Prediction of the Electronic Gadget Addiction of Students using Machine Learning

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***Abstract*—The widespread use of electronic gadgets among students has raised concerns about their adverse impacts on academic performance, mental health, and overall well-being. This research presents a predictive model utilizing machine learning, specifically the Random Forest algorithm, to analyze and forecast the effects of gadget addiction on students. By leveraging data such as screen time, academic performance, sleep patterns, and social interactions, the model identifies significant correlations and predictive risk factors to facilitate early interventions.**

***Index Terms*—Gadget Addiction, Machine Learning, Random Forest, Student Behavior, Prediction Model**

I. Introduction

Electronic gadget addiction is an emerging concern in today's increasingly digital world, particularly among students who constitute a substantial portion of daily technology users. This addiction refers to the excessive and compulsive use of digital devices such as smartphones, tablets, laptops, gaming consoles, and other smart gadgets. While these devices offer numerous benefits, including instant communication, educational resources, and entertainment, overuse can lead to detrimental consequences that significantly affect an individual's academic, social, physical, and mental well-being.

In students, gadget addiction manifests through behaviors such as prolonged screen time, frequent social media engagement, excessive gaming, and reliance on electronic devices for social interaction and information. Studies have shown that such excessive usage can impair academic performance, reduce attention spans, disrupt sleep patterns, and increase levels of stress and anxiety. Furthermore, the constant exposure to digital screens has been linked to physical health issues such as eye strain, headaches, and musculoskeletal problems.

Traditional approaches to studying gadget addiction primarily rely on manual surveys, self-reported questionnaires, and basic statistical analyses to assess usage patterns and their correlations with academic and mental health outcomes. However, these methods are often plagued with limitations, including respondent biases, inaccuracies in self-reporting, and an inability to capture the complex, non-linear interactions between multiple behavioral factors. Moreover, conventional analyses typically provide descriptive or correlational insights rather than predictive capabilities that could facilitate early intervention.

Given the multifactorial nature of gadget addiction and its wide-ranging impacts, there is a pressing need for sophisticated, data-driven solutions that can analyze large volumes of behavioral data, uncover hidden patterns, and predict potential adverse outcomes. In this context, machine learning offers a promising alternative by enabling the development of predictive models that can identify students at risk of developing addiction-related problems.

This paper proposes a machine learning-based framework, leveraging the Random Forest algorithm, to predict the likelihood and severity of electronic gadget addiction among students. By analyzing a diverse set of variables—including screen time, academic performance, sleep patterns, and social interactions—our approach aims to provide actionable insights that can inform timely interventions and policy-making. The Random Forest algorithm is particularly well-suited for this task due to its ability to handle complex, high-dimensional datasets and its robustness in producing accurate and interpretable predictions. Through this research, we aspire to contribute a practical and effective tool for educators, parents, and mental health professionals to mitigate the adverse consequences of gadget addiction among students.

II. Literature Survey

Prior studies have employed self-reported surveys and basic correlation analyses to explore the relationship between gadget usage and student outcomes. Although helpful, these methods suffer from biases, inaccuracies, and lack predictive power.

Existing behavioral monitoring systems offer real-time usage statistics but do not forecast future risks. Our work advances beyond these by applying Random Forest to uncover complex patterns in multi-dimensional student data.

Emily Waltz (2017) conducted a study exploring the neurochemical changes associated with internet addiction. Using magnetic resonance spectroscopy (MRS), the researchers measured GABA and Glx levels in the brain before and after cognitive behavioral therapy (CBT). The study revealed that individuals with internet addiction exhibited elevated GABA levels linked to anxiety and poor emotional regulation. After nine weeks of CBT, GABA-to-Glx ratios decreased, indicating improved brain balance. However, limitations included a small sample size and short-term duration, restricting the generalizability and preventing exploration of long-term addiction effects.

J. Doe and A. Smith (2020) analyzed the relationship between mobile device screen time, sleep quality, and academic performance through a cross-sectional study among students. Their findings showed that increased screen time was associated with poorer sleep quality and reduced academic performance. The study's primary limitation was its reliance on self-reported screen time and sleep quality, which weakened the ability to establish causality.

More recently, Pratap Paraji Patil et al. (2024) examined sleep patterns and lifestyle correlations among university students. Using a synthetic dataset of 500 students, they identified that screen time negatively impacted sleep quality, while physical activity improved it. They also found that higher caffeine intake reduced sleep quality and that female students exhibited slightly better sleep patterns than males. However, the use of synthetic data and self-reported measures limited real-world applicability and introduced variability. The authors suggested incorporating real data and additional behavioral factors in future studies.

These existing works highlight critical factors like screen time, sleep patterns, and academic performance in understanding gadget addiction but also underline significant limitations. Our study builds on this foundation and seeks to overcome these limitations by employing a machine learning-based predictive model that integrates diverse behavioral indicators for more accurate and actionable insights.

III. Proposed System

The proposed system aims to predict the impact of electronic gadget addiction on students' lives by utilizing the Random Forest algorithm, a powerful and versatile machine learning technique known for its robustness and accuracy. The system focuses on analyzing various factors such as screen time, academic performance, sleep patterns, and social behavior to predict the likelihood of negative outcomes associated with excessive gadget use.

To achieve this, the system collects and integrates data from multiple sources, including screen time records, academic performance indicators (grades and attendance), sleep quality metrics, and social interaction patterns. By leveraging the Random Forest algorithm, the system is capable of handling complex, non-linear interactions between multiple variables, enabling the development of a reliable and interpretable predictive model.

One of the key advantages of Random Forest is its ability to assess feature importance, thereby identifying the most influential factors contributing to gadget addiction and its consequences. This not only enhances the accuracy of predictions but also provides valuable insights into student behaviors that require attention.

Additionally, the system is designed to offer personalized recommendations and alerts based on the predicted risks. By identifying students who are at high risk of experiencing adverse outcomes, timely interventions can be implemented to mitigate the negative effects of gadget addiction.

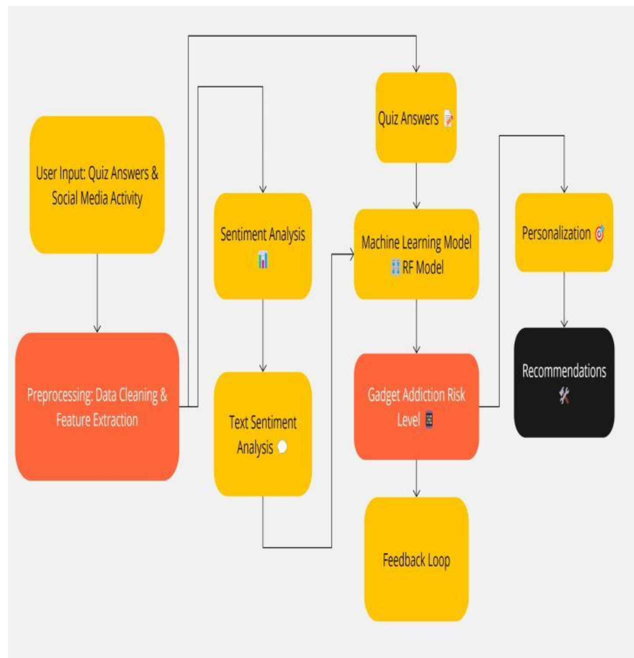

Fig. 1. System Architecture Diagram

The architecture of the proposed system consists of four core modules:

1) Data Collection: Aggregation of screen time data, academic records, sleep patterns, and behavioral information from diverse sources.
2) Data Cleaning and Feature Engineering: Preprocessing the collected data by handling missing values, removing duplicates, and crafting new derived features that enhance predictive performance, such as the ratio of study time to screen time.
3) Model Training: Splitting the dataset into training and testing sets, followed by training the Random Forest model on the training data. The model learns patterns and relationships between the features and the target variable (impact level of gadget addiction).
4) Evaluation and Prediction: Assessing the model's performance using metrics such as accuracy, precision, recall, and F1-score. Once validated, the model is deployed to predict the likelihood of negative outcomes for new student data, along with recommendations for risk mitigation.

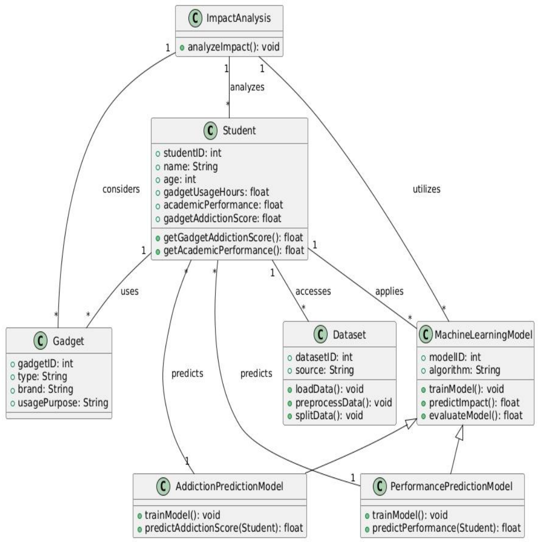

Fig. 2. Class Diagram of the System

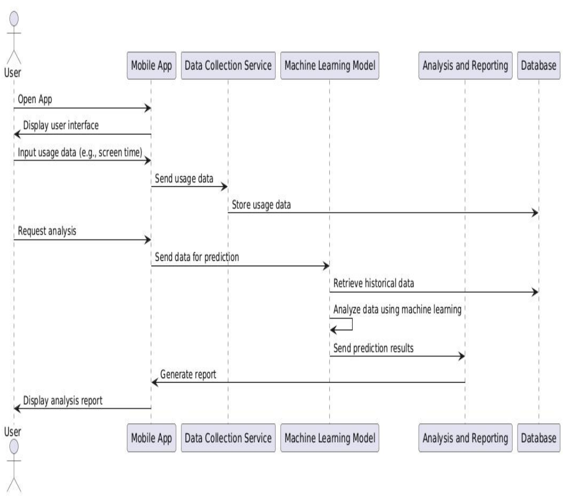

Fig. 3. Sequence Diagram Showing Component Interactions

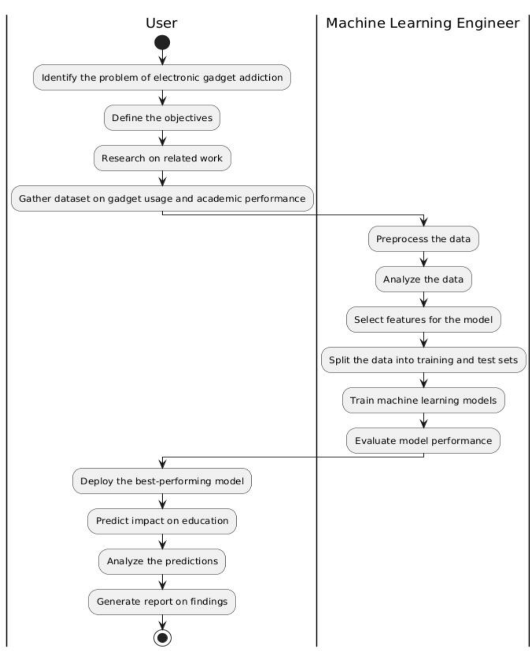

Fig. 4. Activity Diagram Depicting Workflow

IV. Methodology

A. Dataset Description

We utilized three datasets: AddictionDataset.csv, STRESS-Dataset.csv, and tweets.csv, covering gadget usage, academic performance, sleep patterns, stress levels, and social interactions. These datasets provided a comprehensive set of behavioral, academic, and social indicators necessary for building a predictive model of gadget addiction.

B. Sentiment Analysis of Social Interaction Data

To capture the social behavior aspect of students, sentiment analysis was applied to social media text data (tweets). Using a sentiment classifier, each student's tweets were analyzed to determine sentiment polarity scores categorized as positive, neutral, or negative. These sentiment scores were incorporated into the dataset as additional features.

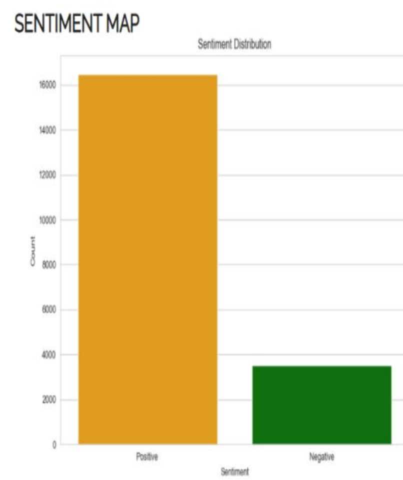

Fig. 5. Sentiment Analysis Map of Social Interaction Data

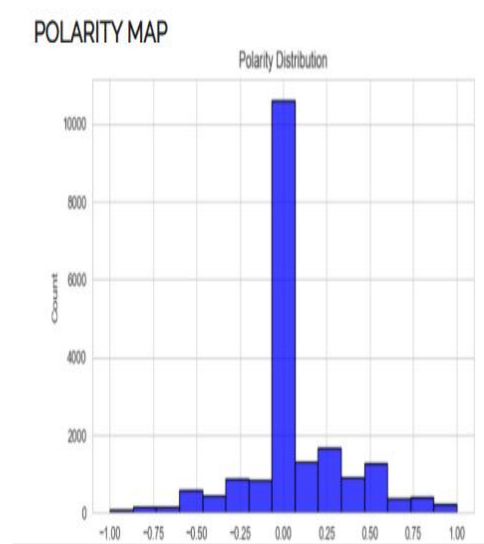

Fig. 6. Polarity Distribution Map from Tweet Data

C. Model Building

The datasets were merged, cleaned, and pre-processed. Key features were engineered, such as the ratio of study time to screen time, sentiment scores, and derived behavioral metrics. We applied the Random Forest algorithm due to its robustness and ability to handle complex feature interactions effectively.

D. Evaluation Metrics

To assess the performance of the model, we employed accuracy, precision, recall, F1-score, and a confusion matrix.

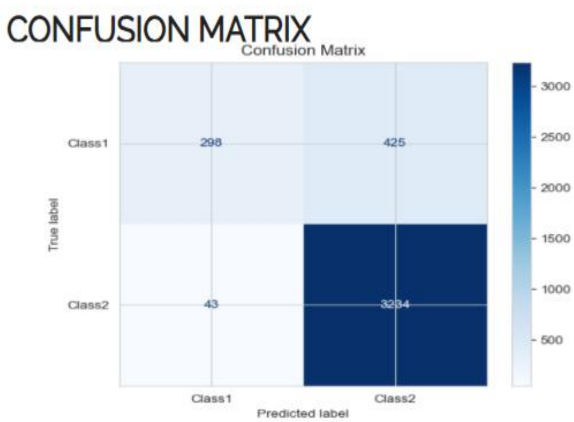

Fig. 7. Confusion Matrix of Random Forest Model Predictions

ACCURACY SCORE

Classification Report:

	precision	recall	f1-score	support
0	0.00	0.00	0.00	93
1	0.97	1.00	0.99	3359
accuracy			0.97	3452
macro avg	0.49	0.50	0.49	3452
weighted avg	0.95	0.97	0.96	3452

Fig. 8. Accuracy Score of the Trained Model

V. Results and Discussion

Our model effectively identified students at risk of negative outcomes due to excessive gadget use. Feature importance analysis revealed that screen time, sleep quality, and academic performance were the most influential predictors. The high accuracy validates the model's ability to generalize across diverse student profiles.

VI. Advantages

- High Accuracy and Robustness: Random Forest outperformed traditional models.
- Complex Interaction Handling: Effectively captures non-linear relationships.
- Feature Importance Insight: Highlights key factors contributing to addiction.

VII. Conclusion and Future Work

This project demonstrates the effectiveness of machine learning, particularly Random Forest, in predicting the impact of electronic gadget addiction on students. By analyzing multi-faceted data, the system enables early detection and proactive interventions. Future work will focus on expanding datasets, incorporating additional behavioral features, and deploying the model in real-time student monitoring applications.

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