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A Machine Learning-Based Approach for Screen Addiction Detection and Digital Wellbeing Using Behavioral Analysis

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Abstract: *In recent years, smartphone use among students has increased significantly, raising concerns about screen addiction and its effects on academic performance, mental health, and overall quality of life. Early detection and control of screen addiction can help students develop healthier digital habits and maintain wellbeing. Existing digital well-being systems mainly focus on monitoring usage duration and providing generic alerts, which are often ineffective in changing user behavior.*

This paper proposes an intelligent, context-aware machine learning-based system to detect addictive behavior and classify user behavior into "productive" and "harmful" categories. The system utilizes behavioral features such as screen time, app usage, and interaction patterns to analyze addiction levels. It further generates personalized recommendations based on user behavior and context awareness. Experimental results indicate that the proposed system is more effective than traditional approaches in detecting addictive patterns and improving digital wellbeing. .

Keywords: Digital Wellbeing, Screen Addiction, Context Awareness, Machine Learning, Behavior Analysis, Personalized Intervention

I. INTRODUCTION

Smartphones and other electronic devices have become an indispensable part of students' lives for accessing information, communication, and entertainment. In recent years, excessive use of these devices has emerged as a serious issue known as screen addiction, which negatively affects academic performance, causes sleep disturbances, and impacts students' mental health [6].

Current digital well-being systems mainly focus on tracking screen time and providing generic alerts to users. However, these traditional approaches are often ineffective in bringing meaningful behavioral changes because they ignore user context and individual differences in application usage [2]. For example, such systems fail to distinguish between productive applications (e.g., educational apps) and non-productive applications (e.g., social media or gaming), which leads to inaccurate assessment of user behavior

To address these limitations, this paper proposes a contextaware system that utilizes machine learning techniques to analyze user behavior patterns. The system considers multiple features such as usage frequency, session duration, application type, and time of usage [4]. to provide a more accurate assessment of screen addiction levels Furthermore, context-aware analysis enables the system to generate personalized recommendations tailored to individual user behavior, thereby improving the effectiveness of digital well-being interventions

Machine Learning

Machine learning is a subset of artificial intelligence (AI) where the system learns from available data [7]. to identify the trend. This helps in managing and extracting valuable information from large amounts of data related to user behavior and in detecting unknown patterns associated with screen usage

In relation to digital well-being, machine learning can be implemented with various parameters like screen usage, frequency of usage, app usage time, and time of use. Using all these features, the system learns the habits of the user, whether normal or addicted. For this classification task there are some supervised machine learning algorithms like decision tree, random forest, and logistic regression that have been successfully implemented. These models can correctly identify patterns of addictive screen usage. Based on these predictions, the recommendation is provided to the users.

Neural Network

A neural network is a model that is inspired by the human brain [12]. Neural networks are comprised of several layers of interconnected nodes, and these interconnected nodes can then determine connections and learn from a set of data. Neural networks may require large datasets and computational resources for effective analysis of user behavior over time [11]. However, using sophisticated learning techniques, the system can gain improvement in the analysis of user behav-ior over time.

This ensures the proposed system will perform better in analyzing the user behavior pattern to give accurate and customized recommendations. The system gains improve-ment in its prediction by learning continuously about user behavior, and hence it becomes more competent as com-pared to a static system. These factors help to overcome the problem of screen addiction effectively compared to older ones [4]. After reviewing many research papers concerning digital well-being and smartphone usage behavior and anal-ysis based on machine learning approaches, we noticed that most of the present systems just monitor the time and send generic alerts[9]. Although these methods increase awareness, there is no intelligent analysis of user behavior to provide contextaware and personalized recommendations. This paper aims to propose a new system that combines machine learning algorithms with behavioral data analysis for efficient detection of screen addiction patterns by analyzing many parameters such as screen usage frequency, session duration, application used, and the time of screen usage. It also detects the screen addiction level, and personalized recommendations are made by comparing it with the standard pattern [10]. The scope of this research is to move beyond simple monitoring and aim for behavior change.

II. LITERATURE REVIEW

Przybylski et al. (2017) investigated the relationship between digital screen time and mental well-being using large-scale behavioral data. The study found that excessive screen usage negatively affects sleep, productivity, and psychological wellbeing, while moderate usage has minimal impact. However, the study primarily focuses on screen time and lacks intelligent behavioral analysis.

Harris (2016) highlighted how modern digital applications are intentionally designed to capture user attention through features such as notifications, infinite scrolling, and reward mechanisms. These design elements contribute significantly to addictive usage patterns, emphasizing the need for behavior-aware systems.

Griffiths (2017) discussed behavioral addiction in the context of technology use, identifying key indicators such as compulsive checking, loss of control, and negative life impacts. These indicators provide a foundation for defining features used in machine learning models for addiction detection.

Lee et al. (2011) emphasized the importance of personalized behavior change systems, suggesting that tailored recommendations are more effective than generic alerts in influencing user behavior. This supports the need for personalized intervention strategies.

The Google Digital Wellbeing Team analyzed existing digital well-being tools, which primarily track screen time and usage patterns. While these tools increase user awareness, they lack advanced analytical capabilities for understanding behavioral patterns.

Donoho (2000) explored high-dimensional data analysis and highlighted the importance of feature extraction and pattern recognition in large datasets. These concepts are essential for analyzing complex user behavior data in machine learning applications.

Fogg (2009) proposed a behavior model stating that motivation, ability, and triggers must converge to influence user behavior. This model provides a theoretical foundation for designing effective recommendation systems.

Vahedi and Saiphoo (2018) found a strong association between excessive smartphone use and increased stress, anxiety, and reduced concentration. This highlights the importance of early detection of harmful usage patterns.

Zhang et al. emphasized the role of context-aware recommendation systems, which adapt suggestions based on user context such as time, activity, and environment, improving recommendation accuracy.

Shlok et al. demonstrated that machine learning techniques can effectively identify hidden behavioral patterns using parameters such as frequency, duration, and usage habits, supporting the feasibility of ML-based addiction detection systems.

III. METHODOLOGY

The suggested system proposes a context-aware digital wellbeing framework that leverages machine learning for monitoring user activity, analyzing user screen usage be-havior, and detecting signs of potential screen addiction [10]. It provides much more insight by considering other context related features in addition to screen time. The system can be thought of as a multi-stage process where each stage allows for analysis of raw data from user activities and derivation of useful insights and actionable recommendations.

Data Collection and Preprocessing

The first stage in the proposed method is the collection of user activity data. This can be either from device usage logs or from a well-designed survey to infer user behavior. The data includes features such as daily screen time, frequency of use, application usage type, session duration, and time of day (especially late at night) [9]. After the data is collected, the next step is data preprocessing to make it coherent.

During preprocessing, missing and inconsistent data is removed to maintain the integrity of the data. Ordinal values, such as responses in categories (i.e., Yes/No) and scales, are converted into numerical values suitable for machine learning models. Also, normalization is performed on the data, such that each of the data features (i.e., screen time, check frequency, etc.) lies on the same scale and does not dominate the output of the model [11].

Feature Extraction and Behavioral Representation:

This step is critical as it converts raw data into an organized form, representing users' behavior clearly. Examples of the features extracted are usage intensity, check frequency, session behavior, nighttime usage feature, and application dependence, each representing a distinct characteristic of the user's behavior [3]. Every user's behavior is converted into a feature vector, which can serve as input to the machine learning model, thus enabling simultaneous pro-cessing of multidimensional behaviors [11].

A detailed explanation of these features is listed in Table I.

TABLE I. : Behavioral Features Used for Screen Addiction Detection

Feature Name	Symbol	Description
Usage Intensity	UI	Total screen time per day (in hours).
Checking frequency	CF	Number of times the device is unlocked/accessed

Session Behaviour	SB	Average duration of a continuous usage session.
Night Usage	NU	Duration of usage between 11.00 PM and 6.00 AM
App Dependency	AD	Time spent on high-risk categories (Social Media, Gaming).

These features collectively describe the behavioral patterns of the use[6]. Each user's behavior is then represented as a feature vector, which serves as the input to the machine learning model [11]. This structured representation enables the system to analyze patterns across multiple dimensions simultaneously [7].

C. Machine Learning Model Training

The primary function of the suggested system depends on utilizing machine learning algorithms to achieve prediction and classification of behavior [11]. Supervised learning techniques are implemented where the extracted feature vectors are mapped to output values signifying screen addiction level.

The training process involves the model learning the correlation between input features and output values [11]. Algorithms such as Decision Tree, Random Forest, and Logistic Regression have been employed to learn these relationships efficiently [4].

Table II lists the chosen machine learning algorithms and explains their specific benefits in this study.

TABLE II: Comparison of Machine Learning Models

Model Name	Purpose	Advantage in proposed system
Decision tree	Behavior Classification	Provides interpretable rules
Random forest	Prediction Improvement	Handles non-linear relationships and reduces overfitting
Logistic Regression	Probability Estimation	Outputs a probability score (0 to 1) for risk calculation.

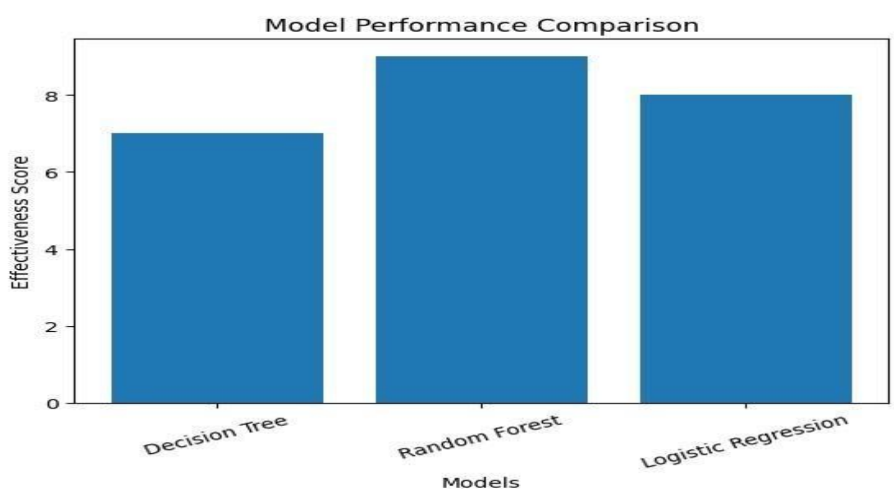


Fig. 1. Comparison of Machine Learning Models Used in the Proposed System

As shown in Fig. 1, Random Forest provides better performance due to its ability to handle non-linear relationships and reduce overfitting [11]. Decision Tree offers simple and interpretable rules for behavior analysis. Logistic Regres-sion generates probability scores, helping in accurate risk estimation [4].
Through training, the model is fed with past data and adjusted internally while prediction errors are minimized. By continuously feeding itself with data, the model learns to generalize and make predictions for unseen inputs [11].

Behavioral Pattern Analysis:
After the training, the model analyzes correlations between features so that user behavior patterns are identified [7]. The process allows hidden patterns and correlations to be revealed in user interactions. For instance, the system can analyze if late-night cell usage contributes to higher screen time usage and if extensive use of social media applications leads to less productivity and more distraction[6]. The process also identifies consistent behavior such as frequently pick-ing up cell phones or long sessions of usage that are indica-tors of struggling with screen addiction.

Prediction Mechanism:
In the prediction mechanism, the trained model is deployed using the input of new user data [11]. When new activity data is acquired, it follows the same cleaning and feature extraction processes, where it constructs a feature vector. The constructed feature vector is then fed into a machine learning model that utilizes its prior knowledge to calculate a prediction score indicating the probability of whether the user is addicted or not [4], [11].

Classification and Decision Process:
The system classifies the users into the categories of "Normal," "Moderate," and "Addicted" based on preset thresholds upon prediction scores that have been achieved by each user [4]. The process allows simplification of decision-making by segmenting users into distinct groups based on the pre-diction score. The classification criteria used by the decision module are defined in Table III.

TABLE III: User Classification Based on Prediction Score

Prediction Score Range	**User category**	**System response**
0.0-0.3	Normal User	Periodic insights and summary reports.
0.3-0.7	Moderate User	Gentle warnings and usage reduction tips.
0.7-1.0	Addicted User	Strict alerts, app limits, and intervention triggers

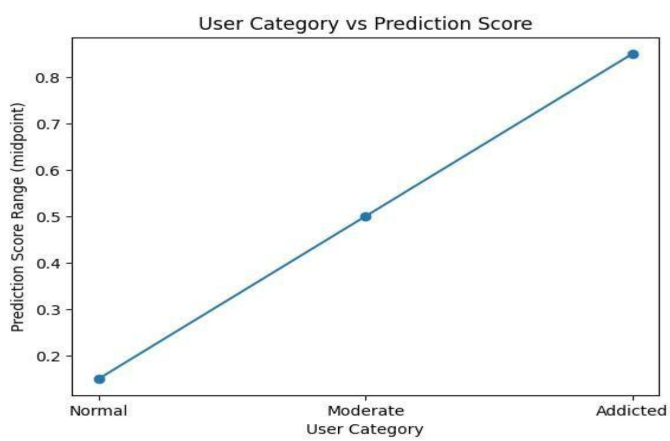
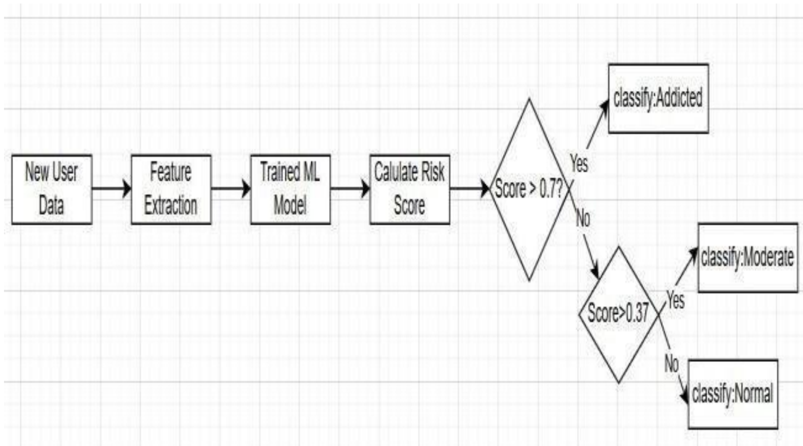


Fig. 2. User Classification Based on Prediction Score Range

As illustrated in Fig. 2, prediction scores are used to classify users into normal, moderate, and addicted categories. Lower scores indicate normal usage, while higher scores reflect increased addiction risk. This classification enables the system to provide appropriate and personalized responses. This classification process simplifies decision-making by categorizing users into clear groups.



G. Recommendation Generation:

Tailored suggestions are generated from the classification results in order to enhance digital well-being [10]. Unlike standard systems that often provide generic warnings, the developed system is able to customize advice based on the specific behavior and addiction risk level [4]. Users who are identified as high-risk may receive strong alerts, such as a limited number of screen minutes, restrictions on the apps they use, and regular break reminders.

H: Feedback Mechanism and Adaptive Learning:

An essential part of the proposed system is the feedback mechanism that enables its continual improvement over time [5]. The system observes users' responses to recommendations, monitors changes in their behavioral patterns, and modifies its subsequent suggestions accordingly. If a user successfully reduces screen time or changes their interaction patterns with the device, the system updates future predictions adaptively [11]. This recursive process contributes to improving the accuracy and effectiveness of the model.

I. System workflow overview:

Overall, the methodology followed is a process flow approach [7]. Where we collected the data and reached the recommendation generation and feedback stage. The integration of all these stages forms a complete system that addresses screen addiction intelligently and adaptively [10].
A step-by-step summary of the system workflow is presented in Table IV.

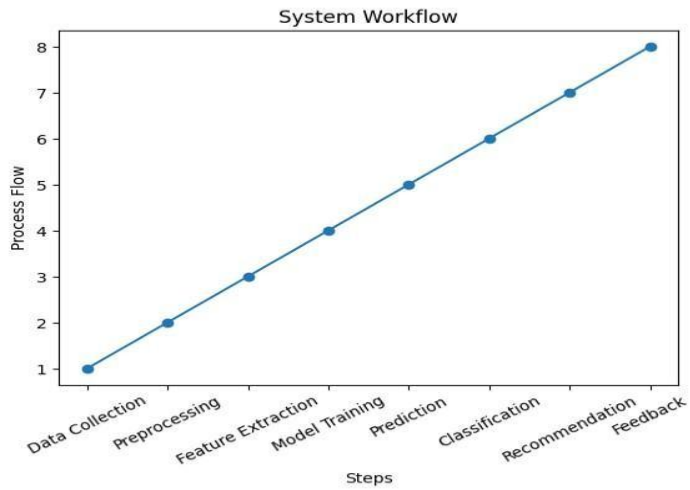


Fig. 3. Workflow of the Proposed Screen Addiction Detection System

Fig. 3 shows the overall workflow of the proposed system from data collection to feedback generation. It includes preprocessing, feature extraction, model training, prediction, and classification stages. The feedback mechanism continuously improves system performance and recommendation accuracy.

TABLE IV: Summary of System Workflow

Steps	Stage Name	Action Performed
1	Data Collection	Gather raw Activity logs and survey responses.
2	Preprocessing	Clean data, handle missing Values, and encode categories
3	Feature Extraction	Generate feature vectors (UI, CF, SB, NU, AD)
4	Model Training	Train decision Tree, Random Forest, and Logistic Regression models
5	Prediction	Compute addiction probability for current user.
6	Classification	Categorizes user into normal, moderate or addicted
7	Recommendation	Generate personalized alerts and usage limits
8	Feedback	Update model based on user response to recommendations.

IV. CONCLUSION

In conclusion, the proposed context-aware digital well-being system provides an effective solution to the growing problem of smartphone overuse and screen addiction. Unlike traditional systems that only monitor screen time, this system uses context-aware machine learning to better understand user behavior by considering factors such as usage frequency, session duration, application type, and time of use.

By analyzing these patterns, the system can identify signs of digital addiction more accurately and provide personalized recommendations to help users improve their digital habits. The feedback mechanism also makes the system more adaptive, allowing it to learn from user responses and adjust according to individual behavior over time.

Overall, this approach is a significant improvement over basic screen monitoring systems because it not only detects unhealthy usage patterns but also offers smart and personalized guidance. With further development and research, such systems can play an important role in promoting healthier technology usage and improving overall digital well-being.

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