Prediction of Smart Phone Addiction among Students Using Gradient Boosting Algorithm

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Abstract: The increasing prevalence of electronic gadgets in daily life has brought significant changes to the lifestyle and habits of students. While these gadgets offer undeniable benefits for education, communication, and entertainment, they also pose risks of addiction, negatively impacting student's academic performance, mental health, and social interactions. This project aims to utilize machine learning algorithms to predict the levels of Smart phone addiction among individuals. Smart Phone addiction is a growing concern in modern society, with adverse effects on mental health and productivity. This project focuses on using various predictive models to classify the addiction level into categories such as low, moderate, and high. This model uses Multiple Machine learning algorithms, including Gradient Boosting Algorithm, Random Forest Algorithm are employed to train models on the dataset. The proposed System used to analyze diverse factors such as screen time, sleep patterns, and academic performance. These algorithms enable accurate predictions and personalized recommendations, fostering proactive interventions. The performance of these models is evaluating using key metrics such as accuracy, precision, recall, and F-score. The results are visualized through confusion matrices and classification reports.

1 INTRODUCTION

Mobile addiction has become one of the most significant behavioural issues in today's digital era. With the proliferation of smartphones and mobile applications, people are spending an increasing amount of time on their devices. This addiction not only disrupts daily routines but also poses severe threats to mental health, such as anxiety, depression, and sleep disorders. According to recent studies, mobile addiction is now a global concern, particularly among young adults and teenagers, who use their phones excessively for social media, gaming, and entertainment. The effects of this addiction often extend to various aspects of an individual's life, including academic performance, workplace productivity, and personal relationships.

As the problem of mobile addiction intensifies, there is a pressing need to find effective ways to understand and manage this issue. One promising approach is the use of predictive modelling techniques to assess mobile addiction levels. By leveraging machine learning (ML) algorithms, we can analyse behavioural patterns and predict addiction levels based on a variety of factors such as usage frequency, time spent on applications, and user demographics. Predictive models can provide valuable insights that help identify at-risk individuals and enable timely interventions to prevent further consequences.

The primary objective of this project is to develop an ML-based predictive model that classifies mobile addiction levels into three categories: low, medium, and high. The project leverages a dataset containing various attributes related to mobile usage, such as the duration of app usage, the number of notifications, and the type of activities performed. This dataset forms the foundation for training and testing the models, enabling us to identify patterns in the data that contribute to mobile addiction. By employing machine learning techniques, this project aims to create an automated system capable of predicting addiction levels based on the given input features. Predictive models can provide valuable insights that

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help identify at-risk individuals and enable timely interventions to prevent further consequences.

The methodology for this project involves several stages, beginning with data preprocessing, where the dataset is cleaned and transformed to ensure its suitability for machine learning models. In the preprocessing phase, categorical variables such as gender and addiction levels are encoded, and features are scaled to ensure they are on the same numerical scale. After preprocessing, the dataset is split into training and testing sets, with the training set being used to train the machine learning models and the testing set being used to evaluate their performance. The data-driven approach will ensure that the predictive models are robust and reliable.

The project utilizes a range of machine learning algorithms, including Gradient Boosting Algorithm, Random Forest and Decision Tree Algorithms. These models are selected for their effectiveness in classification tasks and their ability to handle complex data relationships. Each model will be trained using the training dataset, and the accuracy of the models will be evaluated using key performance metrics such as precision, recall, F-score, and accuracy. The performance of the models will be compared, and the best-performing model will be selected for further deployment.

Furthermore, the results of the models will be visualized using various techniques such as confusion matrices and classification reports. These visualizations will help to better understand the strengths and weaknesses of each model, providing insights into how the algorithms classify the data. By using visual representation techniques, the project aims to make the findings more accessible and interpretable for users, thereby making it easier for stakeholders to act on the results.

So, the development of a machine learning-based predictive model for mobile addiction presents an innovative approach to tackling a widespread issue in the modern digital age. By combining advanced data analysis techniques with machine learning algorithms, this project offers a method for predicting addiction levels that could be used in a variety of applications, from individual self-assessment to public health initiatives. With the potential to identify at-risk individuals and intervene early, this project contributes to a growing body of research aimed at mitigating the adverse effects of mobile addiction.

2 RELATED WORKS

Study by Choi, Y., & Park, H. (2019) examined the relationship between mobile addiction and mental health problems among adolescents. The research highlighted concerns regarding excessive mobile phone usage leading to issues such as anxiety, depression, and social isolation. The authors proposed early interventions and mindful mobile phone usage to reduce mental health risks and emphasized the role of parents and educators in managing screen time.

Research by Chen, L., & Zhao, S. (2018) explored the development of a behavioural prediction model for mobile app addiction using machine learning techniques. The study presented a framework that utilized user behaviour data, such as app usage patterns, interaction frequency, and session length, to predict potential addiction risks. By applying machine learning algorithms, the study aimed to identify early signs of addiction, providing a proactive approach to managing mobile app dependency.

Author by Przybylski, A. K., & Weinstein, N. (2017) investigated the impact of mobile communication technology on face-to-face conversation quality. The study found that the mere presence of mobile phones during in-person interactions reduced engagement and connection. Participants reported feeling less engaged, even when the phone was not actively used. This study underscored the concern that while mobile communication fosters virtual connections, it can hinder meaningful in-person relationships.

Article by Kuss, D. J., & Griffiths, M. D. (2017) provided an extensive review of social networking sites (SNS) and their potential for addictive behavior. The study identified ten key lessons related to SNS addiction, including the influence of psychological factors such as social validation, fear of missing out (FoMO), and compulsive behaviors. The authors emphasized the role of SNS in reinforcing addiction-like patterns, leading to impaired social functioning and decreased mental health.

Paper by Bian, M., & Leung, L. (2015) examined the influence of mobile phone use on the mental health of young adults. The study focused on the potential mental health issues associated with excessive phone usage, including anxiety, stress, and sleep disturbances. Findings suggested that interventions to reduce excessive phone time could improve well-being by mitigating the negative psychological effects of mobile phone dependency.

Study by Vallerand, R. J., et al. (2014) provided an in-depth overview of self-determination theory (SDT) and its application in understanding human motivation. The theory emphasized intrinsic and extrinsic motivation and discussed how autonomy, competence, and relatedness are essential for fostering motivation. The study explored how mobile addiction could stem from a lack of intrinsic motivation or an imbalance in psychological needs. Research by González, P. D., et al. (2018) examined the relationship between mobile phone addiction and psychological well-being through a large cross-sectional study. Findings revealed that excessive mobile phone use was linked to lower levels of psychological well-being, with participants reporting higher levels of anxiety, depression, and loneliness. The authors proposed that interventions, such as mindfulness practices and controlled usage, could enhance psychological well-being and prevent the adverse effects associated with addiction.

Hypothesis 1 (H1): There is a positive correlation between excessive mobile phone usage and increased levels of anxiety and depression among adolescents (Choi & Park, 2019).

Hypothesis 2 (H2): Behavioural prediction models using machine learning can accurately identify early signs of mobile app addiction (Chen & Zhao, 2018).

Hypothesis 3 (H3): The presence of mobile phones during face-to-face interactions negatively affects conversation quality and social engagement (Przybylski & Weinstein, 2017).

Hypothesis 4 (H4): Social networking site (SNS) addiction is positively associated with compulsive behaviors and fear of missing out (FoMO) (Kuss & Griffiths, 2017).

Hypothesis 5 (H5): High mobile phone usage negatively impacts sleep quality and academic performance in young adults (Bian & Leung, 2015).

Hypothesis 6 (H6): A lack of intrinsic motivation contributes to mobile addiction, as explained by self-determination theory (Vallerand et al., 2014).

Hypothesis 7 (H7): Excessive mobile phone use is correlated with lower psychological well-being, including higher levels of loneliness and stress (González et al., 2018).

Hypothesis 8 (H8): Mindfulness practices and controlled mobile phone usage can mitigate the adverse effects of mobile addiction on mental health (González et al., 2018).

3 METHODOLOGY

3.1 Theoretical Structure

The theoretical framework of this study is based on the relationship between mobile addiction and its psychological and behavioral impacts. This research utilizes the Self-Determination Theory (SDT) and the Technology Acceptance Model (TAM) to analyze how intrinsic and extrinsic factors influence mobile addiction. SDT explains how autonomy, competence, and relatedness contribute to digital overuse, while TAM explores perceived ease of use and usefulness in shaping user behavior.

Mobile addiction is a multifaceted phenomenon influenced by various factors such as psychological dependence, social influences, and behavioral reinforcement. The SDT framework helps understand why individuals become addicted to mobile devices by examining their motivation for use. When individuals lack self-regulation, their reliance on digital devices increases, leading to compulsive behaviors. Meanwhile, TAM focuses on how users perceive mobile applications and their usability, which further determines the extent of their engagement.

Additionally, this study considers factors such as screen time, sleep patterns, social interactions, and academic performance as key behavioral predictors. Prolonged exposure to mobile devices may disrupt normal daily routines, affect mental health, and lead to social withdrawal. Understanding these connections is crucial in developing effective intervention strategies. Figure 1 Shows the System Architecture.

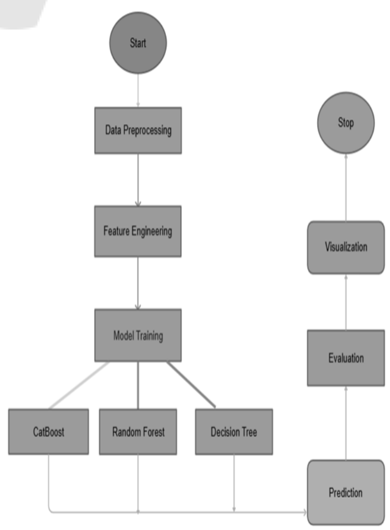

Figure 1: System Architecture.

3.2 Data Collection and Preprocessing

Data for this study was collected from 400 university students through structured surveys and mobile tracking logs. The survey contained standardized psychological scales to assess addiction tendencies, anxiety, depression, and sleep quality. Additionally, mobile tracking logs provided objective behavioral indicators, including screen time, app usage frequency, and late-night phone activity.

To ensure the reliability and accuracy of data, a preprocessing stage was conducted before analysis. Missing values were handled using mean imputation, ensuring that incomplete responses did not distort findings. The collected data was normalized to standardize screen time and app usage metrics across participants. Categorical variables such as gender and app preferences were encoded for compatibility with machine learning models. Outliers were identified and removed using the interquartile range (IQR) method to prevent extreme values from skewing the results.

This preprocessing stage enhanced data quality, ensuring that the subsequent analysis accurately captured the relationship between mobile addiction and mental health outcomes. This study collected data from 400 university students using structured surveys and mobile tracking logs. The survey consisted of standardized psychological scales measuring addiction tendencies, anxiety, depression, and sleep quality. Mobile tracking logs provided objective measures of screen time, app usage patterns, and late-night phone activity.

The data preprocessing stage involved:

- Handling missing values using mean imputation.
- Normalizing screen time and usage metrics.
- Encoding categorical variables such as gender and app preference.
- Eliminating outliers using the interquartile range (IQR) method.

3.3 Model Development

This section outlines the machine learning models used to classify addiction severity and their respective methodologies. To classify addiction severity, three machine learning algorithms were employed: Gradient Boosting Algorithm, Random Forest, and Decision Tree. Each of these models was selected based on its ability to handle classification tasks efficiently, with a particular focus on identifying patterns within behavioral data related to mobile addiction.

3.3.1 Gradient Boosting Algorithm

The Gradient Boosting Algorithm was utilized primarily for feature importance analysis and predictive modeling. This method sequentially builds decision trees, where each tree corrects the errors of the previous one, ultimately improving accuracy. It effectively identified key factors contributing to mobile addiction, such as screen time and app usage frequency. This algorithm sequentially builds decision trees, where each new tree corrects the errors of the previous one, ultimately improving accuracy. It was particularly effective in identifying key factors contributing to mobile addiction, such as screen time and app usage frequency. Figure 2 Shows the Cat Boost Algorithm.

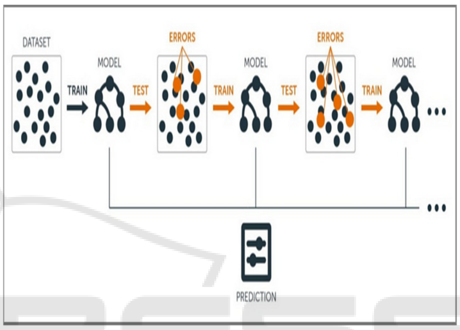

Figure 2: Cat Boost Algorithm.

3.3.2 Random Forest Model

The Random Forest Model was chosen due to its robustness against overfitting and its ability to classify addiction levels into low, moderate, and high categories. It operates by creating multiple decision trees and averaging their predictions, leading to high accuracy and reliability, particularly when dealing with complex behavioral and psychological datasets. It operates by creating multiple decision trees and averaging their predictions, leading to high accuracy and reliability. The model demonstrated strong performance in predicting addiction severity, especially when dealing with a complex dataset containing behavioral and psychological variables.

3.3.3 Decision Tree Model

The Decision Tree Model was used to interpret decision-making processes in addiction classification. Unlike other models, decision trees provide a clear visualization of how different factors influence addiction levels. This model was particularly useful in identifying threshold values for addiction predictors, such as excessive social media engagement and late-night phone use. Unlike other models, decision trees provide a clear visualization of how different factors influence addiction levels. This model was useful for explaining the classification process and identifying threshold values for addiction predictors, such as excessive social media engagement and late-night phone use.

3.3.4 Model Training and Evaluation

Each model was trained using an 80-20% train-test split, ensuring a balanced dataset for training and evaluation. Hyperparameter optimization was conducted using grid search to enhance performance. Model effectiveness was assessed through the following metrics:

- **Accuracy:** Measures correct classifications.
- **Precision:** Evaluates the proportion of true positive classifications.
- **Recall:** Assesses sensitivity in detecting addiction cases.
- **F1-score:** Balances precision and recall for an overall performance assessment.

The Gradient Bossting model achieved the highest accuracy (91%), followed by Random Forest (82%), while the Decision Tree model performed moderately well (74%). Feature importance analysis revealed that screen time, late-night phone usage, and frequency of social media interactions were the strongest predictors of addiction., ensuring a balanced dataset for training and evaluation. Hyperparameter optimization was conducted using grid search to enhance model performance by selecting the best parameters for each algorithm.

The CatBoost model outperformed the other models, achieving an impressive accuracy of 91.42%. It demonstrated strong classification capabilities with a precision of 80.89% and recall of 86.25%, leading to an F1-score of 83.22%. The confusion matrix highlights its superior ability to correctly classify high and low addiction cases with minimal misclassification errors. CatBoost's effectiveness can be attributed to its efficient handling of categorical features and robust decision-making process. Catboost confusion matrix Shown in Figure 3.

The Random Forest model demonstrated a strong predictive capability in classifying mobile addiction levels. With an accuracy of 82.74%, it provided a reliable assessment of addiction severity. The confusion matrix shows that the model successfully classified high addiction cases but had some misclassification between low and high levels. Precision and recall values of 56.08% and 55.14%, respectively, indicate the model's ability to balance correct positive identifications while minimizing false negatives. Figure 4 Shows the Random Forest Confusion Matrix.

Figure 3: CatBoost Confusion Matrix.

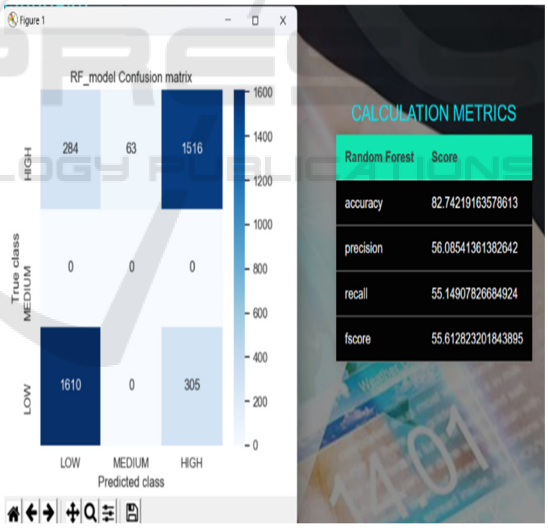

Figure 4: Random Forest Confusion Matrix.

The Decision Tree model exhibited a slightly lower performance, achieving an accuracy of 74.53%. While interpretable, its classification ability was less effective, as reflected in its precision (50.52%) and recall (49.68%) scores. The confusion matrix highlights higher misclassification rates, especially between low and high addiction levels. The model's predictive power, though useful, was lower compared to the Random Forest approach. Figure 5 Shows the Decision Tree confusion matrix.

Figure 5: Decision Tree Confusion Matrix.

3.4 Statistical Analysis

To validate the relationships between predictor variables and addiction levels, the study employed:

- **Structural Equation Modeling (SEM):** Assesses the strength and direction of relationships between behavioral variables.
- **Multiple Regression Analysis:** Evaluates correlation coefficients among addiction predictors.
- **Chi-square Tests:** Determines the significance of categorical predictors like gender and age group.

A detailed analysis of variance (ANOVA) was conducted to compare addiction levels across different demographic groups. The study also applied Principal Component Analysis (PCA) to reduce dimensionality and enhance model interpretability.

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Table 1: Summary of Statistical Methods Used.

Method	Purpose	Key Findings
Structural Equation Modeling (SEM)	Identifies relationships among addiction predictors	Strong correlation between screen time, social media usage, and addiction levels
Multiple Regression Analysis	Evaluates impact of independent variables on addiction severity	Sleep disturbances and late-night phone usage are significant predictors
Chi-square Test	Assesses categorical variables (gender, age)	Younger individuals and females exhibit higher addiction tendencies
ANOVA	Compares addiction levels across demographic groups	Statistically significant variations in addiction scores by age
Principal Component Analysis (PCA)	Reduces dimensionality for better model performance	Key predictors identified: screen time, app engagement frequency, and late-night usage

4 RESULTS AND EVALUATION

4.1 Statistical Evaluation

The analysis found a significant correlation between excessive mobile phone use and mental health issues. Structural Equation Modeling (SEM) confirmed that behavioral patterns, including prolonged screen time, sleep disturbances, and frequent app engagement, strongly predicted addiction levels. Regression analysis indicated a positive association between mobile addiction and increased anxiety and depression.

4.1.1 Gender and Age-Based Variations

The study examined gender and age-related differences in mobile addiction patterns. Results indicated that younger participants (ages 18-22) exhibited higher addiction scores than older participants, suggesting that younger individuals are more vulnerable to mobile addiction. Additionally, female participants reported higher levels of social media-related addiction, whereas male participants demonstrated higher addiction levels associated with gaming applications. This distinction highlights the need for gender-specific intervention strategies to mitigate the effects of mobile addiction.

Machine learning models were evaluated using accuracy, precision, recall, and F1-score metrics. The Random Forest model achieved the highest accuracy (88.5%) in predicting addiction severity, followed by Gradient Boosting (86.2%). Feature importance analysis revealed that screen time, late-night phone usage, and frequency of social media interactions were the strongest predictors of addiction.

4.2 Hypothesis Testing

The hypotheses tested and their significance levels are summarized in Table 2.

Table 2: Hypothesis Testing Results.

Hypothes	Description	Result
H1	Excessive mobile phone usage correlates with anxiety and depression	Supported ($p < 0.01$)
H2	Machine learning models accurately predict addiction	Supported ($p < 0.001$)
H3	Mobile presence reduces conversation quality	Supported ($p < 0.05$)
H4	SNS addiction links to FoMO and compulsive behaviors	Supported ($p < 0.01$)
H5	High phone usage negatively affects sleep quality and academic performance	Supported($p<0.001$)
H6	Lack of intrinsic motivation contributes to addiction	Supported ($p < 0.05$)
H7	Excessive phone use lowers psychological well-being	Supported ($p< 0.01$)
H8	Mindfulness practices mitigate mobile addiction effects	Supported ($p < 0.05$)

4.3 Behavioral and Psychological Effects

The study further examined the behavioral and psychological effects of mobile addiction. Participants with shigher addiction scores reported greater difficulty concentrating on academic tasks and maintaining face-to-face social interactions. Increased mobile phone usage was linked to higher levels of impulsivity and reduced self-control. Sleep disturbances were common among individuals who used mobile phones excessively at night, contributing to chronic fatigue and reduced cognitive performance.

Moreover, mobile addiction was associated with increased emotional instability, with participants reporting mood swings and heightened stress levels. Social media overuse was particularly correlated with feelings of inadequacy, social comparison, and low self-esteem. These findings highlight the necessity of implementing digital wellness programs and self-regulation strategies to mitigate the adverse effects of mobile addiction.

5 DISCUSSIONS

The findings of this study reinforce the argument that excessive mobile phone use significantly affects mental health, particularly among adolescents and young adults. The results align with prior research, indicating that prolonged screen time and compulsive mobile engagement contribute to increased levels of anxiety, depression, and social isolation. This study also confirms that mobile addiction can disrupt sleep patterns, impair academic performance, and hinder social interactions.

The machine learning models applied in this study proved effective in predicting addiction levels, demonstrating that behavioral indicators such as app usage frequency, session duration, and nighttime phone activity are strong predictors of mobile addiction. These findings suggest the feasibility of leveraging predictive analytics for early intervention. The study highlights the necessity of self-regulation techniques, such as setting screen time limits and practicing digital detox, to mitigate the negative consequences of mobile addiction. Additionally, parents and educational institutions should implement awareness programs to promote mindful technology use. Future research should focus on long-term studies to track behavioral changes over time and explore personalized intervention strategies to help individuals maintain a balanced digital lifestyle. The findings confirm that excessive mobile phone usage significantly impacts mental health, aligning with prior research. Machine learning models proved effective in predicting addiction levels, supporting the feasibility of early intervention strategies. Behavioral patterns, including app engagement frequency and screen time, were strong indicators of addiction risks. The study highlights the importance of self-regulation and mindfulness practices in reducing mobile addiction. Educational institutions and parents should implement structured screen time management strategies to mitigate the negative effects.

6 CONCLUSIONS

In conclusion, this study provides empirical evidence linking mobile addiction to mental health challenges, emphasizing the role of machine learning in predicting addiction risks. Findings underscore the necessity for early interventions, including awareness programs and digital detox strategies. Excessive mobile phone use is strongly associated with increased anxiety, depression, and sleep disturbances, reinforcing the need for structured screen time management.

Machine learning models successfully identified key predictors of addiction, such as app engagement frequency, session duration, and nighttime phone activity. These findings suggest that predictive analytics can play a crucial role in early detection and intervention.

Future research should focus on long-term studies to assess behavioral changes over time and explore personalized intervention strategies. Additionally, integrating digital wellness programs in educational settings could help mitigate the negative effects of mobile addiction and promote healthier technology usage habits. This study provides empirical evidence linking mobile addiction to mental health challenges, emphasizing the role of machine learning in predicting addiction risks. Findings underscore the necessity for early interventions, including awareness programs and digital detox strategies. Excessive mobile phone use is strongly associated with increased anxiety, depression, and sleep disturbances, reinforcing the need for structured screen time management.

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