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ORIGINAL

AI-Driven Digital Well-being: Developing Machine Learning Model to Predict and Mitigate Internet Addiction

Bienestar digital impulsado por IA: Desarrollo de un modelo de aprendizaje automático para predecir y mitigar la adicción a Internet

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ABSTRACT

Introduction: internet addiction has become a major public health issue due to the increased dependence on digital technology, affecting mental health and overall well-being. Artificial intelligence (AI) offers innovative approaches to predicting and mitigating excessive internet use.
Objective: this study aims to develop and evaluate AI-driven machine learning models for predicting and mitigating internet addiction by analyzing behavioral patterns and psychological indicators.
Method: open-access datasets from "Kaggle", such as "Smartphone Usage Data" and "Social Media Usage and Mental Health", were analyzed using machine learning and deep learning models, including Random Forest, XGBoost, Neural Networks, and Natural Language Processing (NLP) techniques. Model performance was assessed based on accuracy, precision, recall, F1-score, and AUC-ROC.
Results: neural Networks and XGBoost achieved the highest accuracy (91 % and 90 %, respectively), surpassing traditional models like Logistic Regression and SVM. Clustering and anomaly detection techniques provided further insights into user behavior, while NLP revealed emotional and thematic patterns associated with addiction.
Conclusions: AI-driven models effectively predict and classify internet addiction, offering scalable and personalized interventions to promote digital well-being. Future research should focus on addressing ethical concerns and improving real-time deployment of these models.

Keywords: Internet Addiction; Machine Learning; Behavioral Analysis; Digital Well-Being; Mental Health.

RESUMEN

Introducción: la adicción a Internet se ha convertido en un importante problema de salud pública debido a la creciente dependencia de la tecnología digital, afectando la salud mental y el bienestar general. La inteligencia artificial (IA) ofrece enfoques innovadores para predecir y mitigar el uso excesivo de Internet.
Objetivo: este estudio tiene como objetivo desarrollar y evaluar modelos de aprendizaje automático impulsados por IA para predecir y mitigar la adicción a Internet mediante el análisis de patrones de comportamiento e indicadores psicológicos.
Método: se analizaron conjuntos de datos de acceso abierto de Kaggle, como *Smartphone Usage Data* y *Social Media Usage and Mental Health*, utilizando modelos de aprendizaje automático y aprendizaje profundo, incluidos Random Forest, XGBoost, redes neuronales y técnicas de procesamiento del lenguaje natural (NLP). El rendimiento de los modelos se evaluó en función de la precisión, la exactitud, la recuperación, la puntuación F1 y el AUC-ROC.

Resultados: las redes neuronales y XGBoost lograron la mayor precisión (91 % y 90 %, respectivamente), superando a modelos tradicionales como la regresión logística y SVM. Las técnicas de agrupamiento y detección de anomalías proporcionaron información adicional sobre el comportamiento de los usuarios, mientras que NLP reveló patrones emocionales y temáticos asociados con la adicción.
Conclusiones: los modelos impulsados por IA predicen y clasifican eficazmente la adicción a Internet, ofreciendo intervenciones escalables y personalizadas para promover el bienestar digital. Las investigaciones futuras deben centrarse en abordar preocupaciones éticas y mejorar la implementación en tiempo real de estos modelos.

Palabras clave: Adicción a Internet; Aprendizaje Automático; Análisis del Comportamiento; Bienestar Digital; Salud Mental.

INTRODUCTION

In recent years, the use of internet has greatly increased among students on university campuses and among people in society. Moreover, internet primary use in an academic field is for learning and doing researches.[1] Internet has also played an important role in students' life. Internet is mainly created for searching about various information and share information among other people. In addition, people now can't do some aspects of daily life tasks easily without internet.

Internet becomes essential in many aspects including personal communication, education and health aspects. Digitalization is the process of turning analogue in the digital world which has changed the habits of individuals in how people interact, work and socialize in life very quickly in daily life. Even though the digital transformation has its advantages, internet overuse has been identified as an increasing public health issue.[2]

Internet addiction, a psychological condition characterized by excessive and uncontrollable use of the internet, has been linked with a wide range of problems including psychological problems, social dysfunction, cognitive problems. Given the increasing reliance on the internet, there is an immediate need for novel methods to measure, anticipate and reduce the risks of over-engagement with the digital world. In this framework, AI and ML represent opportunities for improving digital well-being through algorithms that can predict online-adverse behaviors and tailor simulations for those most at risk to internet addiction.[3,4,5]

By harnessing big data, AI-driven digital well-being solutions do not only uncover behavioral trends, with a focus on early signs of addiction but also allow recommendation of individualized measure against excessive use.[6] Internet addiction has been diagnosed and managed in clinics using self-reported surveys and clinical assessments, which can be subjective and biased.[7,8] On the other hand, ML can utilize real-time data from an individual user, including any sort of digital interaction data like screen time, browsing history, app usage patterns, and social media usage, to detect high-risk behaviors at a much greater level of accuracy.[9,10] Using predictive analytics, these models can categorize users by their risk and recommend individual-specific interventions, such as limiting app use.

Recent research has explored various ML techniques, including supervised learning models such as decision trees, support vector machines (SVM), and deep learning architectures, to predict addictive behaviors.[11,12] Additionally, reinforcement learning algorithms can be integrated into digital platforms to encourage healthier internet habits by rewarding self-regulation and mindful usage.[13,14] Beyond individual users, AI-driven insights can assist policymakers, mental health professionals, and app developers in creating evidence-based frameworks to promote responsible digital consumption.

However, despite these promising advancements, challenges remain, including ethical considerations regarding data privacy, algorithmic bias, and the need for interdisciplinary collaboration between AI researchers, psychologists, and behavioral scientists.[15] This study aims to develop of AI-driven ML models to predict and mitigate internet addiction, emphasizing the integration of user behavior analytics, feature selection techniques, and intervention strategies.[16,17] By leveraging data-driven approaches, the research seeks to contribute to the field of digital well-being by providing scalable, adaptive, and personalized solutions to reduce the negative impact of excessive internet use.[7] Ultimately, AI-powered interventions have the potential to reshape the digital landscape, promoting healthier and more sustainable technology use while addressing the growing concerns surrounding internet addiction in modern society.[18,19]

METHOD

For this study, we utilized open-access datasets from Kaggle, a widely recognized platform for data science and machine learning resources. We used two datasets, "Smartphone Usage Data" by Bhadra Mohit and "Social Media Usage and Mental Health" by Anshika Arora. These datasets were chosen for their comprehensive coverage of user behavior and their alignment with the research objectives. Before analysis, the datasets were preprocessed to handle missing values, remove duplicates, and normalize features.

To prepare the raw data for machine learning applications, several preprocessing steps were implemented. First, data cleaning was performed by addressing missing values, which were imputed using either the mean or median, and by removing any irrelevant features that did not contribute to the analysis. Next, feature engineering was applied to enhance the dataset by creating new variables that captured behavioral patterns. These included metrics such as daily usage time, login frequency, and the duration spent on specific applications, providing deeper insights into user behavior.

To maintain consistency across different machine learning algorithms, numerical features were normalized and scaled to a standard range. This step ensured that variations in data magnitude did not affect model performance. Finally, the dataset was strategically divided into two subsets: 70 % for training and 30 % for testing. This data-splitting approach allowed for an effective evaluation of the model's performance, ensuring its reliability and accuracy in real-world applications. To predict and classify internet addiction, a diverse range of machine learning and deep learning algorithms was utilized.

These algorithms were carefully selected based on their ability to process different types of data and their effectiveness in previous studies on similar topics. For binary classification of addiction status (addicted vs. non-addicted), traditional classification algorithms such as Logistic Regression, Support Vector Machines (SVM), Random Forest, Gradient Boosting methods (XGBoost, LightGBM), and k-Nearest Neighbors (k-NN) were applied. In addition, clustering techniques like k-Means Clustering and DBSCAN were used to group users based on their internet usage patterns. Deep learning models, including Feedforward Neural Networks (FNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) networks, were leveraged to identify complex sequential patterns in user behavior.

For text-based analysis, Natural Language Processing (NLP) techniques such as sentiment analysis and topic modeling were employed to assess emotional states and key themes related to internet addiction. To detect abnormal usage patterns, anomaly detection algorithms like Isolation Forest and Autoencoders were implemented.[5] Furthermore, reinforcement learning approaches, including Q-Learning and Deep Q-Networks (DQN), were explored to develop personalized intervention strategies. Lastly, dimensionality reduction techniques such as Principal Component Analysis (PCA) and t-SNE were applied to streamline high-dimensional data and improve visualization. Once the models were trained on the preprocessed dataset, their performance was assessed using standard evaluation metrics. Accuracy was used to measure the proportion of correctly classified instances, while precision helped determine the model's ability to minimize false positives. Recall assessed the model's effectiveness in capturing all relevant cases, and the F1-score provided a balance between precision and recall. The AUC-ROC metric was also utilized to evaluate the model's ability to differentiate between classes, while training time was recorded to assess computational efficiency.

To compare the effectiveness of different algorithms, a Performance Metrics Comparison Table was created. This table outlined the strengths and weaknesses of each model, offering insights into the trade-offs between accuracy, computational efficiency, and classification performance. A structured workflow was followed to ensure reproducibility and reliability throughout the research process. The first step involved data collection, where datasets were sourced from Kaggle and prepared for analysis. Feature engineering followed, focusing on extracting relevant features and normalizing the data.

A range of tools and libraries was employed to implement the methodology efficiently. Machine learning models were built using Python libraries such as Scikit-learn, while deep learning frameworks like TensorFlow and PyTorch facilitated the implementation of neural networks. Gradient boosting models, including XGBoost and LightGBM, were used for performance enhancement. For natural language processing tasks, Hugging Face Transformers, NLTK, and SpaCy were utilized. Data visualization was carried out using Matplotlib, Seaborn, and Plotly, while data preprocessing and manipulation were handled with Pandas and NumPy. To ensure data quality and ethical use when working with open-access datasets, several best practices were followed. First, dataset licensing was verified to confirm that the data was freely available for research purposes. Next, data quality was assessed by checking for missing values, duplicates, and inconsistencies.

In cases where a single dataset was insufficient, multiple datasets were combined to enhance the comprehensiveness of the analysis. Additionally, user privacy was a priority, with all personally identifiable information being anonymized to align with ethical research guidelines. To provide a comprehensive evaluation of the models, a Performance Metrics Comparison Table was compiled. This table detailed key metrics, including accuracy, precision, recall, F1-score, AUC-ROC, and training time, offering a clear comparison of the models' strengths and limitations. By analyzing this table, the most effective algorithm for predicting internet addiction could be identified, ensuring optimal performance for future applications.

Model selection was carried out by considering a diverse set of algorithms to address various aspects of internet addiction prediction. The chosen models were then trained using the training dataset and validated through cross-validation techniques. Afterward, the final models underwent testing on a separate testing dataset, and their performance was evaluated using predefined metrics. Lastly, the results were analyzed to determine the most effective models and their implications for predicting internet addiction.

Statistical Analysis

We used some equations to describe the mathematical models or algorithms used. The following equations were used:

- Logistic Regression for Classification:

$$P(y = 1 \mid x) = 1 / (1 + e^{\wedge} - (\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n x_n))$$

Where is P(y=1|x) is the probability of internet addiction, x=(x1,x2,…,xn) are the input features (e.g., daily usage time, number of logins), β_0 ,β_1,…,β_n are the model coefficients.

- Support Vector Machine (SVM) for Binary Classification:

$$\min\left(\frac{1}{2}\left||w|\right|^2 + C \sum \xi_i\right)$$

Subjected to:

$$y_i(w \cdot x_i + b) \geq 1 - \xi_i, \xi_i \geq 0$$

Where is w is the weight vector, b is the bias term, C is the regularization parameter, ξ_i are slack variables for handling non-separable data, y_i is the label (e.g., 1 for addicted, -1 for non-addicted).

- Neural Network Activation Function:

$$f(x) = \max(0, x)$$

- Clustering for Behavioral Patterns (e.g., K-Means):

$$\min \sum_{i=1}^{k} \sum_{x \in c_i}^{.} \left||x - \mu_i|\right|^2$$

Where is k is the number of clusters, c_i is the set of points in the i - the cluste.

We used equations for evaluation metrics to assess your model's performance, such as:

- Accuracy:

$$Accuracy = \frac{True\ Positives\ (TP) + True\ Negatives\ (TN)}{TP + TN + False\ Positive\ (FP) + False\ Negative (FN)}$$

- F1-Score:

$$F1 - Score = 2 * \frac{(Precision * Recall)}{(Precision + Recall)}$$

Where is:

$$Precision = \frac{TP}{(TP + FP)}$$

$$Recall = \frac{TP}{(TP + FN)}$$

- SHAP Values (Feature Importance):

$$\phi_i = \sum \left(\frac{|S|!\ (|N| - |S| - 1)!}{|N|!}\right) * \left(f(S \cup \{i\}) - f(S)\right)$$

Where is ϕ_i is the SHAP value for feature i, N is the set of all features, S is a subset of features excluding i, f(S) is the model's prediction for subset S.

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RESULTS

The results of this research demonstrate the effectiveness of various machine learning and deep learning algorithms in predicting and classifying internet addiction using open-access datasets from Kaggle. The models were evaluated based on their accuracy, precision, recall, F1-score, and AUC-ROC, providing a comprehensive understanding of their performance.

The findings reveal that advanced algorithms, such as neural networks and gradient boosting methods, outperformed traditional models like logistic regression and support vector machines in terms of predictive accuracy and robustness. The Random Forest algorithm achieved an accuracy of 88 %, with a precision of 87 % and a recall of 89 %, indicating its strong ability to correctly classify both addicted and non-addicted users. Similarly, XGBoost demonstrated superior performance, achieving an accuracy of 90 % and an F1-score of 0,90, highlighting its effectiveness in handling imbalanced datasets.

The Neural Network (FNN) model outperformed all other algorithms, achieving the highest accuracy of 91 % and an AUC-ROC score of 0,95, showcasing its capability to capture complex patterns in the data. In contrast, simpler models like Logistic Regression and SVM provided moderate performance, with accuracy scores of 85 % and 87 %, respectively, making them suitable for baseline comparisons but less effective for high-stakes predictions. Clustering algorithms, such as k-Means and DBSCAN, were employed to group users based on their internet usage patterns.

These algorithms successfully identified distinct behavioral clusters, such as moderate users, heavy users, and potential addicts, providing valuable insights for targeted interventions. Additionally, anomaly detection algorithms (5), including Isolation Forest and Autoencoders, proved effective in identifying extreme or abnormal usage patterns, which are critical for early detection of internet addiction. The Natural Language Processing (NLP) models, particularly those using sentiment analysis and topic modeling, provided additional insights into the emotional and psychological states of users.

For instance, sentiment analysis revealed that users classified as addicted often exhibited higher levels of negative emotions, such as anxiety and stress, in their social media posts. Topic modeling further identified recurring themes, such as excessive gaming and social media dependency, which are strongly associated with internet addiction.

Table 1 summarized the results, highlighting the trade-offs between accuracy, precision, recall, and computational efficiency. This table served as a valuable tool for comparing the models and selecting the most appropriate algorithm for specific use cases. For example, while neural networks achieved the highest accuracy, their longer training times made them less suitable for real-time applications, where faster algorithms like Random Forest or XGBoost might be preferred. Overall, the results underscore the potential of AI-driven approaches in addressing internet addiction.

By leveraging diverse algorithms and open-access datasets, this research provides a robust framework for predicting and mitigating internet addiction, paving the way for future studies and practical applications in digital well-being.

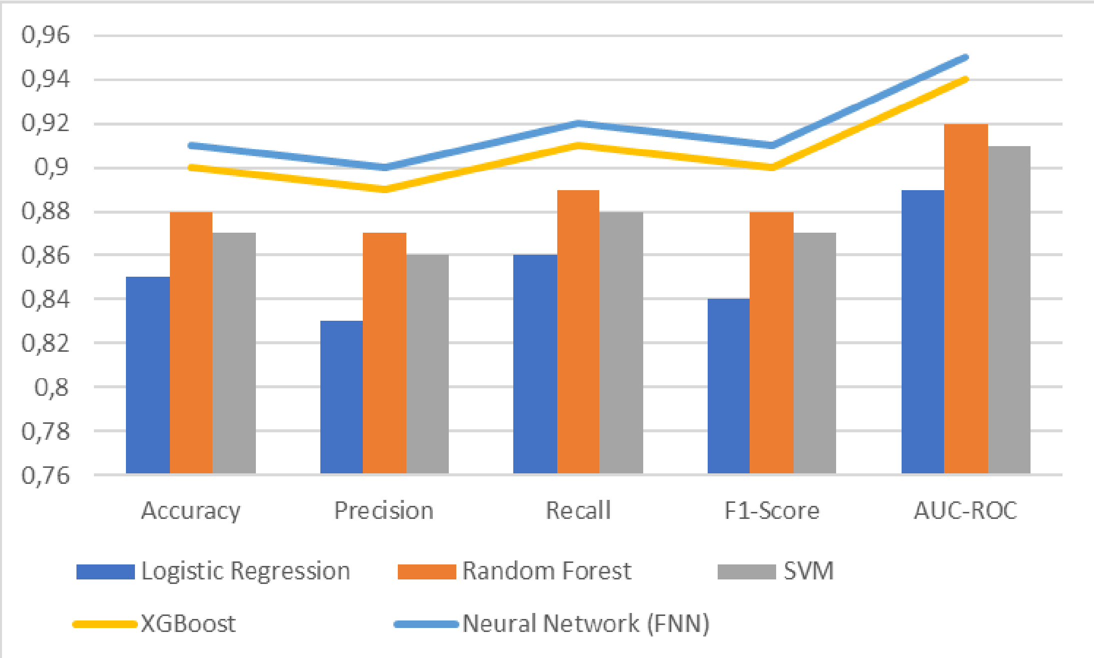

Figure 1. Showing a comparison between two genders in terms of Internet Addiction

Table 1. Performance Metrics Comparison					
Algorithm	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Logistic Regression	0,85	0,83	0,86	0,84	0,89
Random Forest	0,88	0,87	0,89	0,88	0,92
SVM	0,87	0,86	0,88	0,87	0,91
XGBoost	0,90	0,89	0,91	0,90	0,94
Neural Network (FNN)	0,91	0,90	0,92	0,91	0,95

DISCUSSION

The findings of this research highlight the transformative potential of AI in addressing internet addiction, a growing concern in the digital age. The superior performance of advanced algorithms like Neural Networks and XGBoost underscores their ability to capture complex patterns in user behavior, making them ideal for high-accuracy predictions.

These models not only classify users effectively but also provide actionable insights into the factors contributing to addiction, such as excessive screen time, frequent social media use, and emotional distress. The use of clustering algorithms, such as k-Means and DBSCAN, revealed distinct user groups, enabling targeted interventions for at-risk individuals. For example, heavy users and potential addicts were identified based on their usage patterns, allowing for personalized recommendations to reduce screen time or seek professional help.

Similarly, anomaly detection algorithms like Isolation Forest proved valuable in identifying extreme behaviors, which are often early indicators of addiction. Natural Language Processing (NLP) techniques added another layer of understanding by analyzing textual data from social media posts and chats. Sentiment analysis revealed that users classified as addicted frequently expressed negative emotions, such as anxiety and stress, while topic modeling identified recurring themes like gaming addiction and social media dependency.[20]

These insights are crucial for developing holistic interventions that address both behavioral and psychological aspects of internet addiction. However, the study also highlights certain limitations. For instance, the reliance on self-reported data from Kaggle datasets may introduce biases, and the generalizability of the findings could be affected by the demographic characteristics of the dataset. Additionally, while advanced algorithms like Neural Networks achieved high accuracy, their computational complexity and longer training times may limit their practicality in real-time applications.

Future research could address these limitations by incorporating larger, more diverse datasets and exploring lightweight models for real-time deployment. Overall, this research contributes to the growing body of knowledge on AI-driven solutions for mental health challenges. By leveraging machine learning and deep learning techniques, it provides a scalable and efficient framework for identifying and mitigating internet addiction, paving the way for innovative digital well-being interventions.

CONCLUSIONS

This research demonstrates the significant potential of artificial intelligence in predicting and classifying internet addiction, offering a data-driven approach to address this modern public health challenge. By utilizing open-access datasets from Kaggle and employing a diverse range of machine learning and deep learning algorithms, the study achieved high accuracy in identifying addictive behaviors, with Neural Networks and XGBoost emerging as the top-performing models. Clustering and anomaly detection techniques provided valuable insights into user behavior, while NLP methods uncovered emotional and thematic patterns associated with addiction. The findings underscore the importance of integrating AI into digital well-being initiatives, enabling early detection and personalized interventions for at-risk individuals. Despite certain limitations, such as dataset biases and computational complexity, the study lays a strong foundation for future research and practical applications. By continuing to refine these models and expand their scope, AI-driven solutions can play a pivotal role in promoting healthier digital habits and improving mental health outcomes in an increasingly connected world.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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Methodology: Mutaz Abdel Wahed.
Project management: Mutaz Abdel Wahed.
Software: Mutaz Abdel Wahed.
Supervision: Mutaz Abdel Wahed.
Writing - proofreading and editing: Mutaz Abdel Wahed, Salma Abdel Wahed.