Deep Learning-Based Prediction of Social Media Addiction Among Students Using Behavioral and Psychological Features

Ika Christine Purba[1,*], Aulia Al-JIhad Safhadi[2]

[1,2]Magister of Computer Sciences, Universitas Gadjah Mada, Indonesia.

ABSTRACT

The widespread use of social media among students has created growing concerns regarding the potential development of social media addiction and its impact on academic performance, mental health, and daily behavior. This study aims to develop a deep learning model to predict social media addiction among students based on behavioral, demographic, and psychological characteristics. The dataset used in this study consists of 705 student records and includes variables such as age, gender, academic level, country, average daily social media usage hours, preferred social media platform, sleep duration, mental health score, relationship status, and conflicts related to social media use. Data preprocessing techniques including categorical encoding and feature scaling were applied before training the model. A deep neural network architecture was implemented to learn patterns associated with social media addiction and was evaluated using a hold out test dataset of 141 samples. The model performance was assessed using several evaluation metrics including accuracy, precision, recall, F1 score, and the area under the Receiver Operating Characteristic curve. The experimental results show that the proposed model achieved an accuracy of 90.78 percent and an AUC value of 0.9682, indicating strong predictive performance in distinguishing addicted and non addicted students. Feature importance analysis revealed that mental health score plays a significant role in predicting social media addiction. These findings demonstrate that deep learning can effectively identify patterns related to problematic social media behavior and may support early detection efforts aimed at promoting healthier digital habits among students.

Keywords Social Media Addiction, Deep Learning, Student Behavior Analysis, Artificial Intelligence, Digital Wellbeing

Submitted 9 June 2026
Accepted 10 July 2026
Published 1 September 2026

Corresponding author
Ika Christine Purba,
ikachristinepurba@mail.ugm.ac.id

Additional Information and Declarations can be found on page 191

INTRODUCTION

The rapid development of digital technology has significantly transformed the way individuals communicate, access information, and interact within society. Among these technological developments, social media platforms have become an essential part of daily life, particularly for students. Social media provides various benefits such as facilitating communication, supporting learning activities, and enabling access to a wide range of information. However, excessive use of social media may lead to problematic behaviors that resemble addictive patterns. Students who spend excessive time on social media platforms may experience difficulties in managing their time, maintaining academic performance, and preserving healthy psychological conditions. As a result, social media addiction has become an important issue in the context of digital society and educational environments [1].

The increasing prevalence of social media usage among students has attracted growing attention from researchers and educators who aim to understand the

How to cite this article: I. C. Purba and A. A. J. Safhadi, "Deep Learning-Based Prediction of Social Media Addiction Among Students Using Behavioral and Psychological Features," *J. Digit. Soc.*, vol. 2, no. 3, pp. 177-192, 2026.

factors contributing to addictive behavior. Several behavioral indicators have been associated with problematic social media use, including prolonged daily usage duration, sleep disturbances, reduced academic engagement, and conflicts in interpersonal relationships. Psychological factors such as emotional wellbeing and mental health conditions are also closely related to patterns of excessive digital engagement. Understanding these factors is important for identifying students who may be at risk of developing unhealthy social media habits. Early detection of such behavior can support the development of effective strategies to promote balanced digital engagement and protect student wellbeing [2].

Recent advances in artificial intelligence and machine learning have provided new opportunities to analyze complex behavioral data and identify patterns associated with technology related addiction. Machine learning techniques have been widely applied to classify behavioral patterns, detect digital addiction, and analyze user behavior across online platforms. These approaches allow researchers to process large volumes of behavioral and demographic data and generate predictive models that can support early identification of problematic technology use. Compared with traditional statistical methods, machine learning models are capable of capturing nonlinear relationships among multiple variables and improving predictive performance in behavioral analysis tasks [3].

Among various artificial intelligence techniques, deep learning has emerged as a powerful approach for modeling complex relationships in high dimensional datasets. Deep learning models can automatically learn hierarchical feature representations and detect subtle patterns within data that may not be easily captured by traditional models. These capabilities make deep learning particularly suitable for analyzing behavioral data related to social media usage. By leveraging deep neural networks, researchers can develop predictive systems that identify individuals who may be vulnerable to social media addiction based on their behavioral and psychological characteristics [4].

Despite the growing application of machine learning techniques in analyzing digital behavior, several limitations remain in existing studies. Many previous works focus primarily on descriptive statistical analysis or traditional machine learning methods without exploring the potential advantages of deep learning architectures. In addition, some studies rely on limited behavioral indicators and do not fully integrate psychological and demographic factors that may influence social media addiction. These limitations highlight the need for more comprehensive predictive models that combine multiple behavioral, psychological, and demographic variables to better understand the mechanisms underlying social media addiction among students.

Furthermore, interpretability and identification of influential factors remain important challenges in predictive modeling of digital addiction. While predictive accuracy is important, understanding the variables that contribute most significantly to addiction prediction is equally critical for developing meaningful interventions and policies. Identifying these key factors can help educators and institutions design targeted programs aimed at promoting responsible digital behavior and improving student wellbeing [5].

Based on these challenges, this study proposes a deep learning-based approach to predict social media addiction among students using behavioral, demographic, and psychological features. The proposed model aims to capture complex relationships between students' social media usage patterns and addiction related behaviors. In addition, feature importance analysis is conducted to identify the most influential factors contributing to addiction prediction. By combining predictive modeling and feature analysis, this study aims to provide insights that can support early detection of problematic social media usage and contribute to the development of healthier digital practices within educational environments.

Literature Review and Related Works

The rapid growth of social media platforms has significantly influenced the daily lives of students, leading to both positive and negative consequences in educational and psychological contexts. Social media enables communication, knowledge sharing, and access to information; however, excessive use may lead to problematic behaviors such as addiction, reduced academic performance, and psychological distress. Previous studies have shown that prolonged exposure to social media platforms can negatively affect students' mental health, emotional stability, and learning performance [6]. The increasing prevalence of digital engagement among students has therefore motivated researchers to investigate the underlying behavioral and psychological factors associated with social media addiction.

Several studies have explored the relationship between social media usage and psychological conditions such as stress, anxiety, and depression. Research findings indicate that excessive digital engagement may contribute to emotional instability and reduced mental wellbeing among students [7], [8]. In addition, the addictive nature of social media platforms is often associated with reward mechanisms that encourage repeated engagement and prolonged online activity [9]. These behavioral patterns may lead to compulsive usage habits, reduced concentration in academic activities, and increased risk of digital addiction [10]. Consequently, understanding the factors influencing social media addiction has become an important research topic in the field of digital society and educational technology.

Recent advances in artificial intelligence have enabled the development of predictive models for analyzing digital behavior and identifying potential risks associated with excessive technology use. Machine learning techniques have been widely applied to analyze user behavior, classify addiction patterns, and detect psychological conditions using data generated from social media platforms [11], [12]. These techniques allow researchers to process large volumes of behavioral and demographic data and discover complex relationships between variables. Predictive models developed using machine learning have demonstrated promising results in identifying individuals at risk of mental health disorders and technology related addiction [13], [14].

Deep learning methods have also gained significant attention due to their ability to model complex nonlinear relationships within large datasets. Deep neural networks are capable of automatically extracting relevant features from data and capturing subtle behavioral patterns that may not be detected using traditional machine learning methods [15]. Several studies have applied deep learning techniques to analyze social media data for detecting psychological conditions such as depression, suicidal tendencies, and emotional distress [16], [17]. These models often outperform conventional algorithms due to their ability to learn hierarchical representations of data and improve classification performance in complex prediction tasks [18].

In addition to psychological analysis, machine learning models have also been applied to study digital addiction behavior among university students. Behavioral indicators such as daily social media usage duration, sleep patterns, and emotional wellbeing have been identified as important predictors of social media addiction risk [19]. Research has also shown that artificial intelligence based predictive systems can help identify early warning signs of digital addiction and support the development of intervention strategies aimed at improving student wellbeing [20]. These approaches provide valuable insights into how behavioral and psychological data can be utilized to understand digital addiction in modern educational environments.

Despite these advancements, several research gaps remain in the existing literature. Many previous studies focus primarily on traditional machine learning techniques or descriptive statistical analysis without fully exploring the potential advantages of deep learning architectures for addiction prediction. In addition, some studies rely heavily on textual social media data while overlooking behavioral and demographic variables that may also influence addiction patterns. Furthermore, limited attention has been given to identifying the most influential factors contributing to addiction prediction in student populations. These limitations highlight the need for more comprehensive predictive models that integrate multiple types of features and provide interpretable insights into social media addiction behavior.

To address these limitations, this study proposes a deep learning based predictive model for identifying social media addiction among students using behavioral, demographic, and psychological features. By combining deep neural networks with feature importance analysis, the proposed approach aims to improve prediction accuracy while also providing insights into the key factors influencing social media addiction. This research contributes to the growing body of work on artificial intelligence driven behavioral analysis and supports the development of data driven strategies for promoting healthier digital habits among students.

Methodology

Research Framework

This study adopts a data driven approach to predict social media addiction among students using deep learning techniques. The research process consists of several sequential stages including data collection, data preprocessing, feature transformation, model training, model evaluation, and feature importance analysis. The objective of this framework is to develop a predictive model capable of identifying students who are at risk of social media addiction based on behavioral, demographic, and psychological indicators. The overall research process is illustrated in figure 1, which shows the workflow of the proposed methodology starting from dataset preparation to model evaluation and interpretation.

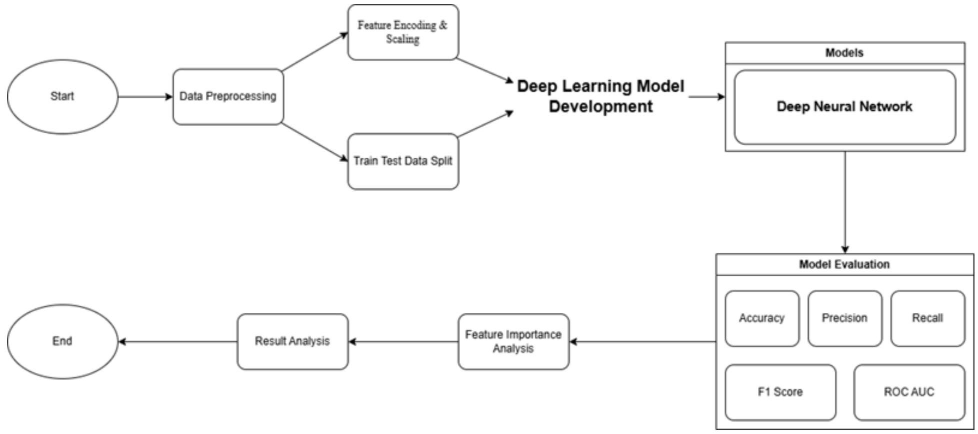

Figure 1 Research Steps

As shown in figure 1, the study begins with dataset preparation followed by preprocessing procedures such as feature selection and data transformation. The processed data is then used to train a deep neural network model. After training, the model performance is evaluated using several classification metrics. Finally, feature importance analysis is conducted to identify the most influential variables contributing to social media addiction prediction.

Dataset Description

This study uses a dataset consisting of 705 student records that describe social media usage behavior and related psychological factors. The dataset includes demographic variables, behavioral indicators, and psychological attributes that may influence the level of social media addiction among students.

The attributes used in this study are summarized in table 1, which describes the types of variables included in the dataset.

Table 1 Description of dataset variables

Variable Category	Attributes
Demographic Variables	Age, Gender, Academic Level, Country
Behavioral Variables	Average Daily Usage Hours, Most Used Platform, Conflicts Over social media
Academic Indicators	Affects Academic Performance
Psychological Indicators	Mental Health Score
Lifestyle Indicators	Sleep Hours per Night
Social Factors	Relationship Status
Target Variable	Social Media Addiction Score

The target variable in the dataset represents the level of social media addiction experienced by each student. In this study, the addiction score was converted into a binary classification label to distinguish between addicted and non-addicted students.

Data Preprocessing

Before training the deep learning model, several preprocessing steps were performed to ensure the dataset was suitable for model training. First, the

Student_ID attribute was removed because it functions only as a unique identifier and does not contribute to prediction. The addiction score was then converted into a binary label representing addicted and non-addicted students.

Next, the dataset features were divided into numerical and categorical variables. Numerical features include age, daily usage hours, sleep duration, mental health score, and conflicts related to social media usage. Categorical variables include gender, academic level, country, most used platform, academic performance impact, and relationship status.

Categorical variables were transformed into numerical format using one hot encoding. This process converts categorical attributes into binary vectors so that they can be processed by the neural network. In addition, numerical features were normalized using standardization to ensure that all variables have comparable scales during model training.

Deep Learning Model Architecture

A deep neural network model was developed to predict social media addiction among students. The model consists of several fully connected layers that enable the network to learn complex relationships between input variables and the target class.

The architecture of the proposed model includes three hidden layers with 32, 16, and 8 neurons respectively. Each hidden layer uses the Rectified Linear Unit (ReLU) activation function to introduce nonlinearity into the model. Dropout layers were applied between hidden layers to reduce overfitting by randomly disabling neurons during training. In addition, L2 regularization was applied to the dense layers to penalize large weight values and improve model generalization.

The output layer consists of a single neuron with a sigmoid activation function, which produces a probability value between 0 and 1 representing the likelihood that a student belongs to the addicted class.

The sigmoid activation function used in the output layer is defined as:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{1}$$

x represents the input value to the neuron.

Model Training

The model was trained using the Adam optimizer with a learning rate of 0.0005 and binary cross entropy as the loss function. Binary cross entropy is commonly used in binary classification problems because it measures the difference between predicted probabilities and actual class labels.

The binary cross entropy loss function is defined as:

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i log(p_i) + (1 - y_i)log(1 - p_i)] \tag{2}$$

y_i represents the true label,

p_i represents the predicted probability, and

N represents the total number of samples.

To prevent overfitting, two training strategies were implemented. Early stopping was used to stop training when validation performance no longer improved. In addition, the learning rate was automatically reduced when the validation loss reached a plateau.

Model Evaluation

The performance of the proposed deep learning model was evaluated using several classification metrics including accuracy, precision, recall, and F1 score. These metrics provide a comprehensive assessment of model performance.

The accuracy metric measures the proportion of correctly predicted samples and is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

TP represents true positives, TN represents true negatives, FP represents false positives and FN represents false negatives.

The precision metric measures the correctness of positive predictions and is defined as:

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

The recall metric evaluates the model's ability to correctly identify positive samples and is defined as:

$$Recall = \frac{TP}{TP + FN} \quad (5)$$

The F1 score represents the harmonic mean of precision and recall and is calculated as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (6)$$

In addition to these metrics, the Receiver Operating Characteristic curve and confusion matrix were also used to analyze the classification performance of the proposed model.

Feature Importance Analysis

To identify the most influential variables affecting social media addiction prediction, feature importance analysis was performed using the permutation importance method. Because deep learning models do not directly provide interpretable feature importance values, a surrogate Random Forest model was used to estimate the contribution of each feature.

Permutation importance measures the decrease in model performance when the values of a particular feature are randomly shuffled. Features that cause larger decreases in prediction accuracy are considered more important in the prediction process.

This analysis provides valuable insights into behavioral and psychological factors that contribute to social media addiction among students.

Algorithm 1: Social Media Addiction Prediction Using Deep Learning

Input: dataset D, feature set X, label Y

Output: predicted addiction class $\hat{y}$and evaluation metrics

Process:

Start

Load dataset D

Remove attribute $Student\_ID$

Convert addiction score into binary label

$$y = \{1, Addicted\_Score \geq \tau \; 0, otherwise$$

Separate dataset into feature set $X$and label set Y

Apply One Hot Encoding to categorical features

Normalize numerical features

$$X_{scaled} = \frac{X - \mu}{\sigma}$$

Split dataset into training and testing data

$$D_{train}, D_{test} = split(D, 0.8, 0.2)$$

Compute prediction

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

Compute binary cross entropy loss

$$L = -\frac{1}{N}\sum_{i=1}^{N} [y_i log(\hat{y_i}) + (1 - y_i) log(1 - \hat{y_i})]$$

Update model parameters using Adam optimizer

Repeat training until convergence or early stopping

Predict class label

$$\hat{y} = \{1, p \geq 0.5 \; 0, p < 0.5$$

Evaluate model performance using:

Accuracy, Precision, Recall, F1 Score, ROC AUC

Perform permutation feature importance analysis

End

Results

Model Performance

The proposed deep learning model was evaluated using a holdout test dataset consisting of 141 samples. Multiple evaluation metrics were employed to assess the classification performance, including accuracy, precision, recall, F1 score, and the area under the Receiver Operating Characteristic curve (ROC AUC). The model achieved an accuracy of 90.78 percent, indicating that the majority of students were correctly classified into the addicted and non-addicted categories. In addition, the model obtained a precision score of 93.67 percent, which suggests that most of the students predicted as addicted were indeed correctly identified by the model. The recall score reached 90.24 percent, demonstrating that the model was able to detect a large proportion of addicted students within the dataset. Furthermore, the F1 score of 0.9193 indicates a strong balance between precision and recall, confirming that the model performs consistently across both evaluation dimensions.

In addition to these metrics, the model achieved a ROC AUC value of 0.9682, which indicates excellent discriminative capability between addicted and non-addicted students. A ROC AUC value close to one implies that the model can effectively separate the two classes across different classification thresholds. This strong performance suggests that the deep learning model is highly effective in identifying patterns related to social media addiction among students. Table 2 summarizes the overall classification performance of the proposed deep learning model. Overall, the results demonstrate that the model provides reliable and robust predictions for detecting students who are at risk of social media addiction.

Table 2 Performance metrics of the proposed deep learning model

Metric	Score
Accuracy	0.9078
Precision	0.9367
Recall	0.9024
F1-score	0.9193
ROC-AUC	0.9682

Confusion Matrix Analysis

To further evaluate the classification performance of the proposed deep learning model, a confusion matrix was generated to examine the distribution of correct and incorrect predictions across the two classes. The confusion matrix provides a detailed view of how well the model distinguishes between students who are addicted to social media and those who are not. As illustrated in figure 2, the model correctly classified 54 students as not addicted and 74 students as addicted, indicating that the model was able to accurately identify the majority of observations in both categories. However, a small number of misclassifications were observed. Specifically, 5 students who were actually not addicted were predicted as addicted, representing false positive cases, while 8 students who were actually addicted were predicted as not addicted, representing false negative cases. Despite these misclassifications, the overall distribution of predictions demonstrates that the model maintains strong classification capability. The relatively low number of false positives and false negatives indicates that the model is effective in distinguishing between addicted and non-addicted students, thereby supporting the reliability of the proposed deep learning approach for identifying social edia addiction among students.

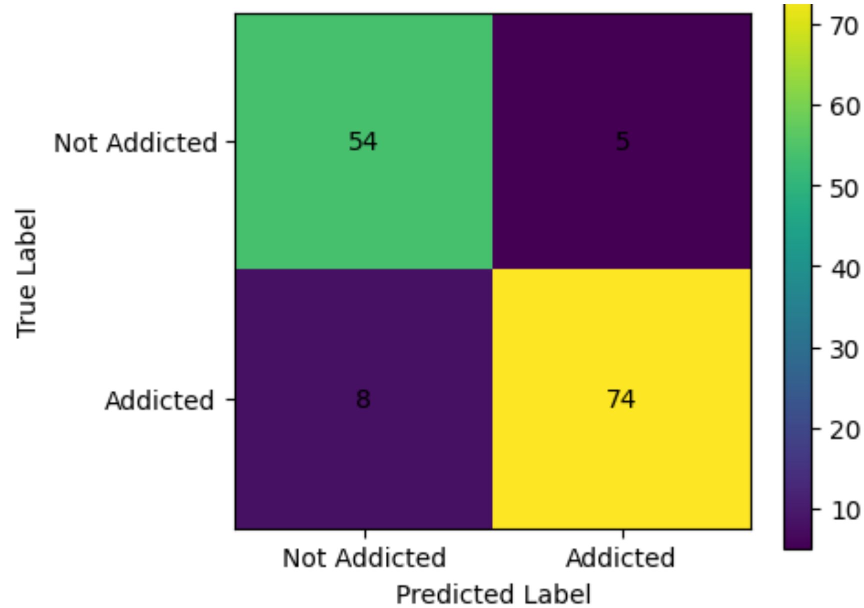

Figure 2 **Confusion matrix of the deep learning model**

ROC Curve Analysis

The Receiver Operating Characteristic curve was used to further evaluate the discriminative capability of the proposed deep learning model across different classification thresholds. The ROC curve illustrates the relationship between the true positive rate and the false positive rate, which provides insight into how effectively the model separates addicted students from non-addicted students. Figure 3 presents the ROC curve generated from the prediction results of the test dataset. As shown in the figure, the curve approaches the upper left region of the graph, which indicates strong classification performance and a high true positive rate with a relatively low false positive rate. The model achieved an Area Under the Curve value of 0.9682, which is considered an excellent result for binary classification problems. An AUC value close to one indicates that the model has a very high probability of correctly distinguishing between addicted and non-addicted students. This result demonstrates that the proposed deep learning model has strong predictive capability and is highly effective in identifying patterns related to social media addiction among students.

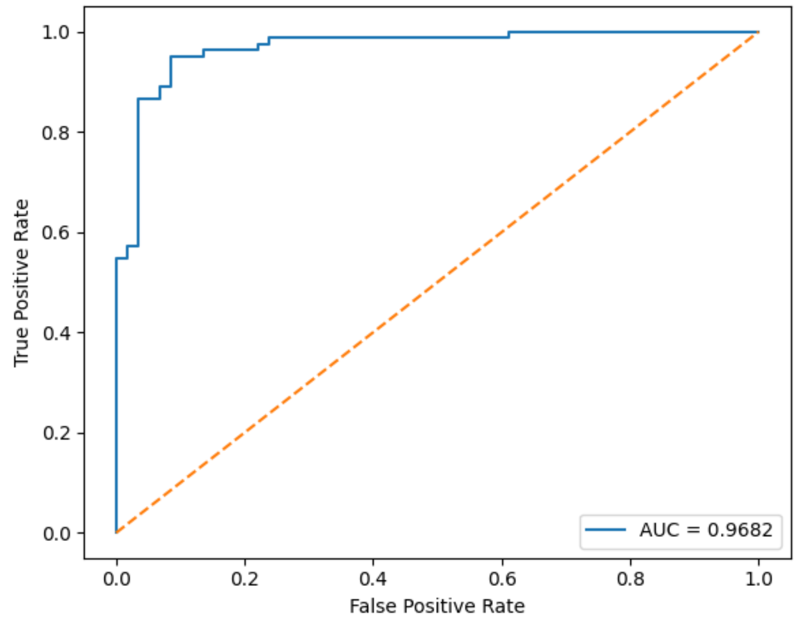

Figure 3 **ROC curve of the proposed deep learning model**

Training and Validation Performance

To monitor the model learning process, the training and validation loss as well as accuracy were analyzed throughout the training phase. Figure 4 presents the training and validation loss curves obtained during the model training process. As shown in the figure, both training loss and validation loss gradually decreased across epochs, indicating that the model progressively learned meaningful patterns from the dataset. The consistent decline in loss values suggests that the optimization process was effective and that the model parameters were successfully adjusted to minimize prediction errors. The absence of sharp fluctuations or divergence between the training and validation loss curves also indicates that the learning process remained stable during training.

In addition to the loss analysis, the training and validation accuracy curves are presented in figure 5 to further evaluate the model learning behavior. The validation accuracy steadily increased during the training process and reached approximately 93 percent, demonstrating that the model was able to generalize well to unseen data. The training accuracy also improved over time, although it remained slightly lower than the validation accuracy. This phenomenon can occur when regularization techniques such as dropout are applied during model training. Dropout temporarily deactivates a portion of neurons during each training iteration, which introduces controlled noise and prevents the model from relying too heavily on specific features. As a result, the training process becomes more challenging for the model, while the validation phase is performed without dropout, allowing the model to utilize its full capacity. Consequently, this behavior suggests that the regularization strategy effectively reduced the risk of overfitting and improved the generalization capability of the proposed deep learning model.

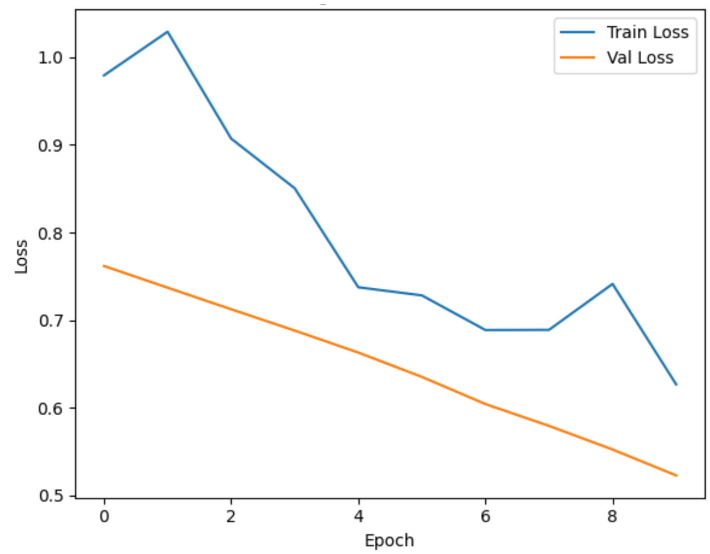

Figure 4 **Training and validation loss during model training**

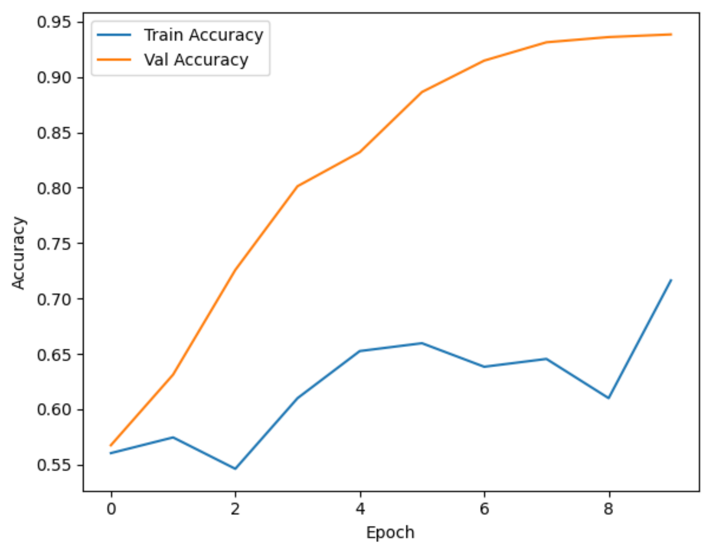

Figure 5 **Training and validation accuracy during model training**

Feature Importance Analysis

To identify the most influential factors affecting the prediction of social media addiction, a feature importance analysis was conducted using the permutation importance method. Because deep learning models do not directly provide easily interpretable feature importance scores, a surrogate Random Forest model was trained using the transformed feature dataset to approximate the relative contribution of each variable. The permutation importance technique evaluates the importance of a feature by measuring the decrease in model performance when the values of that feature are randomly shuffled. Features that cause a larger decrease in performance when permuted are considered more influential in the prediction process. Figure 6 presents the results of the feature importance analysis, highlighting the variables that contribute most significantly to the prediction of social media addiction. This analysis helps provide interpretability to the predictive model by revealing which behavioral, psychological, and demographic factors play the most important roles in determining students' social media addiction levels.

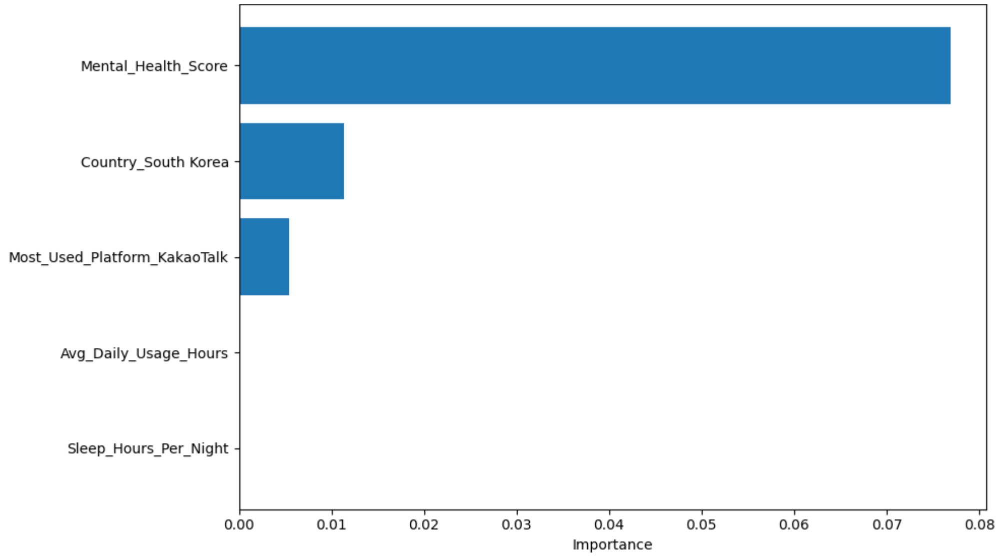

Figure 6 **Top features influencing social media addiction prediction**

The analysis reveals that Mental Health Score is the most influential predictor of social media addiction. This suggests that students with poorer mental health conditions may be more vulnerable to excessive social media usage.

Other influential factors include country-specific variables, preferred social media platforms, and behavioral indicators such as daily social media usage hours and sleep duration. These findings highlight the importance of psychological and behavioral factors in predicting social media addiction among students.

Discussion

The results of this study indicate that the proposed deep learning model is effective in predicting social media addiction among students. The model achieved an accuracy of 90.78 percent and an AUC value of 0.9682, which demonstrates strong predictive capability and excellent discriminative performance. These findings suggest that deep learning techniques are capable of capturing complex relationships between multiple behavioral, psychological, and demographic variables related to social media usage. The high precision and recall values further indicate that the model performs well in correctly identifying both addicted and non-addicted students. This balanced performance is important because reliable identification of at-risk individuals can support early detection efforts and help institutions design appropriate interventions aimed at reducing excessive social media use among students.

The confusion matrix results also support the reliability of the proposed model. The model correctly classified the majority of observations in both classes, with only a small number of misclassifications observed in the prediction results. Specifically, the number of false positive and false negative cases remained relatively low, indicating that the model maintains consistent performance when distinguishing between addicted and non-addicted students. In practical applications, this level of classification accuracy is valuable because early identification of problematic social media usage may allow educators, counselors, and policymakers to implement preventive measures that promote healthier digital behavior. Furthermore, the feature importance analysis revealed that mental health score plays a significant role in predicting social media addiction, suggesting that psychological wellbeing is closely related to patterns of excessive social media use. This finding reinforces the importance of considering both behavioral and psychological factors when analyzing technology related addiction in student populations.

Conclusion

This study developed a deep learning model to predict social media addiction among students using behavioral, demographic, and psychological variables derived from the dataset. The experimental results demonstrate that the proposed model achieved strong predictive performance, with an accuracy of 90.78 percent and an AUC value of 0.9682, indicating that the model can effectively distinguish between addicted and non-addicted students. The confusion matrix analysis further confirmed that the majority of observations were correctly classified, with only a small number of false positive and false negative predictions. In addition, the feature importance analysis revealed that mental health score is one of the most influential predictors of social media addiction, highlighting the strong relationship between psychological wellbeing and excessive social media usage. Behavioral indicators such as daily social media usage duration and sleep patterns also contributed to the prediction process, indicating that both psychological and behavioral factors play important roles in understanding digital addiction among students. Overall, the findings of this study demonstrate that artificial intelligence-based approaches can provide valuable insights for identifying students who may be at risk of problematic social media usage and can support the development of early intervention strategies aimed at promoting healthier digital behavior in the academic environment.

Declarations

Author Contributions

Conceptualization: I.C.P. and A.A.J.S.; Methodology: A.A.J.S.; Software: I.C.P.; Validation: I.C.P. and A.A.J.S.; Formal Analysis: I.C.P. and A.A.J.S.; Investigation: I.C.P.; Resources: A.A.J.S.; Data Curation: A.A.J.S.; Writing Original Draft Preparation: I.C.P. and A.A.J.S.; Writing Review and Editing: A.A.J.S. and I.C.P.; Visualization: I.C.P.; All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

The data presented in this study are available on request from the corresponding author.

Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] S. A. Gloria and S. Akbar, "The Impact of Social Media Usage to Academic Performance," *Jurnal Pendidikan Kedokteran Indonesia: The Indonesian Journal of Medical Education*, vol. 8, no. 2, p. 68, pp. 1-9, Jul. 2019, doi: 10.22146/jpki.45497.

[2] Z. Iqbal, N. Zeb, and A. Hussain, "The Impact of Social Media Usage on Academic Performance of University Students: Moderating Role of Time of Use," *Russian Social Science Review*, vol. 2, no. 1, pp. 234–246, Jun. 2018.

[3] J. M. Wickramasurendra, D. Jagoda, and R. M. L. Rathnayake, "Factors Influencing Social Media Addiction among G.C.E. Advanced Level Students in Sri Lanka: A Case Study in Colombo District, Sri Lanka," *Sri Lanka Journal of Social Sciences and Humanities*, vol. 1, no. 2, p. 1, pp. 1-11, Aug. 2021, doi: 10.4038/sljssh.v1i2.33.

[4] C. S. Andreassen, T. Torsheim, G. S. Brunborg, and S. Pallesen, "Development of a Facebook Addiction Scale," *Psychological Reports*, vol. 110, no. 2, pp. 501–517, Apr. 2012, doi: 10.2466/02.09.18.PR0.110.2.501-517.

[5] C. Montag, H. Yang, and J. D. Elhai, "On the Psychology of TikTok Use: A First Glimpse From Empirical Findings," *Frontiers in Public Health*, vol. 9, no. March, Art. no. 641673, pp. 1-6, Mar. 2021, doi: 10.3389/fpubh.2021.641673.

[6] W. Ning and F. A. Inan, "Impact of social media addiction on college students' academic performance: An interdisciplinary perspective," *Journal of Research on Technology in Education*, vol. 56, no. 1, pp. 1–16, Apr. 2023, doi: 10.1080/15391523.2023.2196456.

[7] J. Zhang, Y. Wang, L. Zhou, J. Wu, H. Li, and T. Zhu, "Correlations between social media addiction and anxiety, depression, FoMO, loneliness and self-esteem among students: A systematic review and meta-analysis," *PLOS ONE*, vol. 20, no. 9, Art. no. e0329466, pp. 1-19, Sep. 2025, doi: 10.1371/journal.pone.0329466.

[8] A. M. Khalaf, A. A. Alubied, A. M. Khalaf, and A. A. Rifaey, "The Impact of Social Media on the Mental Health of Adolescents and Young Adults: A Systematic Review," *Cureus*, vol. 15, no. 8, Art. no. e42990, Aug. 2023, doi: 10.7759/cureus.42990.

[9] M. D. Griffiths, D. J. Kuss, and Z. Demetrovics, "Social Networking Addiction: An Overview of Preliminary Findings," in *Behavioral Addictions: Criteria, Evidence and Treatment*, K. Rosenberg and L. Feder, Eds. Oxford, U.K.: Elsevier, vol. 2014, ch. 6, pp. 119–141, 2014, doi: 10.1016/B978-0-12-407724-9.00006-9.

[10] A. Masood, A. Luqman, Y. Feng, and F. Shahzad, “Untangling the Adverse Effect of SNS Stressors on Academic Performance and Its Impact on Students’ Social Media Discontinuation Intention: The Moderating Role of Guilt,” *SAGE Open*, vol. 12, no. 1, pp. 1–14, Mar. 2022, doi: 10.1177/21582440221079905.

[11] J. Cheng, M. Bernstein, C. Danescu-Niculescu-Mizil, and J. Leskovec, “Anyone Can Become a Troll: Causes of Trolling Behavior in Online Discussions,” in *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (CSCW)*, vol. 2017, no. February, pp. 1217–1230, 2017, doi: 10.1145/2998181.2998213.

[12] M. De Choudhury, M. Gamon, S. Counts, and E. Horvitz, “Predicting Depression via Social Media,” in *Proceedings of the International AAAI Conference on Web and Social Media (ICWSM)*, vol. 7, no. 1, pp. 128-137, 2013, doi: 10.1609/icwsm.v7i1.14432.

[13] M. J. Paul, A. Sarker, J. S. Brownstein, and A. Nikfarjam, “Social Media Mining for Public Health Monitoring and Surveillance,” in *Proceedings of the Pacific Symposium on Biocomputing*, vol. 2016, no. 2016, pp. 468-479, 2016, doi: 10.1142/9789814749411_0043.

[14] B. Balakrishnan, S. Muthumarilakshmi, D. Krishnan, and R. Sivakoumar, “Predictive Modelling of Social Media Behaviour Using Deep Learning: A Big Data Analytics Approach,” in *Proceedings of the Fifth Congress on Intelligent Systems*, vol. 2025, no. May, pp. 609–619, May 2025, doi: 10.1007/978-981-96-2694-6_40.

[15] M. Kosinski, D. Stillwell, and T. Graepel, “Private traits and attributes are predictable from digital records of human behavior,” *Proceedings of the National Academy of Sciences (PNAS)*, vol. 110, no. 15, pp. 5802–5805, Mar. 2013, doi: 10.1073/pnas.1218772110.

[16] B. Bokolo and Q. Liu, “Deep Learning-Based Depression Detection from Social Media: Comparative Evaluation of ML and Transformer Techniques,” *Electronics*, vol. 12, no. 21, Art. no. 4396, pp. 1-20, Oct. 2023, doi: 10.3390/electronics12214396.

[17] H. Zogan, I. Razzak, X. Wang, and S. Jameel, “Explainable depression detection with multi-aspect features using a hybrid deep learning model on social media,” *World Wide Web*, vol. 25, no. January, pp. 281–304, Jan. 2022, doi: 10.1007/s11280-021-00992-2.

[18] B. Chen, X. Yao, Y. Cao, and M. Chen, “Application of Deep Neural Network-Based Social Media Data Analysis in Brand Management,” *Journal of Organizational and End User Computing*, vol. 37, no. 1, pp. 1–34, Jun. 2025, doi: 10.4018/JOEUC.383053.

[19] O. Abdullahi, M. Bahari, S. Miskon, and M. H. A. Yazid, “Social Media Addiction and Academic Performance: A Bibliometric Analysis Approach,” *International Journal of Academic Research in Business and Social Sciences*, vol. 14, no. 1, pp. 1217-1228, Jan. 2024, doi: 10.6007/IJARBSS/v14-i1/20536.

[20] L. Zhao, “Social Media Addiction and Its Impact on College Students' Academic Performance: The Mediating Role of Stress,” *The Asia-Pacific Education Researcher*, vol. 32, no. 2, pp. 81-90, Nov. 2021, doi: 10.1007/s40299-021-00635-0.