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Electronic Gadgets Addiction Prediction using Deep Learning

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***Abstract*—NeuroGadget – Addiction Predictor is a web-based application designed to help identify and quantify an individual's risk of developing addictive behaviors using data-driven methods. The system provides an accessible interface where users can securely log in and submit relevant information such as behavioral patterns, lifestyle factors, psychological indicators, and other risk-related attributes. This input is processed by a prediction engine (e.g., machine learning or rule-based model, depending on implementation) that estimates the user's probability of addiction risk and categorizes it into meaningful levels (such as low, moderate, or high). From a technical standpoint, the application is built as a modern front-end client (e.g., React/Next.js with Typescript) that emphasizes usability, responsiveness, and clarity of user flow - from authentication and data entry through to results display and follow-up recommendations. The system is designed with modular components, allowing UI elements like the login page, forms, and result dashboards to be easily extended or replaced as the project evolves. On the back end (or via integrated APIs), the predictor can leverage trained models, validation logic, and data storage while enforcing security and privacy best practices for sensitive user data. Overall, NeuroGadget provides a structured foundation for integrating neuroscience, psychology, and data science into a single platform focused on addiction risk prediction, with room to grow into clinical support tools, research dashboards, or self-help interventions. The model studies several things like how often students use gadgets, their grades, how they interact with others, and their mental health. The data comes from surveys and behaviour tests, which help the Random Forest method spot how different factors are connected and make accurate predictions. Through this project, we hope to learn more about gadget addiction and its effects, and encourage a better balance between technology and education.**

***Index Terms*—Smartphone Addiction, Machine Learning, Deep Learning, Random Forest, Behavioral Analysis, Digital Wellness**

I. Introduction

NeuroGadget – Addiction Predictor is an advanced software tool designed to support the early identification of gadget addiction risk through systematic assessment and data-driven analysis. Addiction is a complex and multifactorial condition influenced by biological, psychological, and social factors. Traditional screening methods often depend on subjective judgment, manual questionnaires, and fragmented data, which may lead to inconsistent and less reliable results. These approaches lack automation, real-time analysis, and the ability to integrate multiple influencing factors into a unified evaluation system.

To overcome these limitations, NeuroGadget provides a structured and interactive environment where user-provided data—such as behavioral habits, emotional state, stress levels, and lifestyle patterns—are analyzed using intelligent models to generate a clear and quantitative risk estimate. Unlike conventional methods, the system ensures consistency, accuracy, and faster assessment by leveraging machine learning techniques. The primary objective is not to provide a medical diagnosis, but to identify potential risk factors, promote self-awareness, and encourage timely intervention or consultation with professionals when required.

From a user perspective, the platform offers a secure login system, an intuitive and easy-to-navigate questionnaire, and a well-organized results interface that presents addiction risk levels in a simple and understandable format. This eliminates the complexity often associated with traditional assessment methods and ensures that even non-technical users can easily interact with the system. From a development perspective, NeuroGadget is built as a modular and extensible system, allowing its prediction models, user interface, and analytical components to be continuously updated and improved based on new research findings and evolving requirements. In addition, the system overcomes the challenges of data privacy and security found in many existing solutions. Instead of relying on server-side processing, NeuroGadget adopts a browser-based approach where all computations are performed locally using modern technologies such as TensorFlow.js. This ensures that sensitive user data is not transmitted or stored externally, thereby maintaining confidentiality and enhancing user trust.

The system collects behavioral and psychological data through a structured survey, processes it using a trained machine learning or deep learning model, and provides instant prediction results through a web-based interface. By combining real-time prediction, privacy-preserving architecture, and user-friendly design, NeuroGadget effectively addresses the limitations of traditional systems. The main aim of this project is to create awareness about digital addiction and provide a reliable self-assessment tool that helps users understand, monitor, and improve their digital habits in a more informed and proactive manner.

II. Ease of Use

A. Need for Digital Addiction Assessment

In the present digital era, smartphones and electronic gadgets have become an essential part of students' daily lives. While they provide numerous benefits such as easy access to educational resources, communication, and entertainment, excessive usage has led to serious concerns regarding digital addiction. Students often experience reduced concentration, poor academic performance, sleep disturbances, and emotional dependency due to prolonged gadget usage. Traditional methods used to assess addiction levels mainly rely on manual questionnaires, psychological surveys, and subjective evaluation techniques. These approaches are not only time-consuming but also prone to inconsistencies due to human interpretation. Moreover, they lack automation, real-time analysis, and scalability for handling a large number of users. Therefore, there is a strong need for an intelligent, automated, and user-friendly system that can accurately assess gadget addiction levels and provide instant feedback. The NeuroGadget system fulfills this requirement by offering a simple and interactive platform where users can input their behavioral and psychological data and receive real-time addiction risk predictions. This approach improves efficiency, accuracy, and accessibility, making it suitable for students and non-technical users.

B. User-Friendly Interface Design

In the present digital era, smartphones and electronic gadgets have become an essential part of students' daily lives. While they provide numerous benefits such as easy access to educational resources, communication, and entertainment, excessive usage has led to serious concerns regarding digital addiction. Students often experience reduced concentration, poor academic performance, sleep disturbances, and emotional dependency due to prolonged gadget usage. Traditional methods used to assess addiction levels mainly rely on manual questionnaires, psychological surveys, and subjective evaluation techniques. These approaches are not only time-consuming but also prone to inconsistencies due to human interpretation. Moreover, they lack automation, real-time analysis, and scalability for handling a large number of users. Therefore, there is a strong need for an intelligent, automated, and user-friendly system that can accurately assess gadget addiction levels and provide instant feedback. The NeuroGadget system fulfills this requirement by offering a simple and interactive platform where users can input their behavioral and psychological data and receive real-time addiction risk predictions. This approach improves efficiency, accuracy, and accessibility, making it suitable for students and non-technical users.

C. Advantages of the Proposed System

The NeuroGadget system provides several advantages in terms of usability, performance, and functionality. One of the key advantages is its ability to perform real-time addiction prediction using a browser-based deep learning model implemented through TensorFlow.js. This eliminates the need for server-side processing and ensures faster response times. Another major advantage is its privacy-first architecture. All user data is processed locally within the browser, ensuring that sensitive personal and psychological information is not transmitted or stored externally. This significantly reduces the risk of data breaches and enhances user trust.

The system performs a comprehensive multi-dimensional analysis by considering various factors such as screen time, emotional dependency, sleep patterns, and academic performance. This results in more accurate and meaningful predictions compared to traditional methods. Additionally, the integration of a rule-based expert system provides personalized recommendations, helping users take necessary actions to improve their digital habits.

D. System Workflow

The NeuroGadget system follows a structured and user-friendly workflow that ensures smooth interaction and efficient processing. The workflow begins with user authentication, where the user logs into the system using simple credentials. After successful login, the user is directed to the survey module, where they provide information related to their gadget usage, behavior, and lifestyle patterns. Once the survey is completed, the input data is passed to the validation and preprocessing module, which ensures that all values are complete, consistent, and in the correct format. The preprocessed data is then fed into the deep learning model, which performs prediction and generates an addiction score ranging from 0 to 100.

The generated score is further processed by the risk categorization module, which classifies the user into different risk levels such as low, moderate, or high. Finally, the results are displayed through an interactive dashboard along with personalized recommendations and behavioral insights. This structured workflow ensures that users can easily complete the assessment process without any confusion.

E. Accessibility and Performance

The NeuroGadget system is designed to be highly accessible and efficient across different environments. Since the application runs entirely in the browser, it does not require installation of additional software or high-end hardware. Users can access the system using any modern web browser such as Chrome, Edge, or Firefox. The offline-first architecture ensures that the system continues to function even without an active internet connection after initial loading. This makes it suitable for use in areas with limited or unstable internet connectivity. In terms of performance, the system is optimized to provide quick responses, with most operations such as survey submission, prediction, and result generation completing within a few seconds. The use of client-side processing reduces server dependency and ensures scalability, allowing multiple users to access the system simultaneously without performance degradation.

III. FORMATTING GUIDELINES

- Ensuring uniform structure and consistent formatting across all sections of the document.
- Maintaining clarity in presentation by using proper headings, subheadings, and standardized terminology.
- Following academic writing standards to enhance readability, correctness, and professional quality of the report.

A. Abbreviations and Acronyms

In this project, all abbreviations and acronyms are defined at their first occurrence to ensure clarity and avoid confusion. For example, terms such as Machine Learning (ML), Deep Learning (DL), and Electronic Gadgets Addiction (EGA) are introduced with their full forms before being used in abbreviated form. This practice improves readability, especially for users who may not be familiar with technical terminology. Common and widely accepted abbreviations such as HTML, CSS, and AI are used directly without repeated definitions. Additionally, abbreviations are avoided in section headings wherever possible to maintain clarity and professionalism. Consistent usage of abbreviations throughout the document helps in maintaining uniformity and enhances understanding.

B. Units

All measurements and values used in the project follow standard conventions to maintain consistency and accuracy. Where applicable, the International System of Units (SI) is preferred. For example, time-related measurements such as screen usage are represented in hours, while percentages and numerical scales are used for representing addiction levels and risk scores. Numerical values are written clearly with appropriate formatting, such as using leading zeros before decimal points (e.g., 0.75 instead of .75). Units are written in a standardized manner, and unnecessary mixing of different unit systems is avoided. This ensures that the data presented is easy to interpret and scientifically accurate.

C. Equations

Although the NeuroGadget system primarily focuses on machine learning-based prediction, any mathematical expressions or equations used in the system are represented clearly and consistently. Variables used in equations are defined immediately before or after their usage to ensure clarity. For example, a prediction score may be represented as a function of multiple input features, where each variable corresponds to a specific behavioral or psychological factor. Equations are formatted properly and numbered where necessary to maintain structure and readability.

D. Some Common Mistakes

To maintain professional quality and consistency, several common mistakes are carefully avoided in this document: The term “data” is treated as plural (e.g., “data are processed”). Proper distinction is maintained between similar words such as “affect” and “effect.” Punctuation is used correctly within sentences and quotations. Technical terms are used consistently without unnecessary variation. Redundant words and informal expressions are avoided to maintain an academic tone. By following these practices, the document ensures clarity, correctness, and professional presentation.

E. Figures and Tables

a) Positioning Figures and Tables: Figures and tables are used to represent complex information in a clear and concise manner. All figures and tables are properly labeled and numbered sequentially. Each figure or table is referenced in the text before it appears, ensuring a smooth flow of information. Figures such as system architecture diagrams, workflow diagrams, and model representations are included to visually explain the system design. Tables are used to present structured data such as feature categories, risk levels, and system components. Each figure and table includes a descriptive caption to help readers understand its purpose. Care is taken to ensure that images are clear, properly aligned, and relevant to the content. This improves the overall readability and presentation quality of the document.

IV. MATHEMATICAL MODEL AND FORMULAS

The NeuroGadget system utilizes a deep learning-based approach to predict the addiction risk score by analyzing multiple behavioral, psychological, and academic features. Although the system primarily operates using a trained neural network model, the underlying mathematical representation helps in understanding how the prediction is generated. The following equations describe the core computations involved in the system.

A. Addiction Score Function

The addiction score is computed as a function of multiple input features collected from the user through a structured survey.

$$Score = f(x_1, x_2, x_3, \ldots, x_n) \tag{1}$$

Here,x1,x2,x3,. . . ,xn represent different input features such as daily screen time, sleep duration, emotional dependency, stress level, academic performance, and social interaction. The function f represents the deep learning model that maps these inputs to a final addiction score.

B. Neural Network Output Calculation

The deep learning model computes the output using a weighted sum of inputs followed by an activation function.

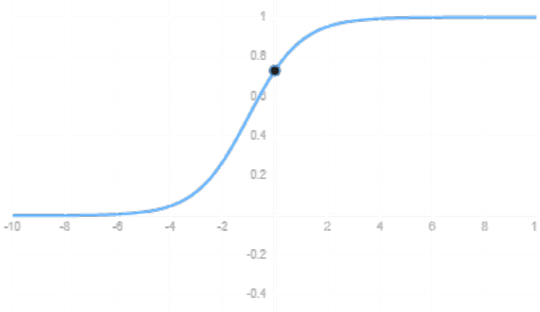

Fig. 1. Addiction Score and Risk Level Dashboard

$$y = \sigma(Wx + b) \tag{2}$$

This equation represents how the neural network processes input data to produce an intermediate or final output.

C. Loss Function

During training, the model minimizes the error between predicted and actual values using the Mean Squared Error (MSE) function.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{3}$$

Where: y i is the actual value, yi is the predicted value, and n is the number of samples. The model adjusts its weights to minimize this error and improve prediction accuracy.

D. Feature Representation

The input data is converted into a numerical feature vector before being passed to the model.

$$X = [x_1, x_2, x_3, \ldots, x_n] \tag{4}$$

This vector contains all the processed inputs collected from the survey and is used as the input layer of the neural network.

E. Addiction Risk Classification

The addiction score predicted by the model ranges from 0 to 100 and is divided into three categories: low, moderate, and high risk. This classification helps users easily understand their level of gadget dependency. A low-risk score indicates balanced usage, while a moderate-risk score suggests the need for behavioral improvements. A high-risk score indicates excessive usage and potential negative impact on mental health, academic performance, and lifestyle, requiring immediate corrective actions.

Addiction Score	Risk Level	Description
0 – 30	Low Risk	Healthy usage, no significant addiction
31 – 60	Moderate Risk	Needs attention and control
61 – 100	High Risk	High addiction, requires intervention

Fig. 2. Addiction Risk Classification Table

V. Conclusion

The NeuroGadget – Electronic Gadget Addiction Prediction system successfully demonstrates the application of machine learning and deep learning techniques to address the growing issue of gadget addiction among students. By analyzing behavioural, psychological, and academic factors, the system is capable of predicting addiction risk levels with improved accuracy. The integration of intelligent algorithms such as Random Forest and Deep Learning models enhances the system's ability to identify complex usage patterns and provide reliable results. The platform not only predicts addiction risk but also offers personalized recommendations through a rule-based expert system, making it both analytical and supportive in nature. The browser-based, offline-first architecture ensures data privacy while maintaining real-time responsiveness. Features such as dashboard monitoring, risk categorization, and export functionality further improve usability and make the system practical for academic institutions and students. Overall, the project provides a structured, data-driven approach to early identification of electronic gadget addiction. It promotes awareness, encourages responsible gadget usage, and supports preventive intervention. With proper implementation and future enhancements, the system can serve as an effective digital wellness monitoring tool for educational environments.

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