Machine Learning and Deep Learning Approaches on Students' Social Media Addiction

Abstract

Using social media too much by students has become a concern because it might hurt their progress in school, their minds, and general health. It examines how many machine learning and deep learning models can predict and classify a student's social media addiction using demographic details, social media actions, and the record's outcome measuring sleep and grades. The data came from many countries to different levels of education. This was processed further to handle gaps and change categorical data into numerical. The addicted_score was divided into three groups called low, medium, and high. The data was scaled for features and divided into 80% for training and 20% for testing to get it ready for model training. The analysis of used models, such as SVM, XGBoost+CNN, CNN+SVM, MLP, and vision transformer. CNN+SVM, and MLP was reached highest accuracy (0.9220) and training time 24.23 and 11.58 seconds. Consider the training accuracy values in MLP (0.0.9263) was highest rather than other models. Integrating various layers in these hybrid approaches helped them process the data more effectively and extract essential features from the tabular information. Hyperparameter optimization increased the achievements of the ML, DL and hybrid models. The results reveal that using an ensemble or a hybrid model works better than relying on DL models. The study points out how ML and DL may assist in determining which students are likely to struggle in their learning and how to help them. To improve the model and resolve some of its drawbacks, future studies may study very large datasets or look at real-time data.

Key words: Social media addiction, ML and DL, Student Performance, Academic Impact, Mental Health

Introduction

Many people worry that social media's role in students' lives could lead to addiction and problems with their schoolwork, mental health, and rest (Savci et al., 2022). As social media use increases, it becomes important to understand and predict social media addiction to develop effective solutions (Ehsan & Basit). This is achieved by using ML and DL techniques to analyze a dataset of 705 student records, which includes demographic information, their usage patterns, and outcomes. Its value lies in offering useful insights for teachers and officials to prevent difficulties and improve student success (Mim et al., 2024).

The purpose is to see how different ML and DL models (such as SVM, XGBoost+CNN, CNN+SVM, MLP, Vision Transformer) handle classifying students based on their social media use into various addiction categories (low, medium, and high). The study aims to identify the approach that provides the best and most efficient results in predicting medicine side effects.

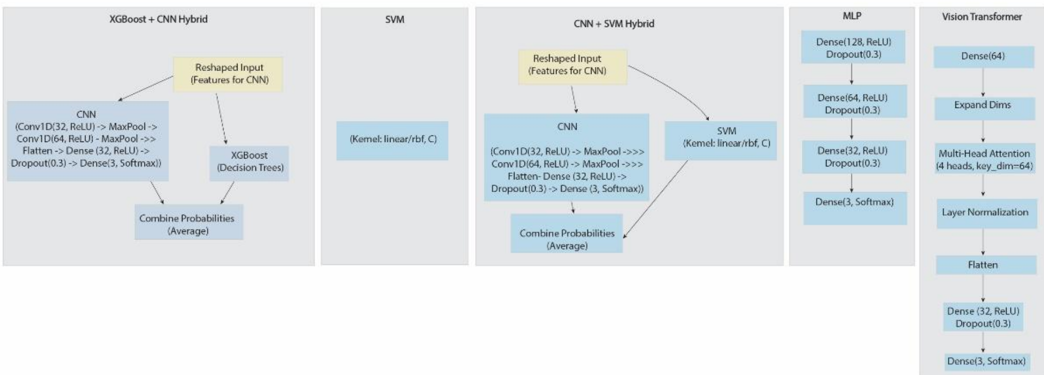
Literature Review

The study (Mim et al., 2024) investigates social media addiction in Bangladesh, linking excessive use of platforms like Messenger to mental health risks. Using machine learning, it achieves 82% accuracy with Random Forest, identifying higher addiction rates among those under 18. This study (Joseph & Maheswari, 2025) examines the relationship between social media addiction and academic dissatisfaction among 943 Bangladeshi students, utilizing machine learning algorithms (XGBoost, KNN, and Gradient Boosting) and LIME. XGBoost excelled with 95% recall, identifying academic stress and social comparisons as key addiction drivers, suggesting targeted interventions. The study (Parasar et al., 2025) uses the TMVM framework, integrating Theory of Mind AI and video modeling, to detect and reduce smartphone addiction in 786 Chennai students (aged 11–19) via facial emotion analysis. Using CNN, TLBO, and CSO algorithms, it achieved significant behavioral improvements ($p<0.000$) in social identity, self-awareness, and responsibility, reducing addiction and enhancing school/social engagement.

Methodology

This study utilized a dataset of 705 student records to predict social media addiction, containing variables like gender, academic level, country, and Addicted_Score. Preprocessing involved removing missing values, encoding categorical variables (e.g., gender, country) using LabelEncoder, discretizing Addicted_Score into low, medium, and high categories, and scaling features with StandardScaler after splitting the data into 80% training and 20% testing sets (random state 42). Training was conducted using hyperparameter tuning. ML models SVM, XGBoost+CNN, CNN+SVM, MLP, and Vision Transformer were developed, incorporating hybrid approaches with convolutional layers. Evaluation metrics included train/test accuracy, precision, recall, F1-score, specificity (via custom confusion matrix), sensitivity, and training time, ensuring a comprehensive assessment of model performance.

Figure 1: Model Architecture



Results and Discussion

The study evaluated the performance of machine learning (ML) and deep learning (DL) models SVM, XGBoost+CNN, CNN+SVM, MLP, and Vision Transformer on a dataset of 705 student records to predict social media addiction levels. Hybrid models like XGBoost+CNN (0.9258 accuracy, 32.53 seconds) and CNN+SVM (0.9187 accuracy, 24.23 seconds) showcased competitive results, leveraging convolutional layers to enhance feature extraction. The Vision Transformer, with a test accuracy of 0.9187 and the shortest training time of 10.59 seconds, exhibited slightly lower specificity (0.9111), suggesting a trade-off between speed and precision.

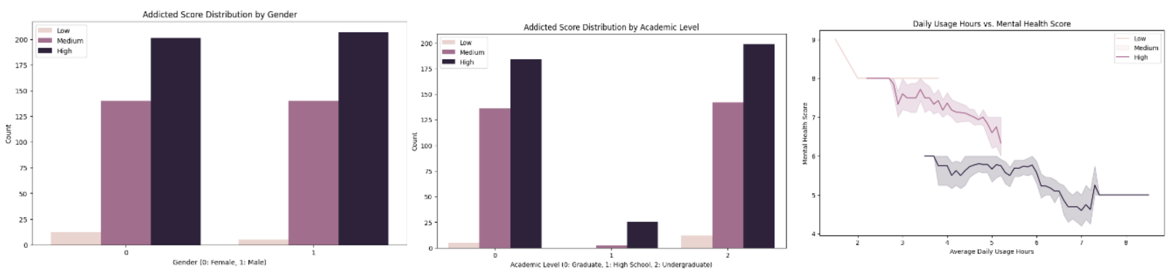
Table 1: Results of social media addiction

Model	Train Accuracy	Test Accuracy	Precision	Recall	F1-Score	Time (s)	Specificity	Sensitivity
SVM	0.9263	0.9163	0.9163	0.9163	0.9163	13.07	0.9165	0.9163
XGBoost+CNN	0.9258	0.9163	0.9165	0.9163	0.9150	32.53	0.9165	0.9163
CNN+SVM	0.9187	0.9220	0.9235	0.9220	0.9220	24.23	0.9212	0.9220
MLP	0.9263	0.9220	0.9235	0.9220	0.9220	11.58	0.9212	0.9220
Vision Transformer	0.9187	0.9107	0.9105	0.9107	0.9090	10.59	0.9111	0.9107

Figure 2 show how an "Addicted Score" is distributed and correlated with various demographic and behavioral variables. In the Fig 2 (a), the number of people with Low, Medium, and High addicted scores is identified based on gender, where Medium and High scores are higher in both males and females, with females showing slightly more results. Fig 2 (b) compares the scores according to education level (Graduate, High school, Undergraduate), showing that undergraduates and graduates have the highest values for Medium and High scores, with undergraduates leading in High scores. The Fig 2 (c) presents a line graph illustrating the negative correlation between hours of daily usage and mental health, indicating that mental health declines when usage exceeds 3-4 hours.

Figure 2: (a) Addicted score by gender (b) Addicted score distribution by academic staff (c) Daily usage hours vs mental score

(a) (b) (c)



The Figure 3 actually examines the use of different platforms at three educational levels: Graduate (0), High School (1), and Undergraduate (2). There are two big bars on the chart each corresponding to the first two levels and a smaller bar on the Undergraduate level. Each of the bars is partitioned into separate segments each denoting a specific platform (numbered 0 to 11 with different colors). Platform 0 (dark blue) demonstrates by far the largest usage with a considerable amount of it measuring to the Graduate level, and the remainder is added by other platforms. High School level is characterized by a lower total usage, but platforms 5 and 6 (red and pink) make the most significant contribution here. Undergraduate level performs the least usage, whilst there is a blend of platforms that have a negligible input. Finally, the Figure 4 density plot by gender shows that both females and males tend to have the highest score distribution around an addicted level of about 4-6, with males exhibiting a slightly broader range than females, providing an overall view of addiction patterns across these variables.

Figure 3: Platform usage by academic level

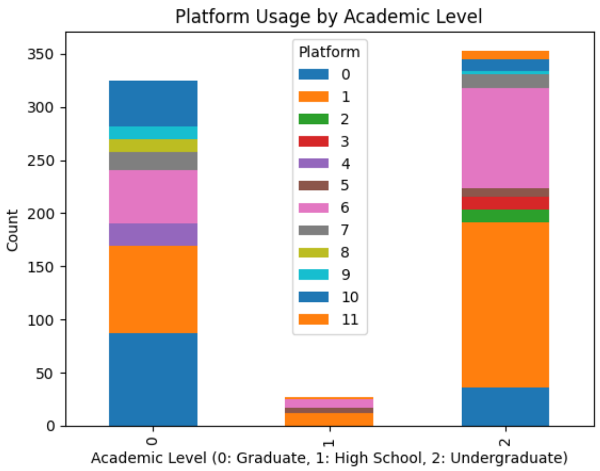
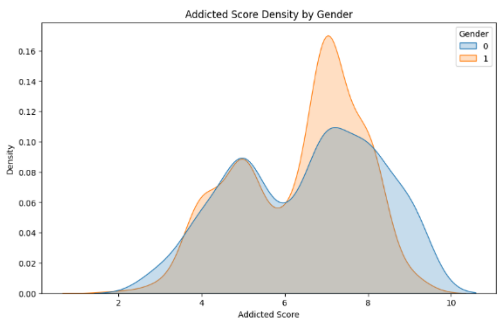


Figure 4: Addicted score density by gender



Implications/Conclusions

The analysis of social media addiction using various machine learning models reveals that CNN+SVM hybrids and MLP achieve the highest test accuracy (0.9220), with excellent precision, recall, and F1-scores. The Vision Transformer has a lower accuracy (0.9107), suggesting room for optimization. Overall, ensemble and hybrid models, particularly MLP and CNN+SVM, are the most effective for this classification task.

Based on the analysis of social media addiction using various machine learning models, it is recommended to prioritize MLP and CNN+SVM for deployment, given their impressive test accuracy of 0.9220 and strong performance across precision, recall, and F1-scores. The Vision Transformer, with a lower accuracy of 0.9107, should undergo parameter optimization to enhance its effectiveness. Lastly, when utilizing hybrid models like XGBoost+CNN, it's advisable to monitor training times to strike a balance between accuracy and computational resource usage, ensuring optimal model selection

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