

# Trapped in the Mobile Screen: A Machine Learning Approach to Predict Nomophobia

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**Abstract**—Modern communication has been revolutionized by the quick spread of cellphones, but an over-reliance on these gadgets has led to a rising psychological ailment called **NOMOPHOBIA** (NO MOBILE PHOne PhoBIA), which is connected to problems with self-esteem and social anxiety. In this research, nomophobia detection prediction using Machine Learning (ML) techniques is proposed. Four ML models such as Naïve Bayes (NB) Classifier, K-Nearest Neighbors (KNN), Multi-Layer Perceptron (MLP), and Support Vector Machine (SVM) are used to predict the outcome. The hyperparameters of all ML models are tuned using the Random Search technique, and all models are cross-validated using the K-fold cross-validation technique. The performance is evaluated using well-known classification performance evaluation metrics such as accuracy, recall, precision,  $F_1$ , and Geometric Mean (GM). It is found that the SVM outperforms other models.

**Index Terms**—Healthcare analysis, mental health, Nomophobia, classification, machine learning

## I. INTRODUCTION

The fear of being unable to use or reach one's smartphone is known as nomophobia, an acronym for "no-mobile phone phobia. [1]. The phrase was first used in a 2008 UK Post Office study that examined the fears of more than 2,100 mobile phone users. The study found that 53 percent of these users had nomophobia. Smartphones are exceedingly popular among youth, with students seen as trailblazers [2]. The advantages that smartphones offer account for their widespread use among college students. Making and receiving phone calls, checking and sending emails, scheduling meetings, surfing the internet, shopping, social networking, seeking information online, gaming, and more are just a few of the numerous daily tasks that smartphones make possible [3]. Many students' lives have been altered as a result of nomophobia [4]. Nomophobia is generally associated with poor academic performance and sleep difficulties in college students [5]. Additionally, it is associated with stress, anxiety, dependence, social issues, low self-esteem, and fear, followed by feelings of annoyance and

compulsive thinking. Nomophobia is significantly widespread among students, as a survey of French students indicated that one-third of college students have this condition [6]. A study conducted on Indian students revealed that the utilization of social informatics in social media and mobile fostered addictive behavior, with 93 percent of participants exhibiting such an obsession that they retained their devices even during sleep [7]. Mobile phones are a source of concern in educational institutions, as their utilization during lectures or demonstrations significantly hinders students' learning capacity and diminishes their academic performance [8]. Students may employ cell phones as alternatives to social anxiety and loneliness [9], [10]. A study involving 786 students identified a substantial association between loneliness and nomophobia, with loneliness serving as a predictor of nomophobia [11]. Young individuals often utilize social media to cope with in-person communication anxiety [12]. Individuals with social anxiety often eschew social engagements, including the establishment of strong friendships; nonetheless, they experience greater comfort and security in virtual environments compared to real-life situations [13]. Self-esteem is defined as a person's subjective evaluation of their own value as a human being [14]. Nomophobia was twice as common among students with low self-esteem as it was among those with normal or high self-esteem, according to a study [15].

Numerous studies have investigated the psychological effects of nomophobia, especially its correlation with social appearance anxiety and self-esteem in students; nonetheless, previous research was predominantly dependent on conventional survey-based statistical analysis. This research will bridge the gap by applying machine learning algorithms to construct a prediction model, using nomophobia as a primary predictor to evaluate social appearance anxiety and self-esteem. Additionally, it will permit early detection and intervention measures, enabling educators and mental health experts to manage social anxiety and self-esteem among students.

## II. RELATED WORK

Yildirim et al. undertook a study investigating the prevalence of nomophobia among youth in Turkey. The findings indicated that 42.6 percent of participants had nomophobia, their main concerns centered on communication and access to information. The research indicated that gender and the length of ownership of smartphones influenced the nomophobic behaviors of young people, while age and the duration of ownership of smartphones did not have an impact [16]. In a meta-analysis with people from 10 countries, the prevalence of moderate to severe nomophobia was found to be 70.76 percent worldwide. Twenty-eight percent of people suffer from severe nomophobia. The group most affected seems to be university students, with a prevalence of severe nomophobia of 25.46 percent [17]. These two studies demonstrate the severity of this issue among youth, particularly college students.

The results of a study indicated that people with high nomophobia scores react to confrontation with tension and behavioral disengagement [18]. Prognostic indicators for nomophobic behavior included gender, age, propensity for procrastination, employment position, social anxiety levels, smartphone usage characteristics, low self-esteem, and self-reported average academic performance [19]. Academic success, self-esteem, and social anxiety are apparent to be the most crucial factors for a student. Self-esteem and problematic smartphone use are often studied together. While people with high self-esteem scores prefer in-person connection, those with poor self-esteem reported using their smartphones excessively through indirect means such as phone calls, texts, and emails [20] [21]. The study, which involved 242 Spanish students, revealed that self-esteem can predict nomophobia through the use of multiple regressions [22]. According to the study, the largest predictor of nomophobia is low self-esteem, followed by extraversion, conscientiousness, and emotional stability. The effect of the therapy to reduce nomophobia on high school students' self-esteem and nomophobia symptoms was examined in [23]. The outcomes showed that nomophobia therapy was a successful treatment for elevating self-esteem and lowering nomophobia. Using a social interaction anxiety scale and a nomophobia questionnaire, 209 students from Punjab, India participated in a descriptive correlational study. There was a weak positive connection between social interaction anxiety and nomophobia [24]. The study found that social interaction anxiety may be a significant predictor of the rising prevalence of nomophobia among college students. Likewise, a t-value of 2.538 at a significance level of 0.012 ( $p < 0.05$ ) showed a positive correlation between nomophobia and social anxiety in teenagers [25]. Together, these studies demonstrate the close relationship—especially among students—between nomophobia, self-esteem and social anxiety. By addressing these psychological aspects with focused interventions, the increasing effects of nomophobia on young people may be lessened.

## III. METHODOLOGY

### A. Study Design

Participation in the cross-sectional survey was voluntary, and Google Forms was used to collect all data. Five sections of Google Forms were created in order to accomplish the study's objectives. Information on the study was given in the first section, and consent was attached, indicating which participants might go to the following stage. In order to gather demographic information, the second portion asked questions about gender, age, location, marital status, smoking status, housing arrangements, and academic level. The third section included the NMP questionnaire (NMP-Q). Yildirim and Correia had created and verified 20 of the statements [26]. The fourth section comprised the Social Appearance Anxiety Scale (SAAS), a self-reporting style scale intended to gauge people's behavioral, emotional, and cognitive concerns about appearance [27]. The last part of the study used the Rosenberg Self-Esteem Scale (RSES) to assess self-esteem [28].

### B. Sampling Strategy

A convenience sample was employed in the research. Universities and colleges in Jaipur, Rajasthan, India, were contacted. In the first place, faculty members from the relevant schools and institutions received a link to the survey. During class, they shared the survey link with the students and asked them to complete the form. This is why the response rate was 100 percent; only those students who were eager to participate were asked to complete the form.

### C. Sample Size

The study comprised 255 students who had been using their phones for at least one to two hours per day for the preceding six months or more. Table I describes the different features of the dataset.

### D. Data Preprocessing

To prepare the dataset for machine learning models:

- The **Class** target variable is encoded using a LabelEncoder (Scikit-Learn).
- Features are scaled using a StandardScaler (Scikit-Learn) to normalize the data and improve model performance.

### E. Model Development

The following machine learning models were implemented:

- **K-Nearest Neighbors (KNN):** a non-parametric technique that uses the nearest neighbors' majority vote to categorize a sample. When the dataset is uniformly distributed, KNN works well for classification jobs due to its simplicity and great degree of flexibility.
- **Naïve Bayes Classifier:** A Bayes-theorem-based probabilistic model that makes the assumption that features are independent. It offers effective computing in big datasets and is especially helpful when the features are categorical.
- **Multi-Layer Perceptron (MLP):** MLP is a supervised artificial neural networks (ANNs). It has three layers: input, output, and hidden. The output nodes in the output

TABLE I  
DATASET DESCRIPTION

Attribute No.	Feature	Description
1	Age	Patient's age in years
2	Gender	Patient's gender (Male/Female)
3	Location	Place of Study
4	Academic Level	Undergraduate or Postgraduate Student
5	NMPQ	Score of Nomophobia Questionnaire
6	Selfesteem	Score of Rosenberg Self Esteem Scale
7	Social anxiety	Score of Social Appearance Anxiety Scale (SAAS)
8	Class	Mild, Moderate, Severe, NoNMP (No Nomophobia)

layer and the hidden nodes in the hidden layers both make use of the activation functions. The synaptic weights of MLP are updated using a learning algorithm in order to train this model using the training data.

- **Support Vector Machine (SVM):** For binary and multi-class classification tasks, SVM, a linear classifier, is best suited. It operates by locating the hyperplane in a high-dimensional space that best divides the data points of several classes.

#### F. Evaluation Metrics

Performance of ML models are evaluated using widely used metrics such as accuracy, precision, recall,  $F_1$ -score, and Geometric Mean (GM) [29].

### IV. EXPERIMENTAL SETUP

#### A. Parameter Settings

The parameters of all the models used in the study are tuned using Random Search technique [30]. The obtained best parameter settings of each model are provided in Table II.

TABLE II  
BEST PARAMETER SETTINGS FOR MODELS

Model	Best Parameters
KNN	'weights': 'distance', 'n_neighbors': 5, 'metric': 'manhattan'
NB	'var_smoothing': 0.00058
MLP	'solver': 'lbfgs', 'learning_rate': 'invscaling', 'hidden_layer_sizes': (50,), 'alpha': 0.01, 'activation': 'logistic'
SVM	'kernel': 'linear', 'gamma': 'auto', 'degree': 5, 'C': 10

#### B. System Configuration

The experiments were conducted on a system having the following specifications:

- 1) **CPU:** Intel(R) Core(TM) i7-9700K @3.60 GHz
- 2) **RAM:** 64 GB
- 3) **Operating System:** Windows 10 Professional 64-bit
- 4) **GPU:** 2 × NVidia Geforce RTX 2070 Super 8GB
- 5) **Software:** Anaconda Navigator 2.6.4

### V. RESULTS AND DISCUSSION

All the models were trained as well as being tested using K-fold cross-validation, and the mean and standard deviation (Std. Dev.) of training accuracies in Table III besides mean CPU time over 10-fold runs are the subjects of the study. A look or to be exact, peeping through the details shows that SVM, KNN, and NB reach a mean training accuracy of more than 97% whereas MLP stands with a slightly lower percentage of 93.25%. The model that consumes the highest computational cost on training is MLP in the models, while to NB belongs the minimal cost.

TABLE III  
TRAINING ACCURACIES AND CPU TIME

Model Name	Training Accuracy (%)		CPU Time (s)
	Mean	Std. Dev.	
KNN	100.00	0.00	0.00052
NB	97.47	0.47	0.00069
MLP	93.25	1.00	0.07856
SVM	100.00	0.00	0.00074

TABLE IV  
MEAN AND STANDARD DEVIATION OF TESTING PERFORMANCE METRICS OVER 10-FOLDS

Method		Accuracy	Recall	Prec.	$F_1$	GM
NB	Best	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>
	Worst	88.46	91.67	90.83	89.95	93.68
	Mean	97.26	97.90	97.69	97.50	98.47
	Std. Dev.	3.91	2.86	3.41	3.58	2.12
KNN	Best	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>
	Worst	92.00	94.44	91.67	91.88	95.86
	Mean	97.65	98.25	97.81	97.81	98.73
	Std. Dev.	3.14	2.27	3.07	3.01	1.65
MLP	Best	96.15	97.22	97.22	96.26	98.01
	Worst	80.77	66.67	66.67	66.67	79.77
	Mean	89.00	87.25	87.83	86.47	91.59
	Std. Dev.	5.77	8.36	8.68	8.36	5.05
SVM	Best	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>	<b>100.00</b>
	Worst	<b>96.00</b>	<b>97.22</b>	<b>95.00</b>	<b>95.75</b>	<b>98.04</b>
	Mean	<b>99.22</b>	<b>99.51</b>	<b>99.14</b>	<b>99.27</b>	<b>99.63</b>
	Std. Dev.	<b>1.57</b>	<b>0.98</b>	<b>1.74</b>	<b>1.48</b>	<b>0.73</b>

Evaluation of each model was performed using different metrics like accuracy, precision, recall,  $F_1$ -score, and GM. These metrics are responsible for the decision of each classifier to accurately separate individuals into different levels of nomophobia severity. The testing results are provided in Table IV and the best results are bold faced.

### A. Naïve Bayes (NB)

NB was the top performer and was able to give an average accuracy of 97.26% with a small standard deviation of 3.91. The maximum accuracy obtained was 100.00%, and the minimum one was 88.46%. Precision and recall were also very good, with the lowest recall being 91.67%, which proved the efficiency of the model in identifying different levels of nomophobia. The F1-score varied from 89.95% to 100.00%, so the data was balanced and this classifier is a good one. The geometric mean (GM) of 98.47 is an additional argument supporting NB's ability to perform well on diverse data splits.

### B. K-Nearest Neighbors (KNN)

KNN showed the greatest mean accuracy of 97.65% along with a small std. dev. of 3.14. The optimal accuracy was 100.00%, while the minimum accuracy was 92.00%, which indicates that the model was consistent on different folds. Precision and recall were quite stable from the perspective of various classes of severity, so the model made correct distinctions between NoNMP, Mild, Moderate, and Severe cases of nomophobia. The F1-score was very similar on the different measurements, which is a strong point for the KNN classifier as a tool for nomophobia detection. GM of 98.73 supported its success even more.

### C. Multi-Layer Perceptron (MLP)

MLP results were promising with a mean of 89.00% and a std. dev. of 5.77. The highest accuracy was 96.15%, but the lowest accuracy was 80.77%, which means that there are some variations from one fold to another. The lowest recall of 66.67% indicates low accuracy in classifying some cases of nomophobia severity. Nevertheless, MLP had a good combo with precision and recall, and it showed an F1-score in the interval from 66.67% to 96.26%. The GM of 91.59 is an indicator that MLP can handle class imbalances to some degree. However, it may still be a good idea to do more fine-tuning for better generalization.

### D. Support Vector Machine (SVM)

SVM outperformed the rest of the classifiers, achieving a good mean accuracy of 99.22% with a standard deviation of 1.57. The highest and the lowest accuracy were 100.00% and 96.00% respectively which means that the model has high consistency. The values for precision and recall were almost perfect with 95.00% and 97.22% being the worst-case scenarios. The F1-score was from 95.75% to 100.00% indicating the correctness of SVM in distinguishing among different nomophobia levels of severity. The GM of 99.63 further makes it clear that SVM is capable of effectively dealing with classification tasks with minimal errors.

### E. Key Observations

- SVM and KNN had the most significant classification performance, with high accuracy, precision, and recall reaching nearly ideal levels.

- Being a relatively simple model, Naïve Bayes perform quite well still and it keeps a mean accuracy of 97.26
- The MLP model seemed to be less efficient in terms of performance and more variant across its folds which implies the necessity for further optimization.
- The data collection process might introduce biases related to demographic factors such as age, academic level, and social anxiety scores, which would in turn influence model performance.
- NB has the least computational cost, therefore, it can be utilized as a convenient and effective way of nomophobia detection real-time in mobile applications.

The result of the study exemplified the fact that SVM and KNN outperformed the rest of the classifiers for detection of nomophobia severity, which was followed by Naive Bayes. Although there were some inconsistencies at MLP, it was still a potential option for further tuning. The findings also point out that machine learning models can accurately be applied to determine nomophobia levels which will have a great potential for psychological assessment as well as a digital well-being research project.

### F. Practical Implications

The outcomes of this work have important practical implications, especially in education, mental health, and digital well-being domains. Institutions can create early intervention plans by using machine learning algorithms to forecast social anxiety and self-esteem based on nomophobia scores. While mental health practitioners can use predictive analytics to identify at-risk individuals and offer tailored support, educational institutions can employ awareness initiatives to inform students about the psychological impacts of excessive smartphone use. Furthermore, mobile apps that incorporate real-time nomophobia assessment can provide tailored suggestions to assist users in managing their smartphone use, thereby enhancing achievement in their academic life with mental well-being.

## VI. CONCLUSION

Nomophobia detection was done using a combination of ML models such as SVM, KNN, NB, and MLP. The most efficient hyperparameters of the models were found with the use of Random Search, and the K-fold cross-validation method was used to check the models' performance. Accuracy, recall, precision,  $F_1$ -score, and GM were the parameters used to compare the models. SVM and KNN came out as the top classifying algorithms with almost perfect accuracy, precision, and recall rates. However, NB performed well too as it had a very high level of accuracy and a very low computational cost.

Despite the achievements that were noted, the image has some drawbacks. Accuracy can be improved with the use of SVM and KNN but cost and scalability also should be taken into account as they directly influence applications in real-time. On the other hand, MLP performed a bit worse at times and showed a larger variation across the folds, indicating further fine-tuning of the settings. Furthermore, the dataset

available was small, and not diverse, demographic-wise, thus this may lead to model generalization issues when different populations are considered.

Further work will emphasize the clarity and trustworthiness of the modeled psychological and educational scenarios as the main issue. Shapley Additive Explanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME) will be the primary tools to demonstrate and provide transparent AI support for many researchers and healthcare providers. Besides that, a class imbalance in the nomophobia dataset is a problem and it should be addressed to enable fair predictions across different gender, age, and academic groups.

In addition, lightweight machine learning models will be designed to be able to be used on cell phone apps and on mental health diagnosis tools that can detect nomophobia in real-time smoothly. The other research will involve model testing in larger and more varied datasets to increase robustness and accuracy. Meanwhile, validation will be gained through the cooperation with the psychologists and educational institutions who are willing to evaluate the Models in the actual world so that nomophobia can be recognized and dealt with.

The introduction of these improvements makes AI-driven nomophobia detection systems be more reliable, understandable, and accessible, resulted in the end of the day in the effectiveness of the early identification and intervention strategies that are focusing on smartphone addiction and digital well-being fields.

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