Machine Learning Classification Model for Identifying Internet Addiction among University Students

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***Abstract*—In this era of globalization, Internet addiction is a concerning issue, especially among university students as they are required to use the internet for academic purposes. However, things might go wrong when they are addicted to the Internet as the Internet does not only provide knowledge but also entertainment such as music, videos, games, social media, etc. Internet addiction was exposed to the public when Young introduced Internet addiction in her study as well as an assessment for Internet addiction known as Young's Internet addiction test (IAT) which is a questionnaire. Nonetheless, there are some issues associated with the questionnaire regarding the integrity and literacy of the participants as well as the experience of the specialist which might introduce inconsistencies in the assessment of one's Internet addiction level. Hence, the machine learning algorithm is introduced to replace the conventional assessment method for Internet addiction. In this study, three machine learning models are developed and compared. The three models include convolutional neural network (CNN), K-nearest neighbours (KNN), and logistic regression (LR). The low Alpha power band of the EEG data is transformed into spectrograms and utilized as the input for the machine learning models. The spectrograms are presented as images and fed into the CNN model. On the other hand, as KNN and LR could not take in images as the input data, the magnitude of each frequency in every time segment of each spectrogram is computed and fed into the KNN and LR. The results show that CNN gives the best performance in terms of overall accuracy, precision, recall, and F1-score, while KNN gives the most consistent performance.**

Keywords- Machine Learning, Internet addiction, EEG, CNN, KNN, LR

I. INTRODUCTION

Owing to the emergence of the Internet and the advanced development of digital technology, the use of the Internet has become prevalent in communities around the world, the Internet is undoubtedly beneficial to human beings in terms of convenience and living quality by easing and simplifying information collection as well as providing entertainment anytime and anywhere. Unfortunately, pros are always accompanied by cons. The widespread Internet access and the advantages provided by the Internet have led to a sort of addiction among Internet users worldwide, which is most commonly known as 'Internet addiction'. Other terms such as 'problematic computer use', 'compulsive computer use', 'pathological Internet use', and 'internetomania' also describe this condition [1].

In this globalization era, it is not surprising that the majority or even all university students worldwide have Internet access and knowledge to use the Internet and digital devices that allow access to the Internet. Many of them are even taught about the usage of digital devices and the Internet. This raised an issue concerning Internet addiction (IA) among university students, which attracts many researchers around the world to study. For instance, the prevalence of IA among university students was 85% at Wollo University, Ethiopia in 2019 [2]; 87.7% at Tanta University, Egypt in 2020 [3]; 94.7% at Obafemi Awolowo University, Nigeria in 2018 [4]; 64.3% at University Putra Malaysia, Malaysia in 2016 [5]; 74% at King Adbulaziz University, Saudi Arabia in 2017 [6]. Based on these results, it is undeniable that the problem of IA among university students in most countries is alarming.

The method implemented to identify the IA level in these studies is in the form of a questionnaire which is known as Young's Internet Addiction Test (IAT). While questionnaire is so popular for its simplicity to measure the IA level of their participants, [7] once mentioned the associated issues in his study. The questionnaire is a kind of self-report measure that is highly dependent on the integrity of the participants while no measure is implemented to detect fake responses; and the literacy of the participants might lead to misunderstanding of the questions which will further cause inaccuracies in the assessment result [7].

To resolve these issues, an electroencephalogram (EEG) can be conducted on the participants instead. According to the definition by Oxford Languages, EEG is a test or record of brain activity that measure electrical activity in different parts of the brain. There are studies conducted on the topics regarding brain activity related to IA with similar techniques such as functional magnetic resonance imaging (fMRI) and positron emission tomography (PET). From the studies, it is shown that IA indeed affects one's brain activity [8]–[10]. Nevertheless, each of these techniques has their strength and limitations. For example, fMRI is very well-known for its weakness in temporal resolution [8], [9]. Besides, both fMRI and PET are much more costly than EEG.

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EEG output is often waveforms that require further processing and analysis which can be time-consuming using manpower. Thus, the machine learning (ML) approach is usually implemented for data processing, feature extraction, as well as classification of the IA level. In this study, different machine learning models for IA identification using EEG data will be explored. Different machine learning models for IA identification using EEG data will be explored. Different machine learning models will be developed to classify the IA level among university students using EEG data. Finally, different machine learning models' performance will be evaluated and compared to select the best model for this problem.

II. Literature Review

The study which is most relevant to this study is conducted by [11] who also used EEG data and machine learning algorithm to classify Internet-addicted subjects in premature stage and non-Internet-addicted subjects. Their study mainly focused on pre-processing the EEG data which consists only of the eyes-closed data as they found it gives good results constantly. The pre-processed data is used to extract useful information to be fed into the classifier which is Random Forest (RF).

In the study by [11], the machine learning algorithm proposed can be divided into three main steps. The first step which implemented Fast Fourier Transform (FFT) and RF classifier is mainly designed to obtain the informative frequency range which is useful for further data processing. The second step is repeating the first step but with different conditions at the input and output. The information obtained from the first step is used as the parameter for the bandpass filter to filter out irrelevant data from the original EEG data. The authors removed bad channels and artifacts from the EEG data. Then, the top ten useful channels are identified with RF classifier. Based on the result, the average of each sub-band of these ten channels is obtained and the three most predictive sub-bands are identified and treated as features.

From an 8-minute EEG data with 62 channels and a frequency of 2500 Hz, the authors had downsampled the data to 250 Hz and reduced it to three averaged sub-bands before actually performing the classification of prematurely-Internet-addicted subjects and normal subjects. This model developed by [11] achieved a balanced accuracy of 94.17%. Apart from the efforts done to pre-process the data, the evenly distributed data which consists of 24 Internet-addicted subjects and 25 non-Internet-addicted subjects also contribute to the performance of the model.

III. Methodology

A. Dataset

This study uses the publicly available dataset provided by [12]. This dataset consists of EEG data recorded from 30 subjects and the IAT results as well as the Big Five personality test results obtained from these 30 subjects. This dataset consists of multiple comma-separated values (CSV) files corresponding to the EEG data recorded for each task executed by each subject.

The authors conducted 11 sessions of EEG data recording for each subject where one task is executed by the subject in each session. The 11 tasks include eyes closed, eyes opened, watching images to trigger happiness, calmness, sadness, fear, memorizing words, browsing the Internet, recalling memorized words, and eyes closed and opened. Each task takes one minute, except for the last task which combines eyes closed and eyes opened, thus taking two minutes.

The EEG data for each task is represented in one CSV file. This study uses only the eyes closed data to perform the classification as it is shown in a few studies that resting-state EEG data is sufficient to represent healthy subjects and addicted subjects [11], [13]. Inside each CSV file, the rows represent the time, while the columns represent the values recorded for every parameter including the attention, meditation, and band waves. In this study, the attention, meditation, and gamma columns are not used as these do not help to identify Internet addiction. This dataset is not evenly distributed. Among 30 subjects, there are four normal subjects, 18 with mild IA, 7 with moderate IA, and one with severe IA. Since there is only one subject with severe IA, the data severe class is excluded from this study. The EEG device used by the author is single channel which is designed to collect the EEG data at the FP1 position.

The splitting of the training set and testing set is done manually to ensure that the testing set consists of the dataset for all classes and that the training set is balanced. In the testing set, there are one eyes-closed EEG data from each class, while the training set consists of nine EEG data where each class contributes three eyes-closed EEG data. Hence, the number of EEG data used during the experiment is 12. Out of the total number of EEG data provided which is 30, 12 eyes-closed EEG data are randomly chosen, but all eyes-closed EEG data from the normal class is included as there are only four normal subjects. In addition, the first five seconds and the last five seconds of the EEG data will be removed manually as it is mentioned in multiple studies that usually these segments of EEG data contain a lot of noise due to the handling of the EEG cap.

B. Data Pre-processing and Transformation

EEG data is very subjective to the individual, thus even for individuals under the same classes of IA, their EEG data might be different in terms of magnitude as well as the signal pattern. Every ML model takes magnitude into account hence it is important to scale the data accordingly so that the ML models learn well.

In this study, the magnitude of every power band is scaled to its maximum and minimum over 50 seconds, which then results in the magnitude of every power band in every EEG data between zero to one. After the pre-processing, every power band of the EEG data is transformed into a spectrogram as it generates more useful features for the ML models to learn the pattern. Through multiple trials, it is decided that the spectrogram of the low Alpha power band provides the most useful information to differentiate between the three IA levels.

C. *Convolutional Neural Network (CNN)*

EEG data is already well-known for its non-linearity and high complexity. Therefore, CNN is a suitable machine learning model for classification problems dealing with EEG data as presented in this study. Figure 1. shows the architecture of the CNN employed in this study. It consists of four convolutional layers with Rectified Linear Units (Elu) activation function, three maximum pooling layers, one dropout layer, two dense layers with REL activation function, and a dense layer with Softmax activation function to produce the outputs. These parameters are determined empirically.

The input to the CNN is the spectrogram figures plotted using the Matplotlib library. Figure 2. shows one of the spectrograms plotted from the low Alpha power band. The classes are one-hot encoded where normal, mild, and moderate are labeled as [0,0,1], [0,1,0], and [1,0,0] respectively. The CNN model is evaluated with categorical accuracy and categorical cross-entropy. It is being trained for 50 epochs with a learning rate of $1e^{-7}$ and an adaptive moment estimation (Adam) optimizer and a Glorot uniform initializer.

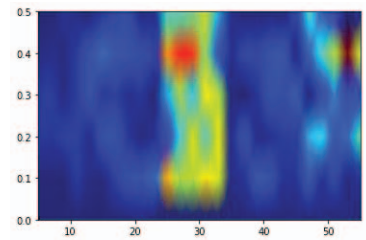

Figure 1. Spectrogram figure

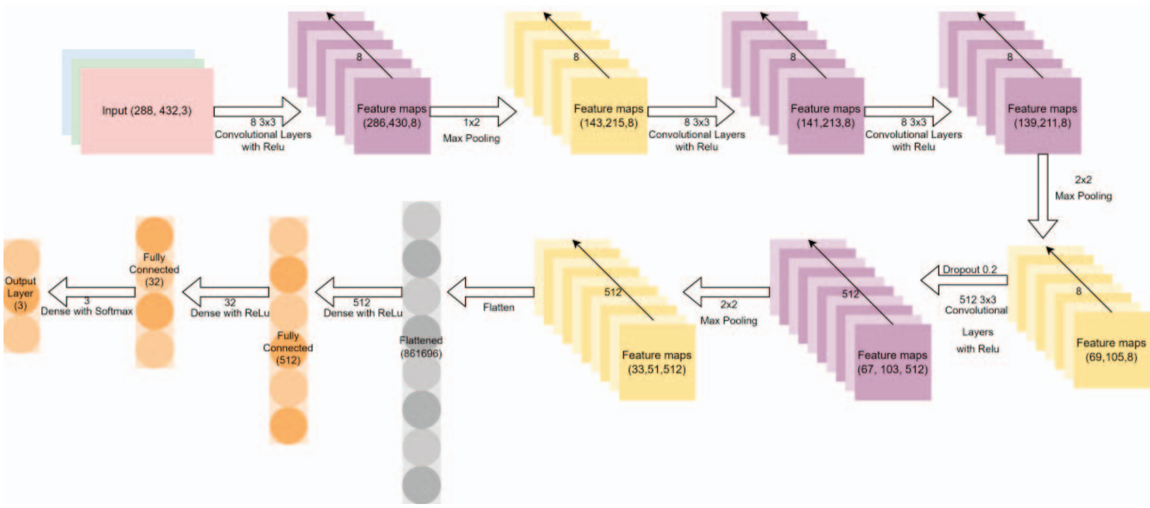

Figure 2. CNN architecture

D. *K-Nearest Neighbours (KNN)*

The number of nearest neighbours is determined empirically hence two nearest neighbours will be considered by the KNN model. The metric used to compute the distance between each data point is Euclidean distance which is the shortest distance between two points. The classes normal, mild, and moderate are labeled as 0, 1, and 2 respectively to emphasize the ordinal relationship between the classes.

For a fair comparison between the models, spectrograms are also used to train the KNN model. Since KNN cannot take in three-dimensional data like CNN, the mean value of the magnitude of each frequency in every time segment is computed and fed into the KNN model. In the spectrogram, there are 26 time segments and each time segment consists of six values corresponding to six frequencies. Hence, the input into the KNN model consists of an array of size N×M where N is the number of subjects which is nine for training data and three for testing data, while M is 26 corresponding to the number of time segments. Figure 3. shows the flowchart of the sampling process of training the KNN model with one spectrogram.

E. *Logistic Regression (LR)*

The parameters involved in LR which include the penalty, solver, and regularization strength are determined empirically. Thus, elasticnet penalty with saga solver and 0.02 l1 ratio is implemented. The regularization strength is set to 1.

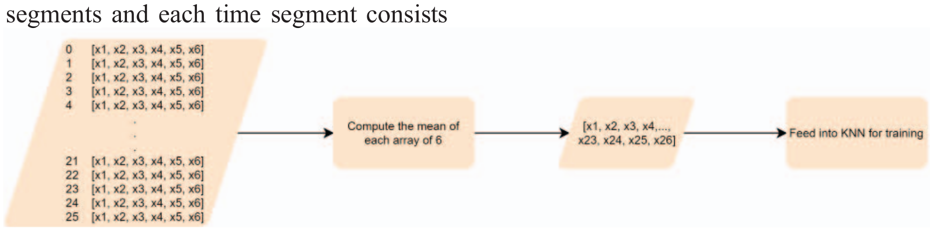

Figure 3. KNN flowchart

The features selection method applied for KNN will be employed for LR as well for a fair comparison between their performance. Hence, similar to KNN, the input data is an array of 9×26 for training, while an array of 3×26 for testing. The training and testing process is similar to that of KNN as shown in Figure 3.

F. *Evaluation Metrics*

A confusion matrix is utilized for a better presentation and analysis of the performance of the models in identifying each class of IA. The confusion matrix provides the value of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) which are used to compute the four metrics which are precision, recall, f1-score, and accuracy. The results are presented class by class, which means each class has its precision, recall, f1-score, and accuracy. This allows a fairer comparison and better analysis of the performance of the models.

IV. Results and Discussion

A. *Performance of Three Models*

Referring to TABLE I. the CNN model can identify more than one class but fails to recognize normal subjects. This might lead to a situation where normal subjects are mistreated as internet-addicted subjects. In addition, the model's performance is inconsistent as shown by the cross-validation result.

On the other hand, looking at the performance of the KNN model, it can be noticed that the KNN model is not able to identify mild subjects and moderate subjects, which is undesirable. Based on the model's training accuracy and testing accuracy, the model might be overtrained, and this perhaps is the reason that the model could only identify one class. However, the model's performance is consistent as shown by the cross-validation accuracy.

Comparing the performance of the KNN model and the LR model, it can be noticed that the performance of KNN and LR are pretty similar. KNN only managed to identify the normal subject, while LR is only able to identify moderate. Both of these outcomes are undesirable. Nonetheless, LR is not as consistent as KNN as depicted by the cross-validation result. The LR model has a cross-validation accuracy with higher variation as compared to the cross-validation accuracy of the KNN model.

It can be concluded that CNN performs the best as an overall comparison. This is because CNN is the only model that can identify two classes, while LR and KNN can only identify one class. Nonetheless, CNN does not give consistent performance as compared to KNN. This might be due to the CNN model being overtrained causing it not generalized.

TABLE I. Performance of Three Models

Evaluation Metrics		**Classes**		
		Normal	***Mild***	***Moderate***
Precision	***CNN***	0.00	1.00	0.50
	KNN	0.33	0.00	0.00
	LR	0.00	0.00	0.33
Recall	***CNN***	0.00	1.00	1.00
	KNN	1.00	0.00	0.00
	LR	0.00	0.00	1.00
F1-Score	***CNN***	0.00	1.00	0.67
	KNN	0.50	0.00	0.00
	LR	0.00	0.00	0.50
Training Accuracy (%)	***CNN***	88.89		
	KNN	77.78		
	LR	66.67		
Testing Accuracy (%)	***CNN***	66.67		
	KNN	33.33		
	LR	33.33		
Cross Validation Accuracy (%)	***CNN***	41.67 ±14.43		
	KNN	33.33 ±0,00		
	LR	50.00 ±16.67		

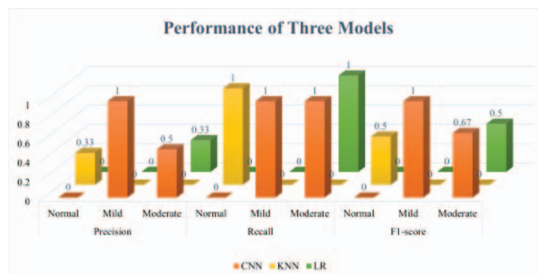

Figure 4. Results Chart

B. *Comparison between CNN and benchmark model*

As shown in Table II., the CNN developed in this study does not achieve the benchmark performance by [11]. There are a few possible reasons for this. Firstly, the dataset used by [11] is equally distributed so they do not have to abandon some of the datasets to have a balanced training dataset, which is the case for this study. Secondly, the dataset used by the author is more than the dataset used in this study. Moreover, the dataset is divided into two classes (binary) only so each class will have a sufficient amount of data for both training and testing. In this study, the dataset used by both training and testing is inadequate due to the limited amount of data in the normal class. Nevertheless, multiclass classification in this study is more challenging compared with binary classification in [11].

Apart from that, the EEG data used by the author consists of more than one channel which further increases the features of the data. The features of the EEG data used in this study are limited because there is only one channel in the EEG data. Besides, the dataset used by the author provides adequate information with a sampling frequency of 250 Hz, while the dataset used in this study is sampled with only 1 Hz which might cause a loss of information as human brain electrical activity is fast and continuously changing. The features used by the author and in this study are pretty similar, but the features used by the author provide more information due to the sampling frequency and the number of channels.

TABLE II. COMPARISON BETWEEN CNN AND BENCHMARK MODEL

Authors	This work	Gross, Baumgartl and Buettner (2020)
Machine Learning Models Employed	CNN	Random Forest
Dataset size	30	49
Dataset distribution	4 normal, 18 mild, 7 moderate, 1 severe	25 normal, 24 addicted
Number of classes	3	2
Training split	9	37
Training distribution	3 normal, 3 mild, 3 moderate	N/A
Testing split	3	12
Testing distribution	1 normal, 1 mild, 1 moderate	N/A
Number of channels	1	62 (23 removed, 39 used)
Sampling frequency (Hz)	1	250
Features	Spectrogram of the low Alpha power band	3 frequency bands selected by the RF's variable importance on the power spectral density of the frequency bands
Balanced Accuracy	41.67 ±14.43 %	94.17 ±6.86 %

V. CONTRIBUTION OF THE RESEARCH

This study contributes information regarding the analysis of EEG data for multi-class IA through machine learning algorithms. Machine learning models are developed to classify multi-class IA by using only single-channel EEG data. This research also presents another possible approach to classify IA levels for the benefit of researchers in the field of psychology.

VI. CONCLUSION

Three machine learning models are developed including CNN, KNN, and LR. CNN gives a balanced accuracy of 41.67 ±14.43 %, while KNN and LR give a balanced accuracy of 33.00 ±0 % and 50.00 ±16.67 % respectively. CNN gives the best performance in terms of overall accuracy, precision, recall, and F1-score, while KNN gives the most consistent performance. The best model developed in this study which is the CNN model does not perform as good as the benchmark model [11] which gives a balanced accuracy of over 90%. This is mainly due to the dataset used in this study.

For future work, it is recommended to increase the training data and testing data while maintaining the balanced distribution of the classes. In addition, the complexity of the data should be leveled up as well so that more information can be extracted from the EEG data. This can be done by increasing the number of channels of the EEG data so that the features available would increase. There is a possibility that the location where the EEG data utilized in this study is taken is not helpful to identify Internet addiction. Thus, increasing the number of channels would increase the range of selection of features, and perhaps better features can be extracted.

Last but not least, it is suggested to increase the sampling frequency so that any important information is not missed. However, a higher sampling frequency might generate more noise which requires a more complex data preprocessing technique.

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