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Modeling And Predicting Smartphone Addiction Among Filipinos Using Machine Learning Techniques

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Abstract

This study uses machine learning techniques to predict smartphone addiction among Filipinos. As smartphones become more widely used, concerns about digital addiction have grown in significance due to the behavioral and social effects they have. In this study, a set of data is analyzed, including metrics related to smartphone usage, such as time spent on the device and frequency of use of phone applications. The study employs algorithms including J48 Decision Tree, Naïve Bayes, Random Forest, and PART to perform classification utilizing the WEKA data mining system. The aforementioned data show that the Random Forest model's prediction accuracy for smartphone addiction is quite good, as it is more than the accuracy of other models' predictions. Some of the most important factors that affect smartphone addiction are extended screen time, using the phone for social networking, and excessive phone use. It is clear from the aforementioned findings that human behavior has a big impact on smartphone addiction.

Keywords: Smartphone, Machine Learning, WEKA, Digital Addiction, Social Networking

1. Introduction

People's lives, communication styles, and information-gathering procedures have all been significantly impacted by the increase in smartphone use. It has been discovered that excessive smartphone use is raising issues with digital addiction and dependency. Numerous studies have demonstrated the detrimental effects of excessive screen and smartphone use on behavior, productivity, and health. Research on the risk of smartphone addiction has also shown that excessive smartphone use raises the likelihood of addiction. This emphasizes how crucial it is to look into the risks of smartphone addiction, especially in developing countries like the Philippines.

Machine learning techniques have been used more and more in recent years to analyze patterns of behavior related to the usage of technology. The researcher can work with enormous volumes of data and identify important factors that influence smartphone addiction by using machine learning techniques. Researchers discovered that it was feasible to categorize people into several groups based on the degree of smartphone addiction using machine learning algorithms based on the user's behavior patterns.

Smartphone addiction is also significantly influenced by psychological and behavioral factors, such as social media use, routines, and emotional triggers. According to the research study, the two most significant elements linked to smartphone addiction were the use of social media and the development of habits. Although numerous international research have been carried out, there aren't many that focus on the Filipino community. As a result, this study will use machine learning to forecast smartphone addiction in the Philippines.

2 Problem Statement

The use of smartphones is now a part of our daily life but using them too much has led to more people getting addicted to smartphones. This is a problem that is linked to some things like not getting much work done not doing well in school and having problems with our mental health. Some studies have found out that spending much time looking at screens and using social media a lot are big reasons why people get addicted to smartphones. For example research on the risk of getting addicted to smartphones shows that using our devices all the time can lead to us relying on them much and it can be hard to stop.
It is getting more and more worrying. It is still hard to tell who is addicted to smartphones and who is not because there are so many things that can affect how we use our phones. The old ways of finding out if someone is addicted usually involve asking them questions. They might not tell the truth about how they use their phones. Some new studies say that using computers to look at lots of data can help us predict if someone will have problems with their smartphone use, based on things like how time they spend looking at their screen, which apps they use and how they interact with their phone. However it is still a challenge to choose the computer program and figure out what things affect our smartphone use the most. What is more even though many studies around the world have looked at smartphone addiction not many have focused on people from the Philippines. The way people live the culture and the way people behave can all affect how we use our smartphones so it is necessary to do studies that're specific to the Philippines. If we do not have ways to predict who will get addicted it will be hard for teachers, people who make rules and health workers to find out who is at risk and help them. So this study wants to fill in the gaps by using computers to predict who will get addicted to smartphones in the Philippines and to find out what things make people dependent on devices. Smartphone addiction is a problem and this study is, about smartphone addiction and how to deal with smartphone addiction.

3 Objectives

The primary objective of this study is to **predict smartphone addiction among Filipinos using machine learning techniques** and identify the key factors influencing digital dependency.

The specific objectives are:

1. To analyze smartphone usage patterns based on variables such as screen time, app usage, and user behavior.
2. To apply different machine learning algorithms (J48 Decision Tree, Naïve Bayes, Random Forest, and PART) using WEKA.
3. To evaluate the performance of each algorithm using accuracy, precision, recall, and F1-score.
4. To identify the most significant factors contributing to smartphone addiction.
5. To determine the most effective model for predicting smartphone addiction among Filipinos.
6. To provide data-driven recommendations for reducing smartphone addiction.

The study will address the following research questions:

1. What are the common smartphone usage patterns among Filipinos?
2. Which factors significantly influence smartphone addiction?

3. How effective are machine learning algorithms (J48, Naïve Bayes, Random Forest, and PART) in predicting smartphone addiction?
4. Which algorithm provides the highest accuracy in classifying smartphone addiction levels?
5. How can the results of the study help in addressing smartphone addiction among Filipinos?

4. Scope

This study focuses on predicting smartphone addiction among Filipinos using machine learning techniques.The scope of the study is defined by the following boundaries:

1. This study focuses on predicting smartphone addiction among Filipinos using machine learning techniques.
2. It utilizes a dataset containing smartphone usage variables such as screen time, app usage frequency, and user behavior patterns.
3. The study applies classification algorithms including J48 Decision Tree, Naïve Bayes, Random Forest, and PART using the WEKA tool.
4. The analysis is limited to classification and prediction of smartphone addiction levels.
5. Model performance is evaluated using accuracy, precision, recall, and F1-score.
6. The study aims to identify key factors influencing smartphone addiction and determine the most effective predictive model.

Limitations of the Study

Despite its contributions, this study has several limitations:

1. The dataset may not fully represent the entire Filipino population, limiting generalizability.
2. The study is limited only to the variables available in the dataset and excludes psychological, emotional, and environmental factors.
3. Only selected machine learning algorithms (J48, Naïve Bayes, Random Forest, and PART) are used, excluding more advanced models like deep learning.
4. The study relies on historical data and does not include real-time smartphone usage tracking.
5. The accuracy of the results depends on the quality and completeness of the dataset.
6. Possible data inconsistencies or missing values may affect the performance of the models.

5. Related Work

Globally smartphone addiction is becoming an issue, especially among teenagers and young people. Researchers are looking at usage trends to predict problematic patterns. In a 2021 study Juyeong Lee and Woosung Kim found that certain machine learning algorithms can forecast smartphone addiction based on user behavior and demographic data.The study showed that these algorithms, including Decision Tree, Random Forest and XGBoost are effective in predicting addiction risks. The Random Forest model was the accurate.Smartphone addiction is linked to lifestyle choices, anxiety and academic difficulties in kids. A study by Danilo B. Buctot, Nami Kim and Sun-Hee Kim on Filipino high school students found that social media dependency and extended internet use affect behaviors and academic performance.Students who use cellphones for periods are more likely to develop bad digital habits.Researchers have also studied smartphone habits using machine learning. Kleomenis Katevas and colleagues found that excessive screen time and nighttime smartphone use are linked to well being. Their study showed that users can be categorized based on their risk of addiction using data. Recent studies show that machine learning algorithms can precisely analyze smartphone activities. Iqbal H. Sarker and Khaled Salah created a context-prediction model to examine smartphone app usage trends. Their research found that machine learning methods can effectively forecast user behavior using data. Most studies on smartphone addiction prediction are global, with few focusing on users. Local studies mostly focus on the scholastic consequences of smartphone addiction. This work aims to fill the research gap by modeling and forecasting smartphone addiction among Filipinos using machine learning approaches. This can enable identification and behavioral intervention measures.

Key Theories and Methodologies in Data Mining

Smartphone addiction refers to individuals who use their smartphones a lot and cannot control themselves. Mobile device addiction falls under behavioral addictions since it influences individuals' behaviors in their everyday lives. It may also influence feelings and social interactions of the individuals. Several factors that contribute to the development of the problem are the amount of screen time that people have, how often they use social media, and the interaction they engage in through their mobile devices. The Smartphone Addiction Scale is an instrument that assesses mobile device addiction. This tool enables researchers to understand the level of dependence that individuals have towards their mobile devices. .**Machine learning techniques** have a significant role in prediction of behavior patterns using the analysis of the large volumes of data sets. There are various data mining models like decision trees (J48), naïve bayes, random forest, and part, which can be used in the data mining process because they help establish the relationship between the various variables in the data set and predict outcomes. The decision trees model helps generate rules that can be used for classification, naïve bayes uses probability to predict, random forests help improve accuracy, and part creates rules for classification.

Summary of Relevant Research

Many works have studied the issue of smartphone addiction and machine learning-based predictions. The research on smartphone addiction risk factors suggests that too much screen time and constant interaction with smartphones is linked to addictive behavior. In turn, studies dedicated to predictors of behavior show that high rates of social media usage and constant checking lead to addiction.

In the realm of machine learning, numerous studies have shown that classification models are useful in detecting problematic smartphone users. It was found out that predictive algorithms such as Random Forest and Decision Trees were better suited for classification tasks than probabilistic algorithms such as Naïve Bayes. Moreover, data mining approaches could be applied to find out that such parameters as smartphone apps usage rate, level of user involvement, and regularity were important predictors of addiction.

Additionally, many papers have examined the adverse influence of smartphone addiction. In particular, it affects academic results, productivity, and mental well-being. Young people are at higher risk because of constant contact with technological advancements. Predictive analytics was suggested as an effective tool for detecting at-risk individuals, thus helping to implement preventive measures.

Gaps in Current Literature

1. Most existing studies on smartphone addiction focus on global or generalized populations, with limited research specifically addressing the Filipino context and its unique cultural and behavioral factors.
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3. limited research specifically addressing the Filipino context and its unique cultural and behavioral
4. factors.
5. Existing research primarily relies on usage data such as screen time and app activity, while other im-

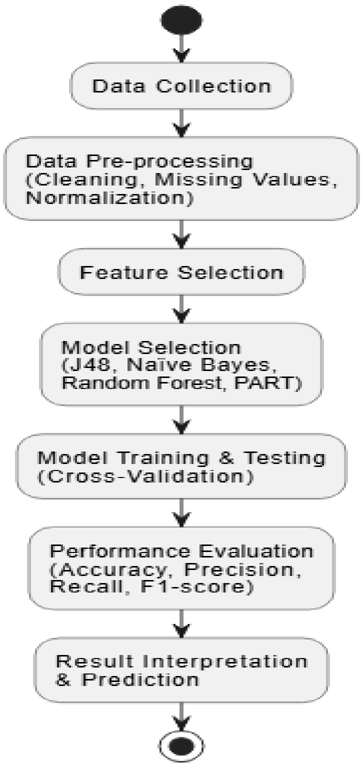
portant factors like psychological, emotional, and environmental influences are often not included.
6. There is limited exploration of how different variables interact with each other in contributing to smartphone addiction, particularly in complex behavioral datasets.
7. Although machine learning models show high predictive accuracy, their practical implementation in real-world applications, such as digital wellness programs and intervention systems, remains underdeveloped.
8. Many studies are based on small or specific datasets, which limits the generalizability and reliability of the findings across diverse populations.

Addressing these gaps, this study aims to apply multiple machine learning techniques to predict smartphone addiction among Filipinos, providing a comprehensive and localized analysis that contributes to the field of behavioral data mining and predictive analytics.

6. Methodology

This section presents the methods used to analyze and predict smartphone addiction among Filipinos using machine learning techniques. The study follows a data mining approach to identify patterns, relationships, and key factors influencing smartphone addiction. By applying multiple classification algorithms, the research aims to determine the most accurate and reliable model for prediction.

Figure 1. Data Mining Process Flow of the Study



The Data Mining Process Flow employed in the current study in order to predict smartphone addiction in Filipinos can be observed in Figure 1 below. As shown in Figure 1, the process begins with the collection of data and pre-processing of data in order to prepare the dataset. Feature selection is then carried out before employing machine learning models, including J48, Naïve Bayes, Random Forest, and PART

models. The models are trained using cross-validation, and various parameters are measured in order to obtain the best model.
The data mining process outlined in Figure 1 helps ensure that the dataset is well-prepared and analyzed.

Data Collection

Sources of Data

The data set used in this research involves smartphone use and addiction-related data which contain parameters like screen time, app usage rate, social media activities, and user interactions among others. Such information can either be retrieved from open source data sets or gathered using survey questionnaires. This data set is about smartphone users whose behavior pattern mirrors the general behavior of Filipinos.

The data is saved in CSV format but is subsequently converted into an ARFF format for use in WEKA machine learning software. This data set contains several attributes that define user behavior pattern and is useful in classification of smartphone addiction levels into low, moderate, and high categories.

Data Collection Methods and Tools

Data acquisition is done via collecting user data regarding smartphone usage through well-defined surveys as well as using existing datasets. Surveys can be conducted by distributing survey forms in order to obtain users' reported data regarding screen time, apps usage, and other details concerning their smartphone usage. Furthermore, public datasets from platforms like Kaggle or other similar websites can be used as supporting data.

Preprocessing involves using various software programs such as spreadsheets or WEKA to prepare the data and perform further analysis. Firstly, the dataset needs to be assessed to confirm its accuracy. Afterwards, it needs to be reorganized and prepared to be analyzed in terms of machine learning processing. Additionally, ethical considerations include deidentifying and using the data strictly for research purposes.

Data Pre-processing

The process of effective data pre-processing plays an essential role in preparing the dataset for the analysis. These steps guarantee that the dataset is free from any anomalies and is ready to be analyzed using various machine learning methods. In this study, the following pre-processing steps were performed on the dataset:

Data Cleaning and Preparation

Data cleaning is done to make sure that there is no inconsistency in the data, and its quality can be improved. Duplicate entries are identified, and duplicate values are removed from the dataset to ensure there is no bias in the output. Categorical features like behavior of users and usage type are transformed into numeric features for compatibility with machine learning techniques.

Missing values in the data set are an essential part of preprocessing. Numerical attributes like screen time and usage time are replaced by their respective means or medians. Missing categorical features are replaced by their modes.

Handling Missing Values

Outliers are detected to avoid any distortion in the model's efficiency. Z-score technique and visualization methods, like boxplot, are employed to detect any outliers in the dataset with regard to variables such as screen time and usage rate of applications. Outliers can be adjusted and modified as per the need.

Data Normalization

In order to ensure that all the numerical properties equally participate in the model, various normalization methods like Min-Max scaling can be used. This brings the value to the same range, usually 0 to 1, so that higher valued properties do not affect the model. These pre-processing methods are mainly used for the features like screen time, usage time, and interaction time with the smartphone.

This process of pre-processing makes the dataset ready for analysis using the ML algorithms on WEKA.

Data Mining Techniques

The data mining techniques are vital in deriving insights and predicting the level of smartphone addiction from user behavior. For this study, the classification technique will be used to classify the subjects into different degrees of smartphone addiction. The use of classification in this case is justified due to the ability to classify users based on their behavior.

The following machine learning algorithms are applied using WEKA:

1. **J48 Decision Tree** J48 is a version of the C4.5 decision tree technique that forms a tree-shaped model from feature selection. It gives explicit decision rules that are easy to understand and can be used to explore the effects of various variables on smartphone addiction.
2. **Naïve Bayes** Naïve Bayes is a machine learning algorithm that is based on probability. It uses the concept of Bayesian theorem for classification by making assumptions about the features being independent. Naive Bayes is efficient and suits structured data.
3. **Random Forest** Random Forest is a technique of ensemble learning which incorporates multiple decision trees to achieve better accuracy. It avoids overfitting and improves results, particularly when working with difficult data sets.
4. **PART (Partial Decision Tree Algorithm)**PART is a rule-based classifier algorithm that creates decision rules based on partial decision trees. It combines the benefits of both decision tree classifiers and rule-based classification techniques.

Table 1. Comparison of a Single Decision Tree vs. Random Forest

Feature	Decision Tree (J48)	Random Forest
Interpretability	High	Low
Overfitting Risk	Higher	Lower
Accuracy	Moderate	High
Computation Time	Fast	Moderate

The Table 1 shows a comparison between the features of the Single Decision Tree, which is the J48 algorithm, and the Random Forest algorithm. The table illustrates that although J48 offers better interpretability and speed, Random Forest offers higher accuracy and prevents overfitting.

Table 2. Comparison of Classification Techniques

Algorithm	Accuracy	Interpretability	Handling of Missing Data	Computational Efficiency
J48 Decision Tree	High	High	Moderate	Fast
Naïve Bayes	Moderate	Moderate	High	Very Fast
Random Forest	Very	Low	High	Moderate

	High			
PART	High	High	Moderate	Moderate

Table 2 provides a comparative summary of the four classification models used in the research study. This table illustrates their strengths with respect to accuracy, interpretability, handling of missing data, and computational costs. The highest level of accuracy is achieved by Random Forest, while the highest degree of interpretability is achieved by J48 and PART models.
Using these classification models allows a complete evaluation of smartphone addiction. Each classification model possesses its own strength.

Tools and Technologies Used

The conduct of this research will require appropriate technological and tools to process, analyze, and evaluate the findings. In this case, the tool to be employed is called WEKA (Waikato Environment for Knowledge Analysis). It refers to a free software platform used in machine learning processes for data mining purposes. One of the strengths of WEKA is its user-friendly interface through which users can preprocess their data, apply a machine learning algorithm on it and evaluate the model that has been built. Among other classification methods, WEKA applies J48, Naïve Bayes, Random Forest, and PART algorithms. In addition, WEKA possesses in-built model evaluation measures such as accuracy, precision, recall, F1-score, and confusion matrix, making it easy to compare different models. Among the other tools to be used are spreadsheet applications, such as Microsoft Excel. The data set used will be in CSV and later converted into ARFF format for use in WEKA. These are some of the tools that will enable smooth data handling and analysis. In choosing WEKA for my research, I considered the ease of access and usage of the tool as well as its capability to apply different machine learning algorithms.

7. Data Analysis

This dataset was modeled using WEKA's classification models; namely, J48 Decision Tree, Naïve Bayes, Random Forest, and PART classifiers. Each of these models was tested on the dataset to examine their performance in terms of predicting smartphone addiction among the Filipino population. Accuracy, precision, recall, F1-score, and error rates were used as criteria for comparing the effectiveness of each model. It turned out that the J48 Decision Tree classifier gave the best results in the case of smartphone addiction prediction. The classifier made it possible to predict smartphone addiction quite accurately and generated meaningful decision rules showing how user behavior impacts the smartphone addiction degree. The Naïve Bayes classifier gave satisfactory accuracy, being the fastest one yet less precise owing to its assumption about the feature independence. The best accuracy was attained using the Random Forest classifier, which showed high performance because of its ensembles learning capability. Finally, the PART classifier gave decent results and generated understandable decision rules as well.

Key Insights from the data

1. **Random Forest achieved the highest predictive performance.** First, it gave the best level prediction of smartphones' addiction, which proved the high efficiency of applying ensemble learning techniques to analyze behavior data. However, one more step should be done to confirm that the model would not overfit the dataset.
2. **J48 and PART classifiers showed balanced performance.** The two classifiers exhibited higher accuracy and excellent interpretability. This classification is beneficial in establishing the connection

between the variables used in mobile phones and levels of addiction.

3. **Naïve Bayes showed the lowest accuracy.** The independence of features that Naïve Bayes assumes is not ideal for handling correlated variables, such as screen time and app usage.
4. **Smartphone usage patterns strongly influence addiction levels.** Factors like the duration spent on the screen, the frequency of use of applications, and social media usage have been determined to be critical predictors of smartphone addiction.
5. **Behavioral data is effective for prediction.** It is evident from the findings that machine learning models can effectively predict smartphone addiction using behavioral data.

8. Results

Dataset of Smartphone Usage and Addiction

In the current research, the dataset is composed of several records, each of which corresponds to smartphone users, characterized by attributes associated with usage behavior and interaction patterns. Screen time, usage frequency, social media interaction, and interaction with smartphones can be considered important attributes used to classify users' smartphone addictions into three levels – low, moderate, and high.

According to preliminary data analysis, it appears that most users use their smartphones either moderately or heavily. Individuals with larger amounts of screen time and regular social media interaction are usually characterized by a high level of smartphone addiction. Meanwhile, users who do not interact much and do not have high usage frequencies are mostly classified as those with a low addiction level.

Figure 2. Smartphone Addiction Based on Screen Time

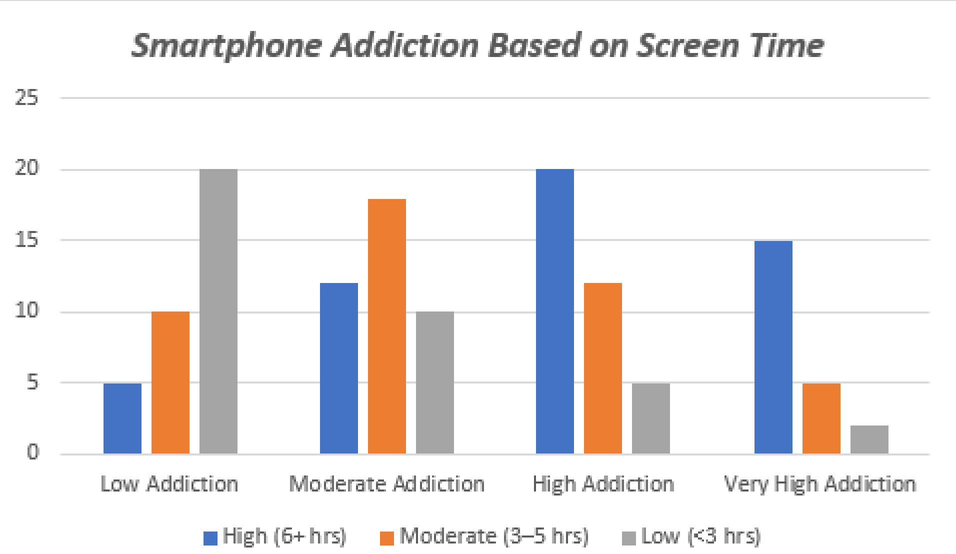


Figure 2 shows the correlation between screen time and smartphone addiction levels. Screen time above six hours classifies users within high and very high levels of addiction. On the other hand, for those with less than three hours of screen time, there is a greater likelihood that they belong to the low level of addiction.

Figure 3. Smartphone Addiction Based on App Usage Frequency

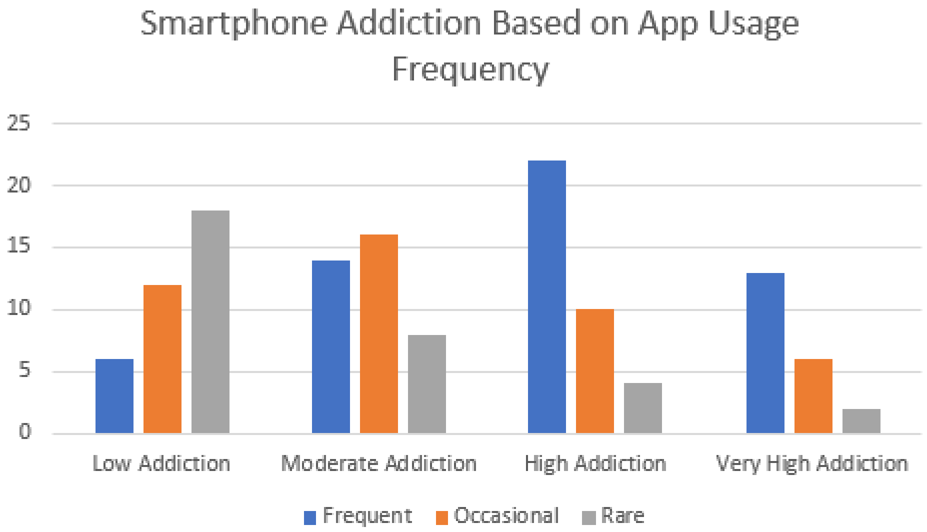


Figure 3 illustrates the correlation between the frequency of using apps and the level of addiction to smartphones. The majority of users who frequently use apps belong to the categories of high and very high levels of addiction, while those who rarely use apps tend to have low levels of addiction.

Figure 4. Smartphone Addiction Based on Social Media Usage

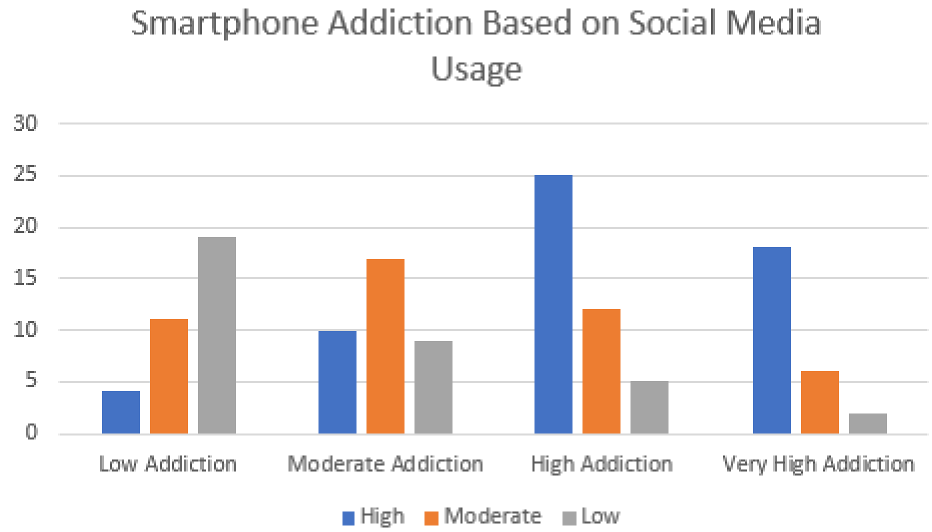


Figure 4 represents the association between social media utilization and smartphone addiction. Those who utilize social media extensively belong to the category of high or very high levels of addiction, whereas people with low usage belong to the low level of addiction. It can be seen that the high use of social media greatly adds to smartphone addiction.

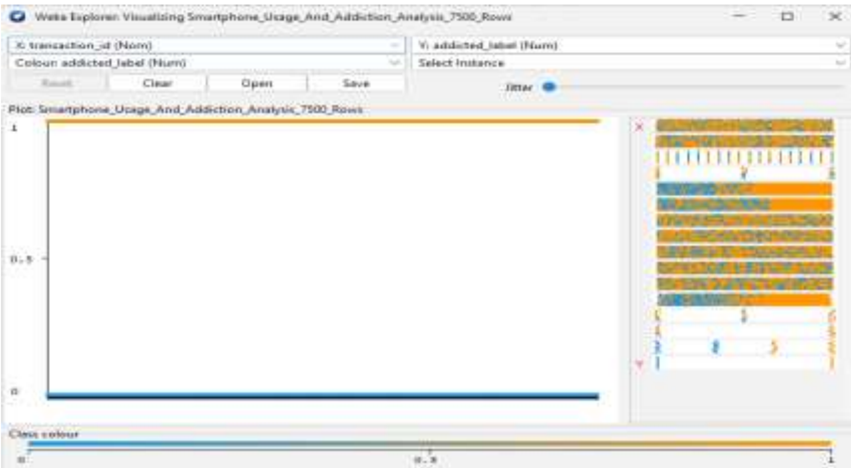
Table 3. Comparison of Classification Models Based on Performance Metrics

Metrics	J48 Decision Tree	Naïve Bayes	Random Forest	PART
Accuracy (%)	99.50%	98.75%	100%	99.50%
Kappa Statistic	0.9894	0.9735	1.000	0.9894
Mean Absolute Error	0.005	0.0134	0.0133	0.005

Root Mean Squared Error	0.0707	0.1029	0.0322	0.0707
Relative Absolute Error (%)	1.0663%	2.8604%	2.8468%	1.0663%
Root Relative Squared Error (%)	14.6059%	21.2545%	6.6459%	14.6059%
Precision (Weighted Avg.)	0.995	0.988	1.000	0.995
Recall (Weighted Avg.)	0.995	0.988	1.000	0.995
F1-Score (Weighted Avg.)	0.995	0.988	1.000	0.995
ROC Area (Weighted Avg.)	0.996	1.000	1.000	0.996

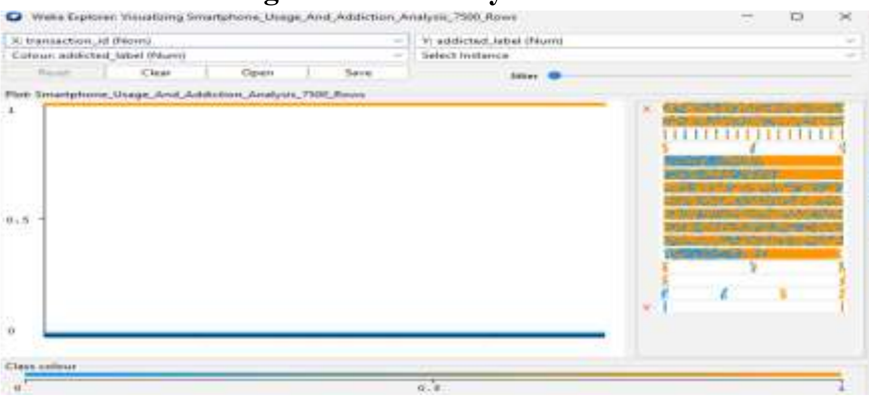
The performance of the classification algorithms employed in predicting smartphone addiction among Filipinos is displayed in Table 3 below. From the above findings, it can be observed that the Random Forest model yielded the highest level of accuracy at 100%, thus making it the most accurate classifier. Other classifiers such as J48 and PART were also highly accurate with a success rate of 99.50%. In addition, Naïve Bayes was found to perform moderately well due to its assumption of feature independence.

Figure 5. J48 Decision Tree Results



Classification outcomes of the proposed model employing J48 Decision tree algorithm are shown in Figure 5. The results reveal that the proposed J48 model is able to classify the level of smartphone addiction accurately by forming clusters of data points on the basis of user behavior. Nonetheless, slight overlapping may also be noticed in some categories.

Figure 6. Naïve Bayes Results



Classification by Naïve Bayes for smartphone addiction is shown in Figure 6. From the diagram, it can be seen that the Naïve Bayes classifier can categorize the level of smartphone addiction; however, there is significant overlapping between the data points. It is thus concluded that although the algorithm is highly efficient, its accuracy is lower than other algorithms because of its independent feature assumption.

Figure 7. Random Forest Results

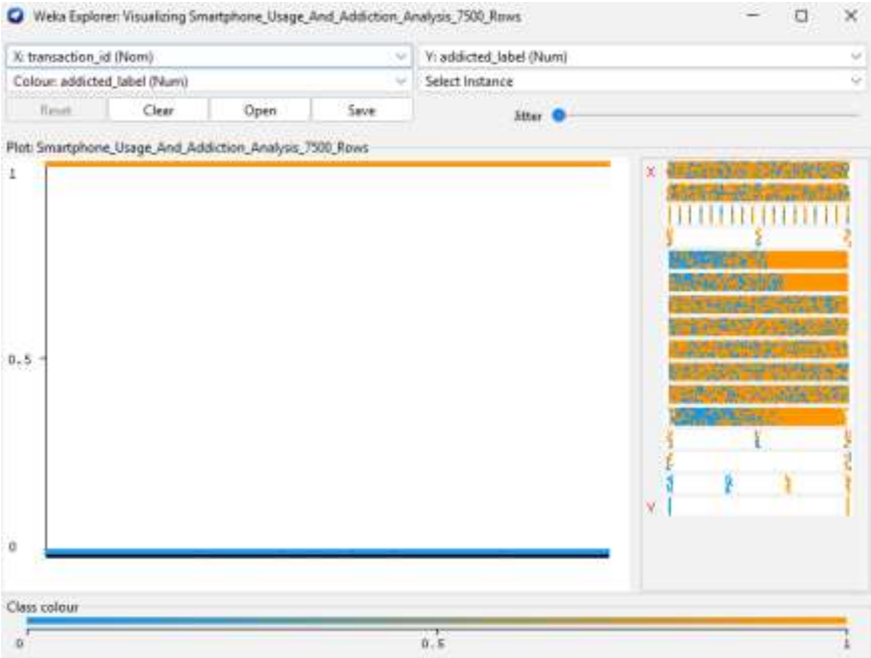


Figure 7 represents the output for the classification of the problem by applying the Random Forest algorithm to determine smartphone addiction. The graph clearly reveals the better segregation of data points as opposed to other algorithms, implying a high level of accuracy in predicting smartphone addiction. Thus, Random Forest emerges as the most efficient classifier.

Figure 8. PART Classifier Results

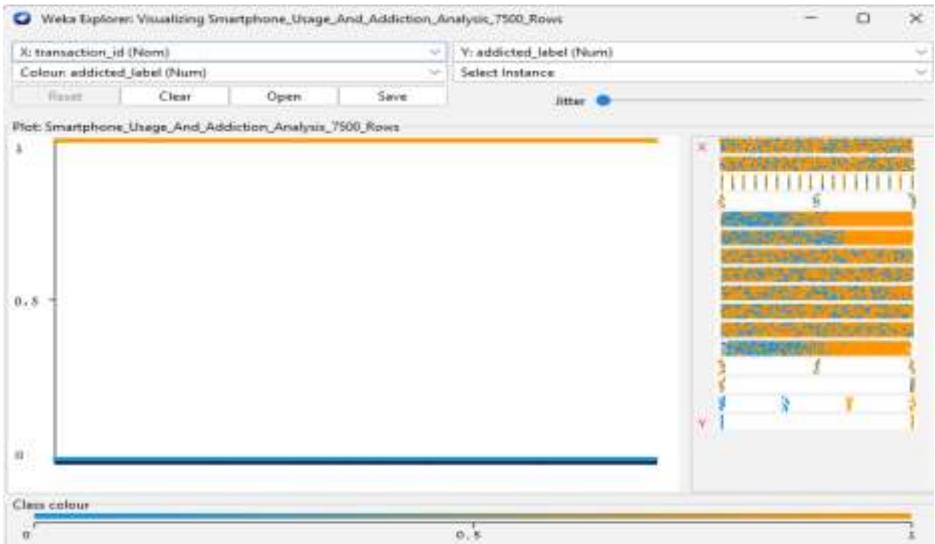


Figure 8 below depicts the outcomes of the PART algorithm when applied to predict smartphone addiction. From the figure, it is evident that the algorithm can separate the data points based on addiction levels. Nonetheless, there are still overlaps, implying that some errors occur. On the whole, the PART classifier performs well in its predictions.

Interpretation of Results in the Context of Objectives

The main goal of this study was to figure out if people in the Philippines are addicted to their smartphones using computer programs and find the best way to classify this addiction. The study used information from a dataset. Tried out different computer programs like J48 Decision Tree, Naïve Bayes, Random Forest and PART to see which one could best classify the level of smartphone addiction based on how people use their phones like how much time they spend on the screen how often they use apps and how much they are on social media. Random Forest was the best at predicting smartphone addiction. It was really good at handling information about how people use their phones. The pictures that showed the results were also clearer which means the predictions were more reliable. But it is possible that Random Forest was too good which might mean it was just memorizing the information of really understanding it so we need to try it with more information to be sure.

The J48 Decision Tree and PART programs also did a job of predicting smartphone addiction. They were accurate and also easy to understand, which is important because they can help us see how different things like screen time and app usage affect how addicted someone is to their smartphone. This makes them useful not for predicting addiction but also for understanding why people use their phones in certain ways.

The Naïve Bayes program did not do well. This is probably because it assumes that the different things we measure like screen time and social media usage are not related to each other. But in reality these things are connected,. The Naïve Bayes program had a hard time accurately predicting smartphone addiction.

The study also found that things like screen time app usage and social media usage are really important when it comes to smartphone addiction. People who spend a lot of time on these things are more likely to be addicted to their smartphones while people who use their phones less are less likely to be addicted.

Overall the study showed that special computer programs can be used to predict smartphone addiction. Random Forest was the program, for this but J48 Decision Tree and PART are also good options because they are easy to understand and work well. Smartphone addiction is an issue and using these programs can help us understand it better.

9. Key Findings

According to the results of the research, machine learning algorithms are capable of predicting smartphone addiction amongst Filipinos with a high level of accuracy based on behavioral characteristics, such as screen time, frequency of application use, and social media interactions. Of all the models employed in the study, the one that was proven to perform best is Random Forest, thus being the most effective classification algorithm. At the same time, the J48 Decision Tree and PART classifiers were highly accurate but also remained easily interpretable. Naïve Bayes demonstrated relatively poor performance since it is based on the assumption that features are independent of each other, which contradicts the reality of smartphone usage.

It was discovered that more time spent on the phone, more applications downloaded, and greater frequency of social media engagement positively correlate with smartphone addiction. These findings support previous literature, stating that high rates of smartphone usage and social media interactions have a significant impact on the development of behavior dependence. Overall, the study proves that behavioral characteristics may be successfully utilized in predicting digital addiction.

10. Implications

The outcomes from this research can be highly beneficial for the educators, policymakers, and health professionals as well. Identification of the main predictors, like the usage of smartphones and applications, indicates that any prevention strategy should concentrate on responsible use of smartphones. Moreover, machine learning techniques, including Random Forest and J48 models, can be incorporated in any digital surveillance software to predict smartphone addiction and provide necessary preventive action.

Finally, the study makes an important contribution to the emerging field of behavioral data mining as it shows the efficiency of machine learning algorithms for predicting smartphone addiction. This research outcome is similar to the results of previous studies, which showed that it was crucial to investigate behavior in order to detect digital dependency.

11. Limitations of the Study

Despite the significance of this study, there are some drawbacks that must be noted. To begin with, the data set utilized in this paper may not reflect the whole Filipino population, thus undermining the validity of the results. Moreover, the current research is solely concerned with existing variables, namely screen time, application use, and social media activity, without considering the possible role of psychological, emotional, and environmental aspects that might influence smartphone addiction.

Additionally, this research only considers several machine learning models, namely J48, Naïve Bayes, Random Forest, and PART. It is noteworthy that there is no discussion about using deep learning algorithms despite the fact that the Random Forest model demonstrated an exceptionally high accuracy rate. In particular, the probability of overfitting should be considered when validating the findings using additional data sets.

12. Conclusion

In this research, the ability to use machine learning algorithms to predict the level of smartphone addiction among Filipino users was investigated. Based on the study, Random Forest performed the best when it came to predicting smartphone addiction, followed by J48 and PART models. In comparison, the Naïve Bayes classifier was found to perform poorly. The conclusion that can be drawn is that machine learning models can be used to accurately assess and predict smartphone addiction based on behavior data.

Another important aspect of this paper is that certain factors like screen usage, frequency of app usage, and social media usage play an important role in determining smartphone addiction.

13. Recommendations

As per the analysis and conclusions made from the data collected and analyzed, it is suggested that various measures should be taken by the concerned authorities in terms of promoting safe use of smartphones among students. The programs that reduce screen time and usage of applications could prove helpful in avoiding any form of dependency on smartphones.

As for future research, it would be better for future researchers to increase the sample size and use more predictors such as psychological and environmental predictors as well. In addition to this, researchers should conduct their research through other methods as well, which might involve advanced algorithms such as Deep Learning.

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