Internet Addiction and Mental Health Prediction Using Ensemble Learning Based on Web Browsing History

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ABSTRACT

The widespread prevalence of Web browsing may lead to Internet Addiction Disorder (IAD), which impacts negatively on Web users' general health. Young people who are very active online are prone to suffer from IAD. It negatively affects their academic performance and social lives. The earlier the detection, the better the treatment. Therefore, this pilot study aimed to predict IAD among the youth to encourage early treatment.

The sample included 30 undergraduate students at Universitas Indonesia (UI). Their Web browsing histories for five weeks were recorded from their laptops and analyzed using the support vector machine (SVM) with radial basis function (RBF) kernel as a machine learning method for prediction. The results were subsequently compared using ensemble learning, such as random forest (RF) and gradient boosting (GB). It was then matched with respondents' responses to an Internet Addiction Test (IAT) questionnaire, which measures IAD levels. Respondents' general health data were collected with the 12-item General Health Questionnaire (GHQ-12). Features from Web browsing histories were extracted to classify activities in five types. These are information retrieval (IR), instant messaging (IM), social networking services (SNS), leisure, and online shopping (OS). The extracted features became input to classify participants' IAD. The results were compared with their IAD results from the IAT questionnaire. Machine learning was also employed to classify the input into respondents' general health (GH) status, which was matched with their responses to the GHQ-12 questionnaire.

The findings revealed that the prediction accuracies were 66.67% for the IAD status and 65.17% for the GH status employing SVM. The precisions for predicting IAD and GH were 63.33% and 44.33%, according to RF. Moreover, the accuracies were 63.33% and 67.17%, according to GB. Results indicated that RF decreased prediction accuracies, but GB was slightly different from SVM.

For each classifier, IAD status was predicted more accurately than GH status. An alternative to improve the outcomes is gaining data from the Internet firewall instead of the Web browsing history from users' laptops. It can provide richer and more realistic records of Web access, which are collected from any devices connected to the university's computer networks. However, it requires consent from the participants and authority managing the infrastructure. If each class has a balanced example, we plan to add more features and employ other types of ensemble learning for higher accuracy. Furthermore, performing a multiclass prediction can demonstrate specific IAD severity levels and the class of mental health status, i.e., anxiety and depression.

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CCS Concepts

• Information Systems→Data Mining • Applied computing→Psychology.

Keywords

Internet addiction; mental health; data mining; Web behavior; Support Vector Machine, ensemble learning.

1. INTRODUCTION

In 2017, the number of Internet service users in Indonesia reached 143.26 million from a total population of 262 million [23]. It has increased every year since 1998, with more than 10 million people since 2014. Most of them (49.52%) were 19 to 34 years old. In 2018, 19.6% of Indonesia citizens accessed the Internet more than 8 hours per day [25]. Internet Addiction Disorder (IAD) is defined as Internet use beyond usual frequencies [7]. The addiction criteria indicate that users access the Internet 38 hours per week or 5 to 6 hours per day. This criterion means that Internet users in Indonesia fulfill the criteria for Internet addiction.

Based on the fifth edition of the Diagnostic and Statistical Manual of Mental Disorder (DSM-5), IAD has been considered by the American Psychiatric Association as a clinical diagnosis [19]. IAD is highly associated with mental disorders, such as depression [13], anxiety, attention-deficit/hyperactivity disorder (ADHD), aggression, and obsessive-compulsive symptoms [24]. As the severity of Internet usage rises, the risk of mental disorders such as depression and stress also increases significantly [20]. The prevalence of this issue has raised numerous concerns in various countries that have over 5% of Internet users suffering from addiction. Such countries include the US [6], China [12], and Taiwan [11]. Moreover, the prevalence is higher in younger people and Asian respondents. This means that IAD could also become a serious problem in Indonesia because more than 50% of Indonesians access the Internet daily [23].

Previous research has demonstrated that Web behavior could represent information overload. It can be analyzed to predict mental health with an accuracy of 72.9% to 83.1% [15]. Zhu used the Internet Usage Behavior Checklist (IUBCL) to measure Internet use behavior and the Psychological Health Inventory (PHI) questionnaire to measure mental health status. Web browsing history could be an alternative to IUBCL or other related questionnaires because it records every Website, which has been accessed within a certain period. It can be an instant and direct reflection of someone's Web behavior. Furthermore, Web behavior records strongly relate to personalities and other psychological traits [16]. One previous study suggested that analyzing Web browsing history could help predict mental health status with an accuracy range of 77.78% to 100% [18].

This study used Web history data to predict not only mental health status but also IAD. It focused on undergraduate students, who represent the largest age group of Internet users in Indonesia. The aim is to present the analysis of Web browsing history using machine learning to predict IAD and mental health status.

2. LITERATURE REVIEW

Many researchers and clinicians have noted that several mental disorders occurred at the same time with IAD. It is demonstrated by previous studies, which predicted IAD severity and mental health status.

2.1 IAD and Mental Health Prediction

One study generated Web usage behavior features and demonstrated that these features could identify mental health status [15]. The respondents included 571 first grade graduate students from the Graduate University of Chinese Academy of Sciences majoring in science and technology, with 73.4% of them being male. The instrument used was the Internet IUBCL to measure Internet use behavior, and the PHI questionnaire [1] to measure mental health status with added validity scales (lie and fake). The researchers suggest logs of Web access, such as IP address, domain, visiting time, URL, requesting status, visited pages, as a better option to gather data on Internet usage. Similar data classification has also been conducted using decision trees, with accuracy above 60% [17], in which the measurement tools were PHI and self-designed questionnaire that consisted of 19 questions.

Instead of using questionnaires to obtain Web behavior data, a browser application named WebMind collected logs of Web access. It was integrated with a support vector machine (SVM) to predict mental health status and a recommender system to generate suggestions for adjusting mental disorders [18]. This study involved 47 graduate students as respondents. The measurement used was the Symptom Checklist (SCL-90) [14]. The preprocessing of the logs included 53 features, such as the number of accessed URLs, time of access, duration of accessing social networks, search engine. The SVM classification accuracy for each of the nine mental health status was above 77% and still had room for improvement.

Previous research results have demonstrated that depression scores were significantly correlated with Internet addiction test scores [8]. Thus, higher levels of Internet use are related to higher levels of depression. One study was performed in college respondents to analyze the relationship between Internet behavior in young adults and mental health issues [20]. A statistical analysis ($\alpha = 0.05$) discovered that lower GPA, less physical activity, and higher depression and stress scores were associated with a high frequency of Internet use. These results encouraged us to conduct this study for young adults.

Research meant to identify IAD has been expanded with the application of machine learning. Prediction of problematic Internet use (PIU) has been performed using recognized forms of impulsive and compulsive traits and symptomatology [22]. The respondents of this study were 18 years and older, resided in Chicago (USA) and Stellenbosch (South Africa). The prediction employed logistic regression, RF, and naive Bayes. Logistic regression and naive Bayes gained Receiver Operating Characteristic-Area Under the Curve (ROC-AUC) of 0.83 (Standard Deviation 0.03), and RF gained ROC-AUC of 0.84 (SD 0.03). This study was limited to three machine learning methods. A further study exploring other types of machine learning should be conducted.

Previous studies have suggested that machine learning could assist in predicting IAD. Various methods have been tried, except for GB. Therefore, it was performed in this study. The results were compared with SVM and RF with preprocessing before the training and with several tunings.

2.2 IAD Assessment

A wide variety of assessment tools have been used in the evaluation. It includes Young's Internet Addiction Test [3], the Problematic Internet Use Questionnaire (PIUQ) [9], and the Compulsive Internet Use Scale (CIUS) [10]. The most commonly used assessment tools are IAT, Young's Internet Addiction Diagnostic Questionnaire (IADQ), Chen's Internet addiction scale (CIAS), and the Internet addiction scale (IAS) [24].

The IAT consists of 20 questions that measure the level of compulsive use, loss of control, negative consequences, and neglecting everyday life [3]. The IAT score based on a Likert scale from 1 ("not at all") to 5 ("always") is valid and reliable, with satisfactory internal consistency (Cronbach's alpha of 0.84). The following scoring method spans between 40-69 as "addicted" and higher than 69 as "possibly addicted."

From the various assessment tools, IAT was chosen to measure addiction levels. Discussions were held with psychologists from the Faculty of Psychology. Some modifications were made to ensure that the respondents similarly perceived the questions. Additionally, GHQ was also employed to detect any depression or anxiety symptoms. GHQ-12 has been used as a good benchmark for detecting possible psychiatric disorders [2].

2.3 Machine Learning

2.3.1 Support Vector Machine (SVM)

It aims to find the optimal hyperplane that maximizes the distance (margin) between two classes of the training data [21]. The hyperplane splits the data into two regions as class representation. Hence, new data can be classified in their respective regions. When the data cannot be separated linearly, a kernel can be used to build an optimal hyperplane for accurate classification.

2.3.2 *Random Forest (RF)*

It is an ensemble technique that can perform bagging with random feature selection in decision tree models [5]. An ensemble of trees is generated like a forest, and the class is decided by vote.

2.3.3 *Gradient Boosting (GB)*

Boosting is also an ensemble technique to train base classifiers on different sets of data [21]. The next training set depends on the error rate of the previous training, which is difficult to classify by the previous training set. It has a higher probability of being included in the next training. The goal is to reduce bias from a weak base classifier. GB implements boosting using a gradient descent optimization in decision trees [4].

3. RESEARCH METHOD

Research has shown that excessive Internet use is related to IAD. This relationship was examined by using a dataset from the Internet browsing history of 40 respondents. They were undergraduate students at UI and aged between 18 and 25 years old. The respondents were young adults, as 49.52% of Internet users in Indonesia are between 19 and 34 years old [23]. It indicates that they have the highest risk of IAD. The browsing histories within the last month were collected from their laptops or personal computers (PCs) with their prior consent. Furthermore, the respondents were required to complete the IAT questionnaires, which is a common tool used for screening IAD severity.

Before IAT was used for assessment, some modifications were applied to make the items more understandable and to ensure that respondents held the same perceptions when answering the items. Validity testing was also performed by consulting experts in the field of psychology. The modifications of IAT were discussed intensively with psychologists from the Student Counseling Service under the Faculty of Psychology, UI. The modifications included the following: (1) As the respondents were Indonesian, the questionnaire items were translated into Indonesian and used diction suitable for young people; (2) the scales were changed from 5 scales (1= not at all to 5 = always) to 4 scales with precise definition (1 = not at all; 2 = seldom, which means 0 to 1 time a week; 3 = often, which means 3 to 4 times a week, 4 = always); and (3) the questions were converted into statements. This change was implemented to allow respondents giving direct answers.

This study not only sought to predict IAD from browsing history. It also sought to predict mental health in general. Therefore, the respondents were asked to complete another questionnaire, namely, the GHQ-12. Results of IAT and GHQ-12 were the target classes that were predicted in this study. The prediction for IAT results and GHQ-12 results were performed separately.

According to a review of several previous studies, Web behavior was classified into five types: information retrieval (IR), instant messaging (IM), social networking services (SNS), leisure (L), and stimulation (represented by online shopping or OS) [16]. Those five types of Web behavior were used to classify every URL accessed by the respondents. The extracted features were processed as follows: the frequency of the accessed URL divided by the number of access days for each person.

After the features were extracted, the classes of IAT (normal, mild, moderate, or severe), and GHQ-12 (normal, depression, or anxiety) were collected from the questionnaire results. Due to the lack of data for the severe class (1 of 40 samples) and the depression class (4 of 40 samples), these classes were transformed into binary form. The IAT classes were normal and disorder; GHQ classes were normal and depression/anxiety. The features were preprocessed by replacing the not a number (NaN) value with 0 and changing the features of access number into ratio per day. Normalization was also applied, namely, min-max or z-score. Besides, the five features (L, IR, SNS, IM, and OS) were also analyzed to determine the correlation and to select the less correlated feature to increase the performance of the model.

The classification was performed using SVM with radial basis function (RBF) kernel, RF, and GB. The performance of the model was evaluated with 10-fold cross-validation. The training process involved 70% of the samples with a random seed of 5. The performance was measured in terms of accuracy, sensitivity, and recall. The optimization in SVM was conducted with gamma (γ) and penalty (C) parameters. Furthermore, the GB optimization employed the following parameters: learning rate, number of estimators, minimum samples to split, minimum leaf samples, maximum depth, maximum features, and subsample fraction. The classification was performed with Python 2.7 running on an Intel Core i7 with 8GB RAM and 64-bit Microsoft Windows.

4. RESULT AND DISCUSSION

Some normalizations were performed to improve classification performance, namely, min-max, z-score, and mean normalization. SVM with RBF kernel was used as the default classifier. It turned out that the accuracy did not increase significantly. Hence, the normalization was not applied any further to the features. The results are shown in Figure 1 for GHQ prediction and Figure 2 for IAD.

Due to the low accuracy, the correlations among the five features were analyzed. The results are shown in Figure 3, with the feature L as f1, IR as f2, SNS as f3, IM as f4, and OS as f5. It reveals that L (f1) and SNS (f3), as well as IR (f2) and IM (f4), had positive correlations.

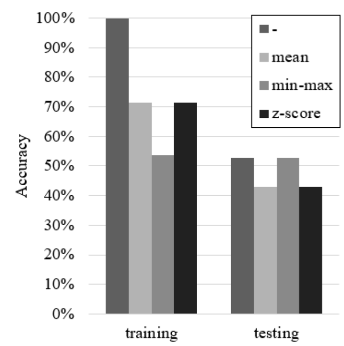

Figure 1. Comparison of normalization effect on the accuracy of GHQ Prediction with SVM with RBF Kernel

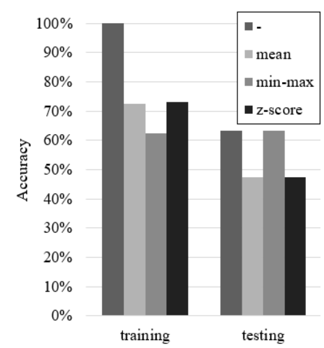

Figure 2. Comparison of normalization effect on the accuracy of IAD Prediction with SVM with RBF Kernel

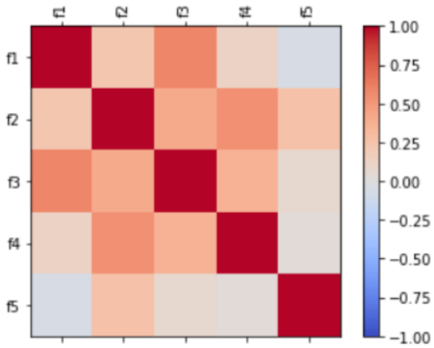

Figure 3. Features correlation of all five extracted features

Table 1. Comparison of feature reduction effect on the classification performance

	IAD Prediction		GHQ Prediction	
	All Features	All Features	All Features	Reduced Features
Accuracy	63.33%	52.67%	52.67%	70.67%
Precision	31.67%	26.33%	26.33%	49.42%
Recall	50.00%	50.00%	50.00%	60.83%

Using one of the two correlated features resulted in an improvement in IAD prediction, but a decrease in the accuracy of GHQ prediction (Table 1). It indicates the correlation of these features did not have any crucial role and could be ignored. Therefore, all five features were kept.

The classification performance of SVM was compared with two ensemble techniques (RF and GB), as indicated in Table 2. Employing RF decreased the accuracy of GHQ prediction, kept the accuracy of IAD prediction the same, and increased both precisions. The results of GB demonstrated the improvement of all performance measures, but the accuracy of GHQ prediction that remained the same. It suggests that GB was more likely to display better performance than single learning of SVM.

It was followed by parameter tuning for SVM and GB to see possible improvement. The package of GridSearchCV from the sklearn library was applied for the tuning. The scoring parameter was set to "accuracy" to find parameter values for the best accuracy. For SVM, the searching for parameters values was performed with gamma (γ) from $1\text{x}10^{-9}$ to $1\text{x}10^{5}$ and a multiplication of 3 to obtain a rich variety of values, and a slack penalty (C) from $1\text{x}10^{-2}$ to $1\text{x}10^{13}$ with a multiplication of 10 ($1\text{x}10^{-9}$, $1\text{x}10^{-8}$, …, $1\text{x}10^{5}$) to fasten the searching. The best combination for GHQ prediction occurred when C = 1.39, γ = 0.1 with a score of 0.57, while the best combination for IAD prediction happened when C = 1.39, γ = 0.01 with a score of 0.7.

Table 3 shows performance improvement for GHQ and IAD prediction after parameter tuning. For GB, the searching was performed using the value of learning rate, number of estimators (how many models were used with a range of 1 to 20), minimum samples to split (2 to 10), minimum samples of leaf (2 to 20), maximum depth (1 to 5), maximum features (1 to 5), and subsample fraction (range 0.6-0.9). Table 4 demonstrates all performance measures increased for GHQ prediction but decreased for IAD prediction. The performance of GB before tuning differed from the performance of SVM after tuning.

Table 2. Comparison of SVM, RF, and GB on the classification performance

	IAD Prediction			GHQ Prediction		
	SVM	RF	GB	SVM	RF	GB
Accuracy	63.3%	63.3%	65.3%	52.7%	44.3%	52.7%
Precision	31.7%	56.3%	52.7%	26.3%	39.2%	53.3%
Recall	50%	60.8%	58.3%	50%	43.3%	53.3%

Table 3. Comparison of SVM before and after parameter tuning on the classification performance

	IAD Prediction		GHQ Prediction	
	Before tuning	After tuning	Before tuning	After tuning
Accuracy	63.33%	66.67%	52.67%	65.17%
Precision	31.67%	53.42%	26.33%	56.33%
Recall	50.00%	60.00%	50.00%	62.50%

Table 4. Comparison of GB before and after parameter tuning on the classification performance

	IAD Prediction		GHQ Prediction	
	Before tuning	After tuning	Before tuning	After tuning
Accuracy	65.33%	63.33%	52.67%	67.17%
Precision	52.67%	31.67%	53.33%	70.00%
Recall	58.33%	50.00%	53.33%	68.33%

5. CONCLUSION

The results of this study indicate that ensemble learning provided better results in IAD prediction and mental health status prediction. The parameter tuning also led to better performance for single classifier and ensemble learning. Additionally, the ensemble learning without parameter tuning provided almost similar results with the single tuned SVM classifier. Nevertheless, this pilot study proved that prediction accuracy still requires enhancement. More data and features, such as demographics and features related to the content of the URL pages, are required to build a better predictor. Moreover, a multiclass prediction to obtain a specific IAD severity level and the class of mental health status (anxiety and depression) are planned for future work. Other ensemble techniques, such as adaptive boosting and boosting SVM, could also be considered.

For further study, gathering browsing history data from the university Internet firewall could provide more realistic information, compared to Web browsing history from users' devices. However, it requires consent from participants and permission from the authority managing the networks. Besides, the implementation of additional applications (add-ins) in the background of users' laptops or mobile devices to collect Internet access histories with the user's permission was also considered. Lastly, the correlation between IAD and mental health will be revisited in larger datasets of Indonesian university students.

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