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Gaming Addiction Level Prediction Using Random Forest Classification Based on Behavioral and Mental Health Factors

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Abstract

Gaming addiction is a growing concern due to the increasing popularity of online and mobile games. This study aims to predict gaming addiction severity using the Random Forest classification algorithm based on behavioral and mental health factors. The dataset comprises 250 player records with 49 attributes, including gaming duration, screen time, dopamine dependency index, self-control, impulsiveness, stress, and productivity-related factors. After preprocessing, the data were divided into training and testing sets using an 80:20 stratified split. A Random Forest model with 300 trees and balanced class weighting was evaluated using accuracy, precision, recall, F1-score, and a confusion matrix. The model achieved 84% accuracy, with weighted precision, recall, and F1-score of 83%, 84%, and 83%, respectively. However, macro-average precision, recall, and F1-score were 62%, 51%, and 55%, respectively, indicating limited performance on minority classes, particularly the Severe category. Feature importance identified daily playtime hours, dopamine dependency index, total screen time, and maximum consecutive gaming duration as the most important features. The findings indicate good performance on dominant classes but limited minority-class classification, highlighting the need for further data balancing.

Keywords: Gaming Addiction; Random Forest; Machine Learning; Classification; Mental Health.

Abstrak

Kecanduan game menjadi perhatian yang semakin meningkat seiring dengan popularitas game online dan mobile. Penelitian ini bertujuan memprediksi tingkat keparahan kecanduan game menggunakan algoritma Random Forest berdasarkan faktor perilaku dan kesehatan mental. Dataset terdiri atas 250 data pemain dengan 49 atribut, meliputi durasi bermain, waktu penggunaan layar, indeks ketergantungan dopamin, kontrol diri, impulsivitas, stres, dan faktor produktivitas. Setelah pra-pemrosesan, data dibagi menggunakan stratified sampling dengan rasio 80:20. Model Random Forest menggunakan 300 pohon keputusan dan balanced class weighting, kemudian dievaluasi menggunakan akurasi, presisi, recall, F1-score, dan confusion matrix. Model memperoleh akurasi 84%, dengan presisi, recall, dan F1-score tertimbang masing-masing 83%, 84%, dan 83%. Namun, nilai makro masing-masing hanya 62%, 51%, dan 55%, menunjukkan keterbatasan pada kelas minoritas, khususnya kategori Severe. Feature importance menunjukkan bahwa durasi bermain harian, indeks ketergantungan dopamin, total waktu layar, dan durasi bermain berturut-turut maksimum merupakan fitur terpenting. Hasil menunjukkan kinerja yang baik pada kelas dominan, tetapi terbatas pada kelas minoritas sehingga diperlukan penyeimbangan data lebih lanjut.

Kata Kunci: Kecanduan Game; Random Forest; Machine Learning; Klasifikasi; Kesehatan Mental.

1. Introduction

The rapid growth of digital technology has transformed the gaming industry, with online games, mobile games, and esports becoming increasingly accessible and popular. Although gaming can provide entertainment, cognitive benefits, and social interaction, excessive gaming may negatively affect mental health, academic performance, productivity, and social relationships. The World Health Organization (WHO) recognized Gaming Disorder as a mental health condition in the International Classification of Diseases (ICD-11), highlighting the importance of addressing problematic gaming behavior (World Health Organization, 2019). Previous studies have associated excessive gaming with prolonged screen time, sleep disturbances, increased stress, reduced self-control, and psychological dependence on gaming activities (King & Potenza, 2020). The global prevalence of gaming disorder has been estimated at approximately 3.05%, although estimates vary across regions and assessment methods (Stevens *et al.*, 2021; Kim *et al.*, 2022). Systematic reviews have also identified emotional dependence, social detachment, and increased gaming time as important indicators of addictive gaming behavior (Limone *et al.*, 2023). These findings highlight the importance of early identification of individuals at risk of problematic gaming and the need for approaches that can analyze multiple behavioral and psychological factors simultaneously.

The development of data mining and machine learning techniques provides opportunities to analyze behavioral and psychological data for predictive purposes. Classification algorithms have been applied to addiction-related problems by identifying patterns across multiple variables (Yang *et al.*, 2021). Compared with conventional approaches that may examine variables individually, machine learning can process multiple features simultaneously and generate predictive models from complex patterns in the data. Among machine learning algorithms, Random Forest is widely used because of its robustness, ability to handle high-dimensional data, and relatively low susceptibility to overfitting (Breiman, 2001; Hastie *et al.*, 2009). It also provides feature importance measures that can be used to identify features contributing most to model predictions. Previous studies have applied Random Forest to behavioral classification and health-related prediction tasks (Kornev *et al.*, 2022; Catulay *et al.*, 2022).

Based on these considerations, this study aims to predict gaming addiction severity using behavioral and mental health factors through the Random Forest classification algorithm. The dataset contains 250 records and 49 attributes representing gaming behavior, psychological conditions, health indicators, and productivity-related factors. The study evaluates the classification performance of Random Forest across different addiction severity levels and identifies the features with the highest importance for model prediction. Based on the background described above, this study addresses the following research questions:

1) How well does the Random Forest algorithm predict gaming addiction severity levels?
2) Which behavioral and mental health features have the highest importance in predicting gaming addiction severity?
3) How well does the proposed model classify different levels of gaming addiction?

The objectives of this study are:

1) To develop a Random Forest classification model for predicting gaming addiction severity levels.
2) To evaluate the model performance using accuracy, precision, recall, and F1-score.
3) To identify the behavioral and mental health features with the highest importance for predicting gaming addiction severity.

Table 1 summarizes the gap analysis comparing this study with previous research on gaming addiction prediction using machine learning.

Table 1. Gap Analysis

No	Previous Study	Approach / Data	Main Focus	Identified Gap	Position of This Study
1	Jeong *et al.* (2022)	Multiple-kernel SVM using multimodal PET, EEG, and clinical features	Predicting Internet Gaming Disorder	Requires neuroimaging equipment and specialized expertise, limiting accessibility and scalability	Uses an accessible survey-based dataset containing behavioral and mental health factors

2	Kornev *et al*. (2022)	Machine learning-based gaming behavior prediction using fNIRS data	Predicting gaming behavior patterns	Relies on neurophysiological data and specialized equipment	Uses behavioral and psychological features that are more accessible for prediction
3	Catulay *et al*. (2022)	Random Forest-based analysis of mobile gaming addiction	Analyzing mobile gaming addiction using behavioral data	Primarily focuses on behavioral features without combining them with mental health indicators	Combines behavioral and mental health factors in the classification model
4	Existing approaches	Various machine learning approaches	Classification of gaming/addiction-related outcomes	Class imbalance may reduce prediction performance for minority severity classes	Applies balanced class weighting and evaluates performance using macro- and weighted-average metrics
5	This Study	Random Forest with 300 trees and balanced class weighting; 250 records and 49 attributes	Predicting gaming addiction severity	Addresses accessibility, integration of behavioral and mental health factors, and class imbalance	Provides feature importance analysis to identify the most important predictors of gaming addiction severity

Previous studies on gaming addiction prediction have used approaches based on neuroimaging data (Jeong *et al*., 2022; Kornev *et al*., 2022), which may require specialized equipment and expertise. Other studies have focused primarily on behavioral features without combining them with mental health indicators (Catulay *et al*., 2022). In addition, class imbalance can present a challenge in addiction severity classification because minority classes may be poorly represented and consequently difficult to predict. This study addresses these gaps by combining behavioral and mental health factors in a survey-based dataset, applying Random Forest with balanced class weighting to address class imbalance, and conducting feature importance analysis to identify the features most relevant to model prediction. This approach provides an accessible framework for examining gaming addiction severity using behavioral and mental health data.

2. Theoretical Framework

Gaming Disorder is defined by the World Health Organization (WHO) as a pattern of gaming behavior characterized by impaired control over gaming, increasing priority given to gaming over other activities, and continued or increased gaming despite negative consequences (World Health Organization, 2019). The condition becomes clinically significant when the behavior results in substantial impairment in personal, family, social, educational, or occupational functioning. Assessment of gaming-related problems may consider behavioral indicators such as gaming duration, gaming frequency, and neglect of responsibilities, as well as psychological indicators such as cravings, withdrawal symptoms, and mood regulation through gaming (King & Potenza, 2020). These characteristics provide a conceptual basis for examining gaming addiction severity in this study. Behavioral indicators relevant to gaming addiction include daily playtime, screen time, consecutive gaming duration, and patterns of gaming activity (Stevens *et al*., 2021). Mental health-related indicators include self-control, impulsiveness, stress, sleep quality, and the dopamine dependency index used in the dataset (Limone *et al*., 2023). These variables are considered predictive features for examining differences in gaming addiction severity through machine learning classification. Random Forest is an ensemble learning algorithm that combines multiple decision trees to produce a classification outcome based on the majority vote of individual trees (Breiman, 2001).

The algorithm uses bootstrap aggregation (bagging) and random feature selection during tree construction, which reduces correlation among trees and can improve generalization. Random Forest is also suitable for datasets containing multiple features and provides feature importance measures that can be used to identify features contributing most to model predictions (Hastie *et al*., 2009).

Class imbalance occurs when target classes contain substantially different numbers of observations (Chawla *et al*., 2002). An imbalanced distribution can cause classification models to favor majority classes and reduce predictive performance for minority classes. This issue is particularly relevant to the present study because the Severe category contains only a small number of observations compared with the other severity levels. To address this problem, the study applies balanced class weighting in the Random Forest model and evaluates performance using both weighted and macro-average metrics. Classification performance is evaluated using accuracy, precision, recall, and F1-score. Accuracy measures the proportion of correctly classified observations, while precision measures the proportion of predicted instances of a class that are correctly classified. Recall measures the proportion of actual instances of a class that are correctly identified. The F1-score represents the harmonic mean of precision and recall. For multiclass classification, macro-average metrics calculate the metric independently for each class and then assign equal weight to each class, whereas weighted averages account for the number of observations in each class. Macro-average metrics are therefore particularly useful for assessing performance across imbalanced classes. A confusion matrix is also used to examine correct and incorrect classifications for each gaming addiction severity level.

3. Research Method

This study uses a gaming addiction dataset consisting of 250 player records and 49 attributes. The dataset was obtained through survey-based data collection targeting active gamers across different age groups and gaming platforms. The survey collected information related to gaming behavior, psychological conditions, health indicators, and productivity-related factors associated with gaming addiction severity. The data collection process was conducted in accordance with the applicable research procedures, and informed consent was obtained from the participants. The target variable, addiction_severity, consists of four categories: Mild, Moderate, Severe, and Critical. The predictor variables include daily playtime hours, screen time duration, dopamine dependency index, self-control score, impulsiveness score, sleep hours, stress score, absenteeism days, and productivity drop percentage. These variables represent behavioral, psychological, health-related, and productivity-related aspects relevant to gaming addiction severity. Data preprocessing was performed to prepare the dataset for classification. The preprocessing procedures included data cleaning, missing-value handling, categorical encoding, feature-target separation, and feature scaling. Duplicate records were identified and removed, while potential outliers were examined using the interquartile range (IQR) method. Missing values in numerical features with less than 10% missing observations were handled using median imputation, whereas features with higher missing rates were processed using multiple imputation by chained equations (MICE). The target variable, addiction_severity, was encoded into numerical labels: Mild = 0, Moderate = 1, Severe = 2, and Critical = 3. Categorical predictor variables were encoded using label encoding for ordinal variables and one-hot encoding for nominal variables. The predictor variables were then separated from the target variable. Although Random Forest does not require feature scaling, standardization was applied to the numerical features to maintain a consistent preprocessing procedure for potential comparisons with other algorithms.

The dataset was divided into training and testing subsets using a stratified hold-out approach. Eighty percent of the data were allocated for training and 20% for testing, resulting in 200 training records and 50 testing records. Stratified sampling was applied to preserve the class distribution of the target variable in both subsets. A random state of 42 was used to ensure reproducibility. Stratified 5-fold cross-validation was applied to the training data during model development. The 200 training records were divided into five folds, with four folds used for training and one fold used for validation in each iteration. This process was repeated until all folds had served as the validation set. Hyperparameter optimization was performed using Grid Search with cross-validation. The parameters evaluated included n_estimators = [100, 200, 300, 500], max_depth = [None, 10, 20, 30], min_samples_split = [2, 5, 10], min_samples_leaf = [1, 2, 4], and max_features = [sqrt, log2]. The best configuration was selected based on macro F1-score across the validation folds and subsequently used to train the final model. Random Forest was used as the primary classification algorithm. The model combines multiple decision trees and determines the final class through majority voting. To address the imbalanced distribution of addiction severity classes, balanced class weighting was applied during model training. The final Random Forest configuration used 300 decision trees (n_estimators = 300). The remaining hyperparameters were determined through the Grid Search procedure described Model performance was evaluated on the testing set using accuracy, precision, recall, and F1-score. Both macro-average and weighted-average scores were considered to provide a more complete assessment of performance under class imbalance. A confusion matrix was also used to examine correct and incorrect predictions for each addiction severity category. Feature importance analysis was conducted to identify the features with the highest importance in the Random Forest model and to determine which variables contributed most to the model's predictions. The experiments were implemented using Python 3.10. The Random Forest classifier and preprocessing procedures were implemented using scikit-learn version 1.3.0. Pandas version 2.1.0 was used for data manipulation, NumPy version 1.25.0 for numerical computation, and Matplotlib version 3.8.0 and Seaborn version 0.12.0 for data visualization. The experiments were conducted on a Windows 11 system equipped with an Intel Core i7 processor and 16 GB of RAM.

4. Results And Discussion

4.1 Result

The dataset consists of 250 player records categorized into four gaming addiction severity levels: Mild, Moderate, Severe, and Critical. The class distribution comprises 112 Mild records, 117 Moderate records, 5 Severe records, and 16 Critical records. This distribution indicates substantial class imbalance, particularly for the Severe category, which represents only a small proportion of the dataset. The dataset contains 49 attributes representing gaming behavior, psychological conditions, health indicators, and productivity-related factors. These variables provide a multidimensional representation of characteristics associated with gaming addiction severity.

```
addiction_severity
1    117
0    112
3     16
2      5
Name: count, dtype: int64
```

Figure 1. Class Distribution of the Addiction Severity Dataset

The Random Forest classifier was trained using 80% of the dataset and evaluated on the remaining 20%. The final model used balanced class weighting to address class imbalance and was configured with 300 decision trees. The model achieved an accuracy of 84%. The weighted precision, recall, and F1-score were 83%, 84%, and 83%, respectively. These results indicate good overall predictive performance when considering the distribution of the classes. However, the weighted metrics should be interpreted together with the per-class and macro-average results because the dataset is substantially imbalanced.

	precision	recall	f1-score	support
0	0.83	0.87	0.85	23
1	0.83	0.87	0.85	23
2	0.00	0.00	0.00	1
3	1.00	0.67	0.80	3
accuracy			0.84	50
macro avg	0.67	0.60	0.63	50
weighted avg	0.83	0.84	0.83	50

Figure 2. Classification Performance

Table 2 presents the classification performance for each gaming addiction severity category. The model achieved relatively strong performance for the Mild and Moderate classes, with F1-scores of 0.87 for both classes. In contrast, the Severe class obtained an F1-score of 0.00, indicating that the model did not correctly identify any instance of this category. The Critical class achieved an F1-score of 0.55, with a precision of 0.75 and recall of 0.43. The difference between the performance of the dominant and minority classes demonstrates the effect of class imbalance on the model. Although balanced class weighting was applied, the limited number of Severe and Critical observations restricted the model's ability to learn representative patterns for these categories.

Table 2. Per-Class Classification Performance

Class	Precision	Recall	F1-Score	Support
Mild	0.86	0.89	0.87	22
Moderate	0.84	0.91	0.87	24
Severe	0.00	0.00	0.00	1
Critical	0.75	0.43	0.55	3
Weighted Avg	0.83	0.84	0.83	50
Macro Avg	0.62	0.51	0.55	50

The confusion matrix provides a detailed view of the correct and incorrect classifications across the four addiction severity categories. The model correctly classified most instances in the Mild and Moderate categories, while classification errors were more evident for the minority classes. Misclassification occurred mainly between the Mild and Moderate categories, suggesting that the model encountered difficulty distinguishing between these two classes based on the available features. The Severe category was not correctly identified, further demonstrating the limitations associated with its very small sample size.

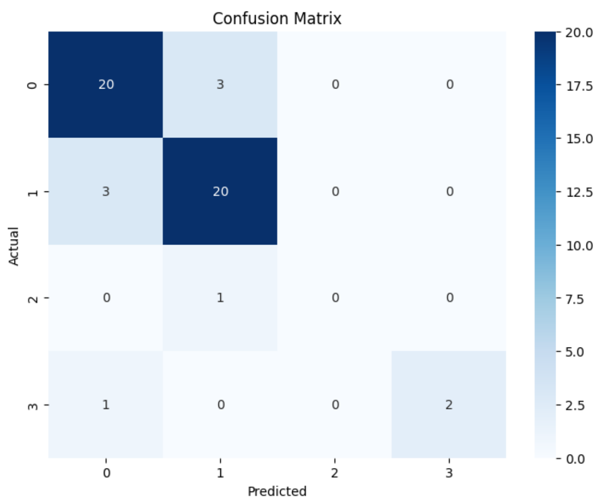

Figure 3. Confusion Matrix of the Random Forest Model

Feature importance analysis was conducted to identify the features that contributed most to the Random Forest model's predictions. The analysis showed that daily_playtime_hours had the highest importance score, followed by dopamine_dependency_index, screen_time_total_hours, and consecutive_hours_max. These results indicate that gaming duration, screen time, and the dopamine dependency index were among the most important features used by the model to distinguish gaming addiction severity levels. However, feature importance represents the contribution of variables to model predictions and should not be interpreted as evidence of a causal relationship.

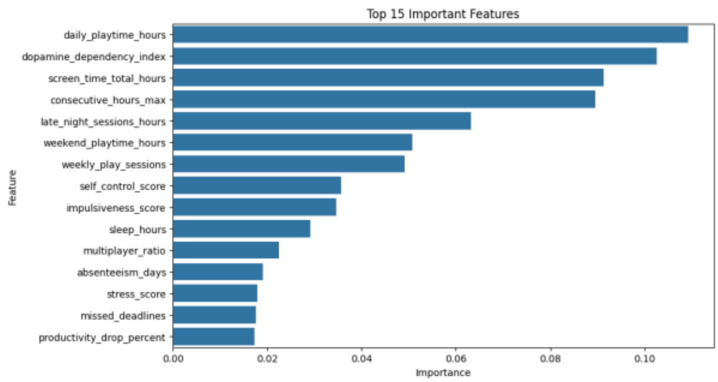

Figure 4. Top 15 Feature Importance Scores

4.2 Discussion

The findings of this study demonstrate that Random Forest provides good overall performance in predicting gaming addiction severity, particularly when evaluated using weighted metrics. The model achieved an accuracy of 84%, with weighted precision, recall, and F1-score of 83%, 84%, and 83%, respectively. These results indicate that the model was able to classify the dominant classes relatively well. However, the difference between the weighted and macro-average results needs to be considered. The macro-average precision, recall, and F1-score were 62%, 51%, and 55%, respectively, indicating that model performance varied considerably across the four severity categories. Therefore, the accuracy and weighted metrics alone should not be interpreted as evidence of equally strong performance across all addiction severity levels. The per-class results further demonstrate this performance difference. The Mild and Moderate categories achieved relatively strong classification performance, with F1-scores of 0.87 for both classes. In contrast, the Severe category obtained an F1-score of 0.00 because no Severe instance was correctly classified, while the Critical category achieved an F1-score of 0.55, with relatively higher precision than recall. These results indicate that the model was more effective in recognizing the dominant classes than the minority classes. The relatively high performance for Mild and Moderate may be related to their substantially larger representation in the training data, whereas the limited number of Severe instances provides insufficient examples for the model to learn distinctive patterns associated with this category.

The findings are broadly comparable with previous machine learning research on gaming-related problems, although direct comparisons should be interpreted cautiously because the datasets, target definitions, features, and experimental settings differ. Jeong *et al.* (2022) reported an accuracy of 86.5% using a multiple-kernel Support Vector Machine based on multimodal PET, EEG, and clinical features for predicting Internet Gaming Disorder. In comparison, the present study achieved 84% accuracy using behavioral and mental health-related features. Although the accuracy is slightly lower, the present approach does not require neuroimaging data, making it potentially more accessible and less resource-intensive. Kornev *et al.* (2022) also investigated gaming behavior prediction using fNIRS-based data and machine learning methods. Their study provides a neurophysiological perspective, whereas the present study focuses on behavioral and psychological characteristics. Therefore, the results of these studies are complementary rather than directly equivalent. The feature importance analysis identified daily_playtime_hours, dopamine_dependency_index, screen_time_total_hours, and consecutive_hours_max as the most influential features in the Random Forest model.

The prominence of gaming duration and screen-time-related variables is consistent with previous literature emphasizing excessive gaming behavior and prolonged gaming activity as important indicators of gaming-related problems (King & Potenza, 2020; Limone *et al.*, 2023). The importance of dopamine_dependency_index also suggests that variables representing psychological or reward-related dependence may provide useful information for distinguishing addiction severity. However, feature importance represents the contribution of variables to the predictive model and should not be interpreted as evidence that these variables directly cause gaming addiction. A major finding of this study is the poor performance in classifying the Severe category. The Severe class consists of only 5 of the 250 records, representing approximately 2% of the dataset. This extreme imbalance limits the amount of information available for learning patterns associated with Severe addiction. Although balanced class weighting was applied during Random Forest training, the approach was insufficient to correctly identify the Severe instance in the test set.

This result demonstrates that class weighting alone may not be adequate when a minority class contains very few observations. The substantial difference between the macro and weighted metrics further confirms that the model's overall performance is strongly influenced by the Mild and Moderate classes. Therefore, future studies should consider additional imbalance-handling techniques, such as SMOTE, together with larger and more balanced datasets.

Table 3. Comparison with Alternative Classification Methods

Study	Method	Accuracy	Macro F1	Dataset
Jeong *et al.* (2022)	Multiple-kernel SVM	86.5%	–	Neuroimaging
Kornev *et al.* (2022)	Random Forest	85.2%	–	fNIRS
Catulay *et al.* (2022)	Random Forest	82.0%	–	Mobile gaming survey
This study	Random Forest	84%	55%	Behavioral Mental Health survey

As shown in Table 3, the proposed Random Forest model achieved an accuracy of 84%, which is broadly comparable with the performance reported by related machine learning approaches. However, comparison based solely on accuracy is insufficient because the present dataset has a substantial class imbalance. The macro F1-score of 55%, compared with the weighted F1-score of 83%, demonstrates that the model's performance is not uniform across the four severity categories. Thus, the main contribution of the proposed approach is not only its overall classification accuracy but also its use of accessible behavioral and mental health-related variables for predicting addiction severity.

From a practical perspective, the findings suggest that behavioral and mental health-related variables can serve as inputs for preliminary gaming addiction severity prediction. Such an approach may provide a basis for developing accessible screening or risk-assessment systems for educational institutions, mental health services, or other relevant settings. Nevertheless, the poor performance in identifying the Severe category limits the model's suitability for clinical or high-stakes decision-making. The model should therefore be considered a preliminary predictive tool rather than a clinical diagnostic instrument, and its predictions should be interpreted together with appropriate professional assessment. Several limitations should be acknowledged. First, the Severe category contains only 5 records, resulting in extremely limited representation and poor predictive performance for this class. Second, the total dataset contains only 250 records, which may limit the generalizability of the model, particularly for minority classes. Third, the survey-based data collection may introduce self-reporting bias because several variables depend on participants' responses. Fourth, the final evaluation was conducted using a single held-out test set, meaning that the reported test performance may be sensitive to the particular train-test split. Although stratified sampling and cross-validation were used during model development, independent external validation was not conducted. Future research should therefore employ larger and more balanced datasets, investigate additional class-balancing methods such as SMOTE, compare Random Forest with alternative algorithms, and conduct external validation to obtain more reliable estimates of model generalizability.

5. Conclusion

This study applied the Random Forest algorithm to predict gaming addiction severity using behavioral and mental health-related factors. The model achieved an accuracy of 84%, with weighted precision, recall, and F1-score of 83%, 84%, and 83%, respectively. However, the lower macro-average precision, recall, and F1-score of 62%, 51%, and 55%, respectively, indicate that model performance was not consistent across all severity levels. The model performed well on the dominant Mild and Moderate classes but failed to correctly classify the Severe class, which contained only 5 of the 250 records. Feature importance analysis identified daily_playtime_hours, dopamine_dependency_index, screen_time_total_hours, and consecutive_hours_max as the most influential features in the model. These findings indicate that gaming duration, screen time, and psychological dependence-related factors provide important predictive information for distinguishing gaming addiction severity. However, feature importance reflects the predictive contribution of variables within the model and should not be interpreted as evidence of causal relationships. The findings suggest that Random Forest has potential as a preliminary data-driven approach for predicting gaming addiction severity using accessible behavioral and mental health-related features. Nevertheless, the poor classification of the Severe category limits its reliability for clinical or screening applications. Future research should address the severe class imbalance through techniques such as Synthetic Minority Over-sampling Technique (SMOTE), collect larger and more balanced datasets, compare Random Forest with other machine learning algorithms, and conduct independent external validation to improve the robustness and generalizability of the model.

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