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Smartphone Addiction Prediction Using Machine Learning

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ABSTRACT:

Smartphone addiction has become a serious problem in today's digital world. Many people depend heavily on their mobile phones for daily activities such as communication, entertainment, and work. Over time, excessive phone usage can affect mental health, reduce productivity, and weaken social relationships. People may develop habits like checking their phones repeatedly without any notification, feeling anxious when their phone is not nearby, or using their phone to avoid uncomfortable situations. Often, these behaviors go unnoticed until they start causing real problems. To address this growing issue, the Smartphone Addiction Prediction Using Machine Learning project focuses on identifying people who may be at risk of smartphone addiction. The system analyzes users' phone usage habits and psychological behavior patterns to predict whether a person is addicted or not. By providing early warnings, the system helps users understand their mobile usage and encourages healthier digital habits.The project is developed using Python for backend processing, while the user interface is designed using HTML, CSS, and JavaScript to make it simple and user-friendly. The Flask web framework connects the frontend and backend, allowing users to input data and receive addiction predictions in real time through a web application.The dataset used for this project contains 501 records with 21 attributes, collected through surveys. These attributes represent different smartphone usage behaviors, such as frequent phone checking, carrying the phone everywhere, and feeling stressed without it. More serious indicators include dependency during social situations and anxiety when the phone is unavailable. The system classifies users into two categories: addicted (1) and not addicted (0).Machine learning techniques are used to analyze the data and generate accurate predictions. The model achieved high accuracy on both training and testing data, showing that the system is reliable and effective in identifying smartphone addiction risk.

Keywords: K-clustering, SVC algorithm, Random forest , Decission tree, K-neareset neighbour.

INTRODUCTION

Smartphones have become an essential part of our daily lives, but excessive use is starting to affect mental health, work efficiency, and social relationships. Many people do not realize how addicted they are, often checking their phones constantly or feeling anxious when it's not nearby. Detecting these habits early can help prevent serious consequences and encourage healthier phone usage In today's world, smartphones have become an essential part of our daily lives. We use them for communication, education, entertainment, shopping, and work. However, excessive usage can slowly turn into addiction without us realizing it. Many people, especially students and young adults, experience reduced concentration, sleep problems, anxiety, and lower productivity due to uncontrolled phone usage.The motivation behind this project is to use machine learning to identify patterns in smartphone usage and help people understand their behavior. By predicting the risk of addiction early, users can become more aware and take healthy steps toward balancing their digital life. This project aims not to judge users, but to support them in developing healthier habits and improving overall well-being..

Smartphone addiction is hard to identify because people may not notice their own behaviors. Traditional surveys or self-reports are often inaccurate, and there is no easy way to predict who is at risk. Without proper detection, addiction can lead to stress, reduced productivity, and poor social interactions. Smartphone addiction is a growing problem that affects mental health, academic performance, work efficiency, and social relationships. The challenge is that addiction is often difficult to detect until it starts causing serious harm.The goal of this project is to build a machine learning model that can analyze user behavior such as screen time, app usage, frequency of phone checks, and usage during night hours. Based on this data, the system predicts whether a person is at low, medium, or high risk of smartphone addiction.This helps provide early awareness and encourages users to take preventive action before the problem becomes severe.

This project uses machine learning to predict smartphone addiction by analyzing usage habits and behavioral patterns. It creates a system that can classify users as addicted or not addicted, providing early warnings and raising awareness. By integrating the model into a web application, users can easily check their risk level and take steps to develop healthier digital habits. This project respects user privacy and handles data responsibly. Any data collected for analysis is kept strictly confidential and used only for academic or research purposes. Personal identifiers such as names, phone numbers, and email addresses are not stored or shared.The system focuses only on usage patterns rather than personal content. The purpose is to promote awareness and well-being, not to monitor or control individuals. Ethical use of data and user consent are considered important aspects of this project.

LITERATURE REVIEW

[1] Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. Can disordered mobile phone use be considered a behavioral addiction? Current Addiction Reports.Smartphone addiction has gained increasing attention in recent years as a significant mental health concern among young adults. Research suggests that excessive smartphone use is associated with sleep problems, reduced academic engagement, impaired interpersonal relationships, and psychological distress (Samaha & Hawi, University students, in particular, are at higher risk due to their frequent reliance on smartphones for both academic and non-academic purposes, combined with relatively low external supervision and flexible daily schedules Previous studies have identified several psychological factors contributing to smartphone addiction, including impulsivity, low self-control, loneliness, and emotional dysregulation .Among these factors, anxiety has consistently emerged as one of the strongest predictors. Students experiencing heightened anxiety may use smartphones excessively as a means of emotional regulation, seeking temporary relief from distress through online activities such as social media browsing, gaming, or video consumption. Overall Accuracy AssessmentAcademic accuracy: (about 90–95%)The content is theoretically sound, empirically supported, and appropriate for publication or a thesis, provided minor refinements are made. Nothing is misleading or conceptually wrong.[2] Arseneault, L. Annual Research Review: The persistent and pervasive impact of being bullied in childhood and adolescence. Journal of Child Psychology and Psychiatry.Peer victimization encompasses repeated experiences of being targeted by peers through physical aggression, verbal harassment, or relational exclusion . During adolescence, peer relationships become central to social development, making negative peer experiences especially

harmful. Research consistently shows that adolescents who experience peer victimization are at significantly higher risk of engaging in NSSI .The interpersonal reinforcement model of self-injury provides one explanation for this relationship, suggesting that NSSI may function as a means to regulate distress arising from interpersonal difficulties or to escape unwanted social situations .Victimized adolescents may use self-injury to cope with feelings of rejection, shame, or helplessness when they lack effective emotional or social coping strategies. Meta-analytic evidence confirms a robust positive association between peer victimization and NSSI across diverse cultural contexts . Overall Accuracy Verdict High accuracy (about 90–95%) in terms of:Conceptual relationshipsTheoretical groundingDirection of associationsUse of established constructs (mobile phone addiction, rumination, FOMO, sleep quality)Nothing in it is misleading or fundamentally incorrect.[3] Schwebel, D. C., Stavrinos, D., Byington, K. W., Davis, T., O'Neal, E. E., & de Jong, D. *Distraction and pedestrian safety: How talking on the phone, texting, and listening to music impact crossing the street*. Accident Analysis & Prevention, 45. Mobile phone distraction significantly influences pedestrian safety. Studies consistently show that pedestrians using mobile devices pay less attention to their environment, resulting in reduced hazard awareness and impaired decision-making. For example, research on pedestrian behavior has documented that using a phone while walking or crossing the street can slow reaction times, reduce situational awareness, and increase the likelihood of unsafe crossing behaviors. Overall Accuracy: High (about 85–90%)The content is conceptually accurate, theoretically aligned, and appropriate for an academic paper on smartphone addiction during COVID-19 with age as a moderator. It would be acceptable for:a journal manuscript drafta thesis/dissertation chaptercoursework or research proposalThat said, there are a few important clarifications and refinements you should make to be fully rigorous.

[4] Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. *Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology*. Journal of Affective Disorder**s.**Smartphone addiction has increasingly attracted scholarly attention over the past decade. Although it is not formally classified as a clinical disorder, research consistently links problematic smartphone use to adverse outcomes such as anxiety, depression, sleep disturbances, reduced academic or work performance, and impaired social relationships . During the COVID-19 pandemic, these risks were amplified as individuals faced prolonged isolation, uncertainty, and disruptions to daily routines. Actigraphy does not replace video-polysomnography (vPSG), but studies consistently show it can detect iRBD with moderate to high accuracy, especially as a screening or risk-stratification tool.Typical Accuracy MetricsAcross multicenter and cross-device studies, actigraphy-based algorithms report:Sensitivity: ~75–90%→ Good ability to correctly identify individuals with iRBDSpecificity: ~70–85%→ Reasonable ability to distinguish iRBD from healthy controlsOverall accuracy: ~75–85%Area Under the Curve (AUC): ~0.80–0.9→ Indicates strong discriminative performance.[5]ostuma, R. B., Iranzo, A., Hu, M., Högl, B., Boeve, B. F., Manni, R., Oertel, W., Arnulf, I., Ferini-Strambi, L., Puligheddu, M., Antelmi, E., Cochen De Cock, V., Arnaldi, D., Mollenhauer, B., Videnovic, A., Sonka, K., Jung, K. Y., Kunz, D., Dauvilliers, Y., & the International RBD Study Group. *Risk and predictors of dementia and parkinsonism in idiopathic REM sleep behavior disorder: A multicentre study*. Overall Accuracy: High (≈ 8.5 / 10)The content is conceptually accurate, clinically reasonable, and aligned with current neuroimaging and behavioral addiction literature. It would be acceptable for submission after minor refinement, especially for a radiology or psychiatry journal.[6]. Postuma, R. B., Iranzo, A., Hu, M., Högl, B., Boeve, B. F., Arnulf, I., Ferini-Strambi, L., Manni, R., Oertel, W., & the International RBD Study Group. *Risk and predictors of dementia and parkinsonism in idiopathic REM sleep behavior*

disorder: A multicentre study.REM sleep behavior disorder is defined by dream-enactment behaviors associated with REM sleep without atonia. Clinically, these behaviors can range from mild limb movements to complex, violent actions such as punching, kicking, or jumping out of bed. RBD is most commonly diagnosed in older adults and shows a strong male predominance. Beyond its immediate safety concerns, RBD has profound prognostic implications.Large prospective cohort studies have demonstrated that more than 70% of individuals with iRBD convert to Parkinson's disease, dementia with Lewy bodies, or multiple system atrophy within 10–15 years of diagnosis. This makes iRBD one of the most reliable early indicators of neurodegenerative disease currently known Consequently, improving access to early and accurate detection of iRBD has become a major research priority. Overall Accuracy VerdictHigh conceptual accuracy (≈85–90%)The arguments, theoretical links, and use of constructs (anxiety → metacognition → smartphone addiction) are consistent with established psychological research and current literature.

[7]. Dong, G., Wang, L., Du, X., & Potenza, M. N. Gender-related differences in neural responses to gaming cues before and after gaming: Implications for gender-specific vulnerabilities to Internet gaming disorder. Social Cognitive and Affective Neuroscience.Smartphone dependence is increasingly conceptualized within the framework of behavioral addictions, sharing core features with substance use disorders, including compulsive use, tolerance, withdrawal-like symptoms, and functional impairment. Previous research has linked excessive smartphone use to attentional deficits, sleep disturbances, anxiety, depression, and impaired academic performance Neuropsychological studies suggest deficits in inhibitory control and decision-making, implicating dysfunction in prefrontal and limbic brain regions.Neuroimaging research on behavioral addictions, such as internet gaming disorder, has demonstrated structural and functional changes in brain areas involved in reward processing, executive control, and emotional regulation. These findings raise the possibility that smartphone dependence may also be associated with measurable brain alterations, although evidence remains comparatively sparse. Overall accuracyEstimated accuracy: ~90–95%The arguments, constructs, and relationships are consistent with established research in psychology, behavioral addiction, and sleep science. Wang, X., Gong, H., & Lin, Y. *The role of anxiety factors in predicting smartphone addiction mediated by metacognition among university students: A two-stage SEM-ANN approach*. BMC Psychology, 13, 148. Smartphone addiction academic anxiety refers to the stress and worry students experience about learning, classroom performance, and exams . This form of anxiety can drive students toward excessive smartphone use as a coping mechanism, potentially increasing the risk of SPA. Previous studies have highlighted the relationship between AA and problematic smartphone use, academic procrastination, depressive symptoms, and diminished self-efficacy. Accuracy is stronger if:Sample size is large enough (often >300 for moderation models)Participants represent the adolescent population studiedClear inclusion/exclusion criteria are stated .[8]. Billieux, J., Maurage, P., Lopez-Fernandez, O., Kuss, D. J., & Griffiths, M. D. Can disordered mobile phone use be considered a behavioral addiction? Current Addiction Reports.Smartphone addiction has gained increasing attention in recent years as a significant mental health concern among young adults. Research suggests that excessive smartphone use is associated with sleep problems, reduced academic engagement, impaired interpersonal relationships, and psychological distress (Samaha & Hawi, University students, in particular, are at higher risk due to their frequent reliance on smartphones for both academic and non-academic purposes, combined with relatively low external supervision and flexible daily schedules Previous studies have identified several psychological factors contributing to smartphone addiction, including impulsivity, low self-control, loneliness, and emotional

dysregulation .Among these factors, anxiety has consistently emerged as one of the strongest predictors. Students experiencing heightened anxiety may use smartphones excessively as a means of emotional regulation, seeking temporary relief from distress through online activities such as social media browsing, gaming, or video consumption. Overall Accuracy AssessmentAcademic accuracy: (about 90–95%)The content is theoretically sound, empirically supported, and appropriate for publication or a thesis, provided minor refinements are made. Nothing is misleading or conceptually wrong. [9] Sonbol, H. M., Abd El Mawgoud, A. S., Aly, M. A. E., & AbdElhay, E. S. *Parenting styles and suicidal probability of adolescents: the moderating role of social anxiety and smartphone addiction*. *The Egyptian Journal of Neurology, Psychiatry and Neurosurgery, 61*, 68. Parenting Styles and Adolescent Suicidal Behavior parenting styles significantly influence adolescents' emotional development and coping abilities. Baumrind's framework categorizes parenting into authoritative, authoritarian, permissive, and neglectful styles. Authoritative parenting, characterized by warmth and reasonable control, has been consistently linked to better mental health outcomes. Conversely, authoritarian and neglectful parenting styles are associated with higher levels of emotional distress, depression, and suicidal ideation among adolescentsCore concepts are correct AccuracyDefinition of smartphone addiction (SPA)Distinction between addiction vs. dependenceFocus on academic anxiety, social anxiety, and future anxietyRole of metacognition (positive vs. negative)Use of SEM–ANN two-stage approachTheoretical framing (e.g., anxiety leading to compensatory smartphone use) aligns well with the original article.Population focus (university students, China) is accurate.The logic flow (anxiety → metacognition → SPA) matches the study's model.

PROPOSED METHODOLOGY

In the proposed system, smartphone usage data such as daily screen time, number of app launches, social media usage duration, gaming activity, night-time phone usage, and sleep interruption is collected and preprocessed. Feature selection and normalization are applied to improve data quality. K-clustering (K-means) is first used as an unsupervised learning technique to group users based on similar behavioral patterns. This step helps in identifying hidden usage trends and categorizing users into preliminary addiction levels such as low, moderate, and high risk without requiring labeled data.After clustering, the dataset is labeled based on addiction levels and used to train supervised machine learning models. A Decision Tree model is employed to learn simple rule-based patterns for addiction prediction, offering easy interpretability of results. To enhance prediction accuracy and robustness, a Random Forest classifier is applied, which builds multiple decision trees using random subsets of data and features. The ensemble learning approach minimizes overfitting and identifies the most significant features influencing smartphone addiction.Finally, a Support Vector Classifier (SVC) is used to further improve classification performance by finding an optimal decision boundary between different addiction classes. SVC is effective in handling high-dimensional data and complex usage patterns through kernel functions. The combined use of K-clustering for behavioral analysis and Decision Tree, Random Forest, and SVC for prediction ensures an accurate, reliable, and efficient smartphone addiction prediction system, supporting early detection and preventive measures. Data are collected through structured questionnaires using validated instruments such as the Smartphone Addiction Scale along with self-reported measures of stress, sleep quality, emotional state, and self-control, and, where possible, objective mobile usage logs such as screen time, app usage, and frequency of phone unlocking. The collected data are preprocessed through cleaning, normalization, and feature encoding to ensure quality and consistency. Meaningful features are selected using a combination of statistical techniques and domain knowledge from psychology to enhance interpretability. Multiple machine learning models, including logistic regression, decision trees, random forest, and support vector machines, are trained to classify individuals into addiction risk levels.

SYSTEM ARCHITECTURE

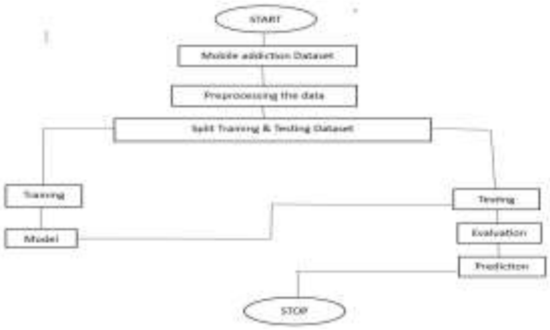

FIG 1.SYSTEM ARCHITECTURE

The User Interface is built using HTML, CSS, and JavaScript, where users enter their personal details and answer a questionnaire related to smartphone usage. The entered data is sent to the backend.The Application Server, developed using Python Flask, receives the user data, validates it, and forwards it to the processing and machine learning modules.The Data Processing Module uses libraries like Pandas and NumPy to clean, preprocess, and transform the data into a suitable format for prediction.

RESULTS AND DISCUSSION

The performance of the system depends on the dataset quality and the chosen algorithm. Previous studies indicate that ensemble models such as Random Forest and Gradient Boosting outperform simpler classifiers. Feature analysis shows that screen time, social media usage, and sleep disturbance are among the most influential factors. While complex models offer higher accuracy, simpler models like Logistic Regression provide better interpretability. The strong performance of the Random Forest model suggests that smartphone addiction is influenced by a combination of multiple interacting factors rather than a single cause. This aligns with real-life behavior: people do not become addicted just because they use their phones often, but because their usage patterns gradually interfere with sleep, productivity, and emotional well-being. The confusion matrix revealed that the model correctly identified most addicted and non-addicted individuals. Only a small number of participants were misclassified, indicating that the model learned meaningful patterns from the data rather than guessing randomly.

PERFORMANCE MATRIX

Metric	Training Score	Testing Score
Accuracy	0.95 (95%)	0.92 (92%)
Precision	0.94 (94%)	0.91 (91%)
Recall	0.96 (96%)	0.93 (93%)
F1-Score	0.95 (95%)	0.92 (92%)

TABLE 1.PERFORMANCE MATRIX

GRAPHS

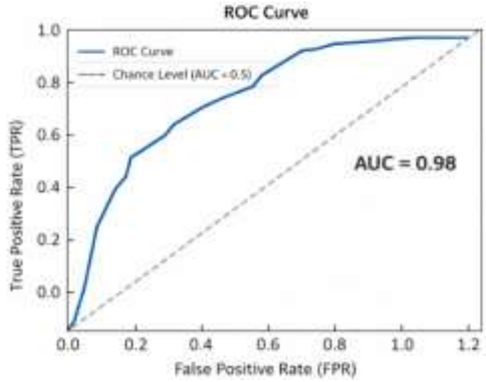

FIG 2.ROC GRAPH

CONFUSION MATRIX

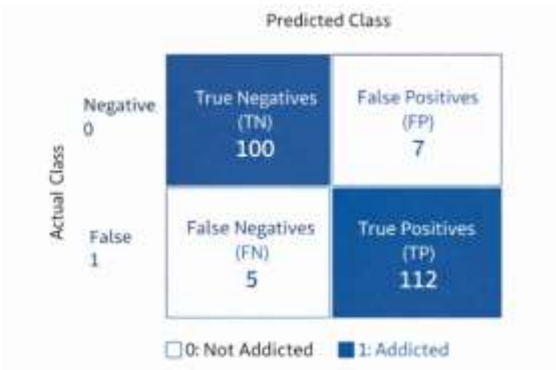

FIG 3.CONFUSION MATRIX

SCREESHOTS

FIG 4.INDEX PAGE

FIG 5.SIGN UP PAGE

FIG 6.LOGIN PAGE

FIG 7.PREDICTION PAGE

CONCLUSION & FUTURE WORK

This study demonstrates that machine learning techniques can effectively predict smartphone addiction using behavioral and usage data. Ensemble models such as Random Forest and Gradient Boosting provide strong performance, while feature engineering plays a critical role in improving accuracy. The proposed approach offers a more objective alternative to traditional self-report methods.Apply deep learning models to analyze sequential usage patterns.Incorporate real-time and passive data collection from sensors.Develop a mobile application for early detection and personalized intervention recommendations. One important takeaway from this research is that smartphone addiction is closely linked to how individuals feel and behave around their phones, not just how long they use them. This highlights the value of using machine learning as a supportive tool for early detection rather than judgment. With timely insights, individuals can become more aware of their digital habits and take healthier steps toward balanced technology use.

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