using machine learning.

In future, deep learning models can be implemented for prediction of nomophobia using real time smartphone usage features. Also, data from social media and wearables such as smartwatches can be integrated with the smartphone usage data to study emotions and behavioral health of users using machine learning and deep learning algorithms.

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