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Exploring nomophobia among university students: Identifying risk factors, correlates, and predictive insights through machine learning

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A B S T R A C T

Nomophobia is a term describing a growing fear in today's world, the fear of being without a mobile device or beyond mobile phone contact. It is the biggest non-drug addiction of the 21st century and is mainly affected by teen-aged students. Those experiencing nomophobia may feel a sense of panic, anxiety, or distress when they are separated from their mobile phones. This work uses different statistical tools to identify the risk factor of nomophobia and machine learning techniques to propose a fresh way to measure and understand nomophobia. To create a predictive model for nomophobia, we gathered information from a broad sample (n = 357) of smartphone users and used a variety of machine learning methods. Using a questionnaire on 17 different factors and performing a statistically significant test ($p<0.05$) and ordinal logistic regression analysis on respondents age, level of education, CGPA, self-evaluation, per-day mobile phone usage, and use of media, we can recognize the most important features causative of nomophobia. The context of maximum phone usage is an important feature that highly affects nomophobia. About 201 respondents are at a moderate level. To develop a predictive model, decision tree (DT), random forest (RF), Gaussian Naïve Bayes (NB), and support vector machine (SVM) are utilized in this study for recognition of nomophobia addiction. Proposing an ensemble method to refine the predictive performance. From the analysis, we have found that the SVM feature selector with ensemble algorithm has classified the extent of smartphone addiction with a 57% accuracy rate. Our findings show that nomophobia tendencies can be accurately captured and predicted by machine learning approaches. The model distinguished between students who had symptoms of nomophobia and those who did not with remarkable accuracy. This study of machine learning-based methods presents a viable tool for diagnosing and treating nomophobia in students, eventually assisting in the creation of focused interventions and preventive measures.

1. Introduction

Cell phone addictions are "possibly the biggest non-drug addiction of the twenty-first century", with college students spending up to nine hours per day on their phones (Parasuraman et al., 2017). Since the introduction of the first mobile phone in 1983, mobile phones have become a major part of everyday life in most societies, leading to smartphone addiction, also known as nomophobia (Vasanthakumari & Wakuma, B, 2019). No-mobile-phone-phobia is a term coined by YouGov, a UK-based research organization (Kumar et al., 2021). Nomophobia refers to the feelings of fear, anxiety, or distress that people feel when they are disconnected from their mobile phones or unable to access them. Some common symptoms are headache, eyestrain, neck pain, disturbed sleep, fatigue, etc. People who are exceedingly dependent on their mobile phones and experience nomophobia often report heightened levels of anxiety when their phones are inaccessible (Notara et al., 2021). Too much use of smartphones and the fear of missing out (FOMO) due to nomophobia can dislocate sleep patterns, leading to sleep deficiency and negatively affecting psychological welfare. As the number of people suffering from

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nomophobia increases, it becomes more important than ever to understand its psychological underpinnings and create effective interventions. While traditional research approaches in psychology have yielded important findings about nomophobia, new technologies like machine learning provide new ways to analyze and model nomophobia, such as understanding nomophobia, data collection, feature engineering, predictive modeling, interventions, and mitigation strategies.

A machine learning-based approach to measuring the mental condition of nomophobia offers promising openings to upgrade our understanding and administration of this marvel. Machine learning techniques have been gradually more employed to assess and evaluate the strictness of this condition (Ellis et al., 2019; Durak, 2019). This study investigates the application of machine learning techniques to compute the relentlessness of nomophobia. Primary data has been collected from reputed university students and administered through questionnaires to evaluate nomophobia levels. Several machine-learning models, such as decision trees, random forests, naïve Bayes, support vector machines, and ensemble classifiers, are used to explore the data and envisage nomophobia classification. By leveraging innovation and data-driven experiences, this research identifies the risk factors and contributing elements that make certain individuals more susceptible to nomophobia. Section 2 covers the entire literature review. The nomophobia data set is described in Section 3. Section 4 contains the methodology section. Section 5 contains the evaluation protocols, results, and discussion. The conclusion given in the final section.

2. Literature Review

Nomophobia, or the fear of being without a mobile phone, is a growing concern in today's civilization. Nomophobia and apprehension of missing out as predictors of smartphone addiction along with college students (Aygul & Akbay, 2019). To enhanced comprehend and measure this psychological circumstance, researchers have turned to machine learning-based approaches Through a literature review, it has been found that machine-learning algorithms can effectively predict nomophobia with high accuracy (Luo et al., 2021; Christina et al., 2022). These algorithms utilize various features such as phone usage patterns, social media activity, and other behavioral data to make predictions. While there is still much research to be done in this field, machine learning-based approaches show immense guarantee in accurately measuring and understanding nomophobia (Al-Mamun et al. 2023). Nomophobia is defined as the fear of being out of cellular phone contact. Studies reported varying commonness rates of nomophobia, with statistics ranging from 50% to 90% among mobile phone users (Yildirim & Correia, 2015). King et al. (2013) found that individuals with higher levels of nomophobia experienced higher levels of nervousness and trauma (Notara et al., 2021). Unnecessary mobile phone use and nomophobia were associated with sleep turbulence, which can have long-term psychological and physical health effects (Parasuraman et al., 2017). Bian and Leung (2015). examined the affiliation amid nomophobia and daily life functioning, finding that it can interrupt academic and professional activities (Gezgin & ÜMMET, 2021). Chóliz (2010) discussed how nomophobia could show the way to challenging mobile phone use and obsession, impacting individual relationships and social functioning. Bragazzi et al. (2019) explored the function of coping strategies in managing nomophobia. They found that individuals utilize both adaptive (e.g., seeking social support) and maladaptive (e.g., avoidance) strategies to deal with nomophobia. Gender differences in nomophobia, with females being more prone to experience it (Yang et al., 2018). Another research found that younger individuals are more likely to suffer from nomophobia, indicating a generational divide (Daei et al., 2019). Technological advancements and the extensive use of smartphones have contributed to the rise of nomophobia. Moreover, cultural and communal factors play a role in the acceptance and prevalence of mobile phone use and nomophobia (Buctot et al., 2020). Certain personality traits, such as neuroticism, have been linked to a higher likelihood of experiencing nomophobia. Neurotic individuals tend to be more anxious and may become more distressed when separated from their Smartphone (De-Sola Gutiérrez et al., 2016; Lepp et al., 2014).

2. Nomophobia Datasets Description

In this analysis, the primary data collection method is used. Among the primary data collection techniques, we followed the "mail questionnaire" and "interviewing" methods. Pabna University of Science and Technology (PUST) had been selected as the target area, and the students were considered the target population in this study. The total sample size used in the current study consisted of 357 university students. A sample is a representative part of the study population. A sample size of 357 has been selected using simple random sampling (SRS) from students at PUST. Sample size determination using formula is

$$n = \frac{N}{(1 + N \times d^2)}$$

where, $n =$ total sample size, N= no. of the student, d= sampling error.

Measuring the level of nomophobia using Likert scale responses. These questions should cover various aspects of nomophobia, such as anxiety when separated from a mobile phone, the need to constantly check the phone, and the impact on daily life. Once we have collected the Likert scale responses, we need to label the data with the severity of nomophobia for each individual. This can be done by defining categories such as "Absence", "Mild", "Moderate", "Severe" nomophobia based on Likert scale scores. Nomophobia response levels are shown in Fig.1 and the detailed demographic information of the dataset are shown in Table 1.

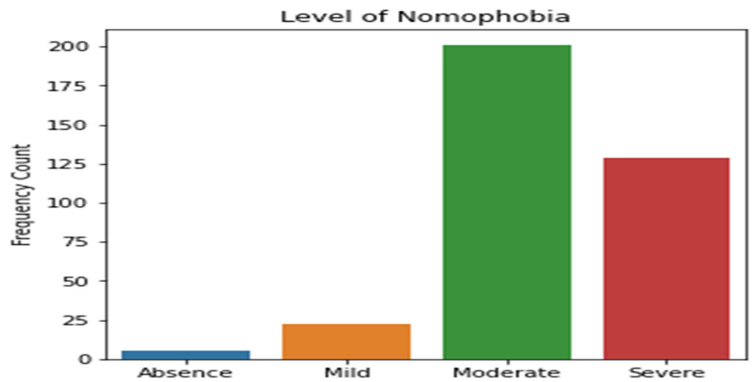


Fig. 1. Bar diagram represents the level of nomophobia

Table 1
Nomophobia Dataset Feature Description

Attributes	Description	Types	Values
Gender	Gender	Nominal	Male, Female
Age	Age	Numeric	Years
Education	Education	Nominal	Graduate,Undergraduate
CGPA	CGPA	Numeric	Score
Self_evaluation	Self_evaluation of smartphone addiction	Nominal	Yes, No
Use per day	Duration of smartphone use per day	Numeric	Hours
Use media	Do you use social media?	Nominal	Yes,No
Use application	Which application do you use most?	Nominal	Application name
Games	Do you play games?	Nominal	Yes, No
Name games	Name of the game applications?	Nominal	Games name
Frequency	Frequency of checking smartphone per hours?	Numeric	Times
Purposes	Perpous of maximum uses	Nominal	Communication, Study & Updates, Entertainment, social Networking, Religious
Context	Context of maximum uses	Nominal	Maximum usage
Checking phone	Checking the phone without any reason	Nominal	Never,sometimes,always
Perception	Perception of ill health	Nominal	Headache, eyestrain, neck pain, disturbed sleep, fatigue
DASS	Would you feel depressed, anxious, stressed?	Nominal	Yes, No
Outcome	Level of nomophobia	Nominal	Absence, mild,moderate, severe

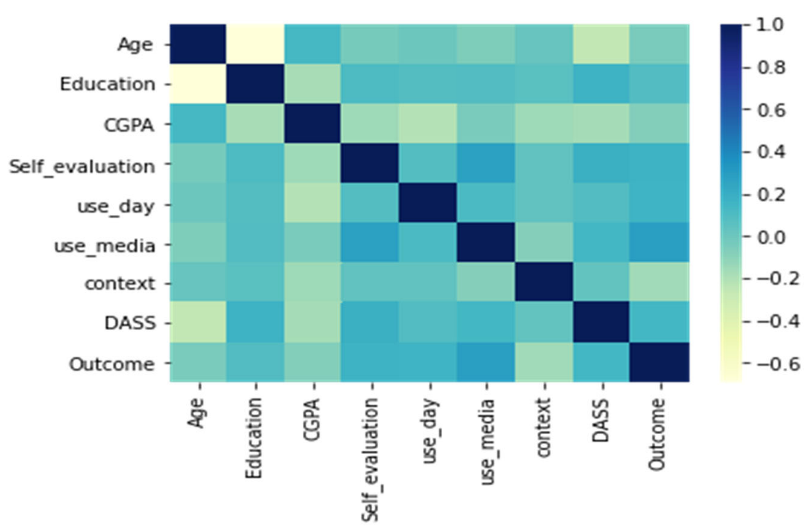


Fig. 2. Correlation heat map plot of the nomophobia features

Preprocessing is done including data cleaned, transformed, and missing values treatment to make it ready to be analyzed or model trained. It is an essential part of the machine-learning pipeline. To determine the addiction level, total scores range from 0 to 140, with 0 indicating no nomophobia, 21 indicating mild nomophobia, 60 indicating moderate nomophobia, and

100 indicating severe nomophobia (Yildirim & Correia, 2015). According to addiction level, it is a multiclass classification problem in machine learning. In Fig. 2, the correlation of various features of our data is shown through a heat map in python. Here we observe all features dependency and select only those features (CGPA, Education) with high dependency that is we can only select those features whose dependency is higher than 0.55.

3. Methodology

In the proposed methodology, we broadly classify it into two sections. We identify the risk factors in the first section, and predictive models are suggested in the second section. The proposed methodology is shown in Fig. 3.

Fig. 3. Proposed ensemble ML based nomophobia addiction diagram

3.1 Risk Factor Identification

It is crucial to identify risk factors based on attributes. To determine the risk factors, we employed a chi-square test for nominal scale attributes and an ordinal logistic regression is performed for ratio scale attributes.

Table 2
Risk factor analysis using Chi-square test ($p < 0.05$)

Factor	P-value	Decision
Gender	0.24	Not associate
Age	0.01	Risk factor
Education	0.00	Risk factor
CGPA	0.00	Risk factor
Self-evaluation	0.04	Risk factor
Use per day	0.**00**	Risk factor
Use media	1.00	Not associate
Use application	0.26	Not associate
Frequency	0.39	Not associate
Purposes	0.34	Not associate
Context	0.00	Risk factor
Checking phone	0.24	Not associate
Perception	0.49	Not associate
DASS	0.00	Risk factor

By using chi- square test statistics we can see that, age, level of education, CGPA, self-evaluation, use per day, use media, context, DASS (depression, anxiety, stressed) are less than 0.05 .So we may conclude that, they are significantly associated with outcome that is level of nomophobia. Ordinal logistic regression is another statistical method for modeling the relationship between an ordinal response variable and one or more explanatory variables. An ordinal variable is a categorical variable with a distinct ordering of the category levels.

Table 3
Risk factor analysis using ordinal logistic regression

Model Variable	coef	std err	t	P>|t|	CI [0.025	0.975]
Intercept	1.7167	0.542	3.170	0.002	0.652	2.782
Age	0.0208	0.021	0.985	0.325	-0.021	0.062
Education	0.1666	0.110	1.513	0.131	-0.050	0.383
CGPA	-0.0212	0.044	-0.480	0.632	-0.108	0.066
Self_evaluation	-0.2064	0.114	-1.809	0.071	-0.431	0.018
use_day	0.0749	0.028	2.674	0.008	0.020	0.130
context	-0.1007	0.028	-3.562	0.000	-0.156	-0.045
DASS	-0.2127	0.100	-2.123	0.034	-0.410	-0.016

From Table 3, we can see that the p-value of self-evaluation, use per day, context, depression anxiety and stress (DASS) are less than 0.05 so there is a statistically significant associated level of nomophobia.

3.2 Proposed Ensemble Predictive model

Common choices for classification problems include Decision Tree Classifier (DT), Random Forest Classifier (RF), Gaussian Naïve Bias classifier (GNB) and Support Vector Machine (SVM). For combining the predictions from multiple models, ensemble learning is also performed that confirms the robust predictive performance. The proposed ensemble method is described in Fig. 4.

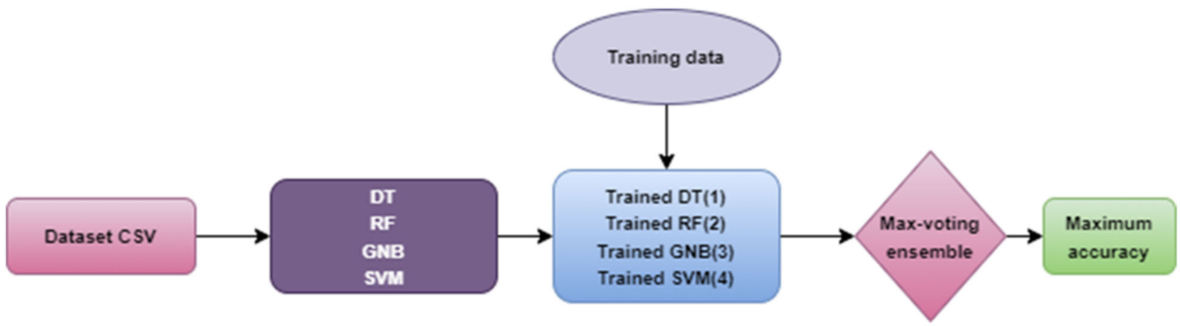


Fig. 4. Proposed ensemble based predictive approach

Train our machine-learning model on the training data using the Likert scale responses as input features and the labeled nomophobia levels as the target variable. Split our dataset into a training set, a validation set, and a testing set. This allows us to train and validate our model's performance on different subsets of the data.

3.3 Evaluation protocols, results, and discussion

This section solely offers results analysis of the level of NOMOPHOBIA utilizing ML classifiers. For our investigation, we split the dataset into 80% training data and 20% testing data. Several performance evaluation matrices, including Accuracy, Precision, Recall, and F1-Score, with some mathematical annotations, which display the descriptions of the performance evaluation matrices.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{FP} + \text{TP} + \text{FN} + \text{TN})} \times 100$$

Precision is defined as a method of determining the quality of a model.

$$Precision = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100$$

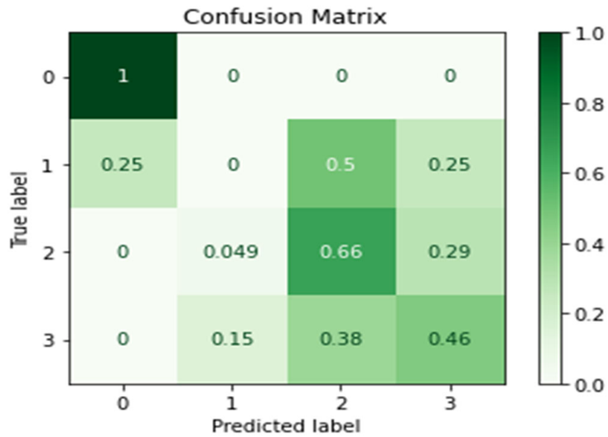
where, recall is defined as a model quantity measurement.

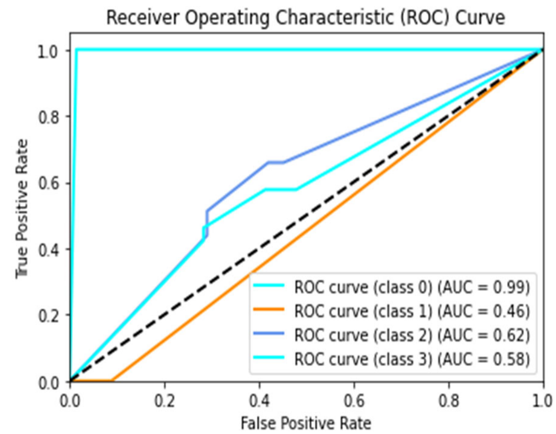
$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \times 100$$

F1-score shows how dependable and accurate a model is.

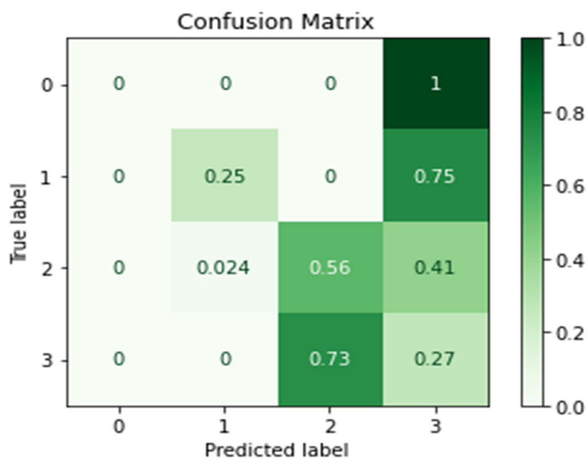
$$\text{F1} - \text{score} = \frac{2 \times (\text{R} \times \text{P})}{\text{R} + \text{P}} \times 100$$

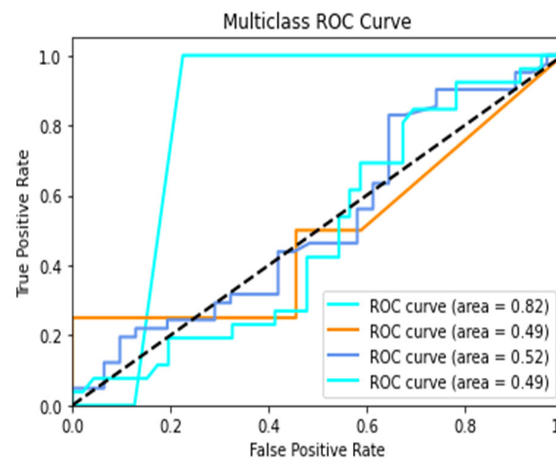
AUC scores are taken into consideration when conducting the proposed research. The results are obtained from different classification algorithm displayed in Fig. 5, Fig.6 and Table 4.





(a) (b)

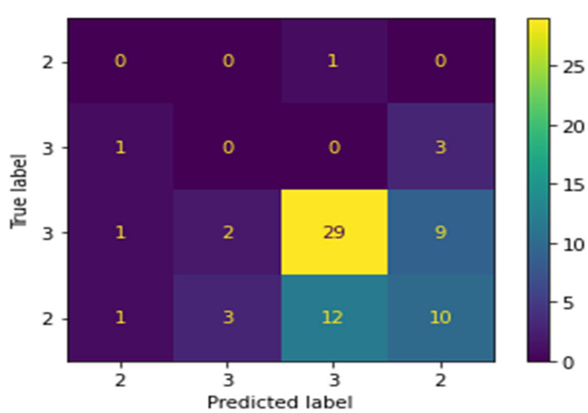


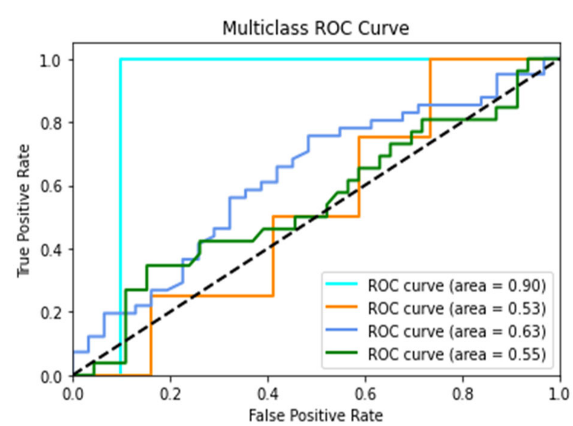


© (d)

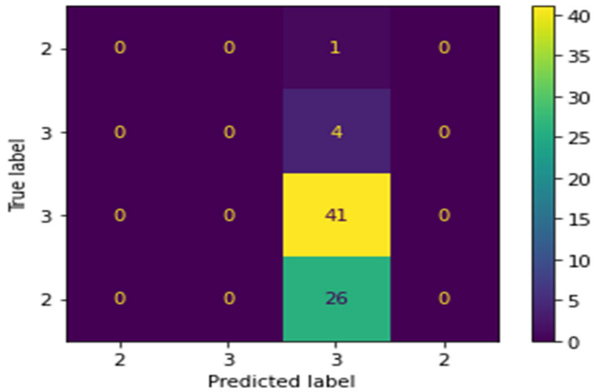
Fig. 5. On the top, (a) and (b) represent decision tree bastree-basedon matrices and ROC curve. Results from random forest displays in (c) and (d).

The ROC curve drawn for the four classes using Decision Tree model and AUC score is 0.99 for the 1st class indicate that this model is highly effective at distinguishing this class from the rest of the other class. The ROC curve drawn for the four classes using Random Forest model and AUC 0.82 for the 1st class indicate that this model is highly effective at distinguishing this class from the rest of the other class.

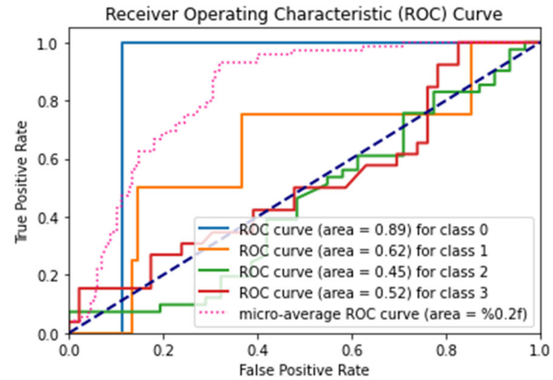




(a) (b)



(c)



(d)

Fig. 6. On the top, confusion matrices and ROC curve of naïve Bayes classification results in (a) and (b). On the bottom (c) and (d) represents SVM performances.

The ROC curve drawn for the four classes using Gaussian Naïve Bayes model and AUC 0.90 for the 1st class indicate that this model is highly effective at distinguishing this class from the rest of the other class. Whereas SVM model and AUC 0.89 for the 1st class indicate that this model is highly effective at distinguishing this class from the rest of the other class.

Table 4
Comparison of classification results obtained from ML and Ensemble Algorithm

Models	Accuracy	Precision	Recall	F1- Score	Ensemble Accuracy
SVM	0.57	0.57	1.00	0.73	
DT	0.56	0.69	0.66	0.68	0.57
RF	0.43	0.55	0.56	0.55	
GNB	0.54	0.69	0.71	0.70	

In Table 4, varieties of classification techniques are compared to classify nomophobia addiction. The highest performance shows a different evaluation performance in SVM whereas naïve Bayes is the least. This study combines four conservative classifiers to create the selection ensemble classifier. From the analysis, we have found that it has classified the extent of Smartphone addiction with a 57% accuracy rate.

4. Conclusion

Using a structured questionnaire, this study has been conducted to measure the psychological condition of nomophobia among 357 students at Pabna University of Science and Technology. The purpose of this study was to identify the cause's factors of nomophobia and classify its addiction level based on machine learning. According to the study, most of the respondents (201) have a moderate level of nomophobia, while 129 respondents are highly addicted. Respondent's age, education year, CGPA, self-evaluation, per-day mobile phone usage, use of media, and the context of maximum phone usage are the important factors that highly affect nomophobia. The study utilized a variety of classification techniques, including DTC, RF, Gauss NB, and SVM. This study combined four conservative classifiers to create the selection ensemble classifier. From the analysis, we have found that the SVM and ensemble classifier recognized smartphone addiction with a 57% accuracy rate.

In conclusion, in the current digital era, nomophobia is a genuine and expanding issue. While there are many advantages to mobile phones, when people grow unduly dependent on them, they may also cause anxiety and other negative effects. Finding a balance between preserving one's physical and mental health with the ease of mobile technology is crucial. Nomophobia can have negative repercussions, but awareness, self-control, and professional assistance when needed can help lessen its impacts and foster a positive connection with mobile devices.

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