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Game Addiction Identification System: Automatic Labelling Severities Level and Classification in Junior High School Student

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Abstract

Introduction: Playing games at a reasonable time has a good effect on teenagers. Addiction to online games with a high frequency causes children to be lazy to do other activities such as social life and education.

Objectives: The data used is a questionnaire with respondents being junior high school.

Methods: This study integrates educational science, psychology, and artificial intelligence to create a system for identifying the severity of game addiction.

Results: The identification system for the severity level of game addiction was created based on seven factors of children's motivation in playing games by utilizing the TOPSIS-FCM artificial intelligence method and the KELM classification. The TOPSIS- FCM method is utilized in determining the initial label. In the early stages, students will be given education about the positive and negative impacts of playing games.

Conclusions: At a moderate level, this can be done by reducing student moods or problems in games.

Keywords: Game Addiction; Machine Learning; Education; Psychology; Artificial Intelligence.

1. Introduction

Technological transformations developing very rapidly make complexity in various areas of life. With the rapid development of technology, automation is possible in the industrial world and the world of entertainment (Keshav et al., 2022). In entertainment, technology is a tool for online games, where each individual only needs a device and the internet to play with other people in real-time. In the long-term playing games with excessive proportions will lead to addiction. The World Health Organization (WHO) has classified game addiction as a new disorder in the International Classification of Diseases (ICD) (Kim et al., 2022). Based on data from the World Health Organization (WHO), around 1.2 billion people are interested in online games, or around 18% of the world (Guo and Li, 2022; Narullita and Yuniati, 2020). Interest in online games is increasing yearly, especially among teenagers (Hebebci, 2022).

Teenagers are in a critical period of growth and development. At this time, some children cannot yet distinguish between good and evil. So that children who have game addiction disorder will be very easily influenced to do bad things in games. In addition, addiction to online games with high frequency causes children to be lazy to do other activities such as social life and education (Guo and Li, 2022).

Education is an essential part of a country, where the country's progress is greatly influenced by the quality of its education (Madani, 2019). Game addiction also affects a student's academic performance, where games distract students from learning. Many students secretly play games during study hours at school, so the teaching and learning process is ineffective (Abbasi et al., 2021; Rajab et al., 2020). Game addiction is considered the main obstacle that hinders students' academic achievement. Several studies have shown that more than 50% of students who are addicted to games have learning disorders and have lower academic average scores than non addicted students (Adžić et al., 2021; Novrialdy et al., 2019). Efforts to treat students with gaming addiction disorder can be made by a psychological approach, knowing the factors that influence children to play games longer than average.

Based on research conducted by (Lemmens et al., 2009), seven indicators were used to measure the severity of game addiction: salience, tolerance, mood modification, withdrawal, relapse, conflict, and problems. With the development of science and technology, research on the severity of game addiction needs to be developed. This study analyzed the severity of game addiction in adolescents using an artificial intelligence approach.

This research integrates educational science, psychology, and artificial intelligence to create a system for identifying the severity of game addiction. The identification system for the severity level of game addiction was created based on seven factors of children's motivation in playing games by utilizing the TOPSIS-FCM artificial intelligence method and the KELM classification. The TOPSIS-FCM method is utilized in determining the initial label, where the TOPSIS method provides data scores according to the factor weights that a psychologist has determined. In contrast, the FCM method groups data based on the shortest distance into three clusters: mild, moderate, and severe. The implementation of data labelling using the TOPSIS-FCM method has previously been carried out by (Zaenab et al., 2020) in determining the evaluation of the development of development areas.

After the automatic labelling process, data classification uses the Kernel Extreme Learning Machine (KELM) method, which constructs a game severity identification system. The KELM method is a development method from Extreme Learning Machine (KELM), a machine learning method that uses matrix operations in the classification process. This study compared the performance of ELM and KELM based on the accuracy, sensitivity and specificity values. KELM is the development of the Extreme Learning Machine method, which was inspired by kernel functions in the Support Vector Machine (SVM) method (Zhao et al., 2022). KELM is one of the neural network methods where the neural network method uses the weight values generated in the training process to predict class labels for data testing. In KELM, weight optimization in the training process is carried out with Moore-Penrose. Optimizing the weights with Moore-Penrose, which is only done in one step, makes the ELM method have lower computational costs and shorter training times than conventional neural networks (Bai et al., 2022; Cai et al., 2020). The kernel function in the KELM method maps data into a higher dimension to properly separate data between classes (Novitasari et al., 2020).

The results of this study are expected to form a Game Addiction Identification System to help treat children who are addicted to games so that they can improve student academic achievement.

2. Objectives

In terms of health, playing games for a long time causes eye fatigue causes a reduced ability of the eyes to adapt to light, and the body becomes tense. In the long term, it can cause vegetative nervous disorders, unbalanced hormones, insomnia and decreased appetite (Zakaria and Adnan, 2022). From a psychological perspective, the negative impact of game addiction is likely to be experienced by adolescents during a period of rapid and unstable development. Teenagers have the main task of forming identity, developing self-concept, and self-evaluation. Game addiction can hinder the process of developing self-identity. It happens because the ideal self in games cannot be integrated with identity in reality. As a result, adolescents will experience long-term identity diffusion and an inability to recognize themselves and others (Jin et al., 2021), which will also affect the social life of game addicts.

Table 1. Questioner and Indicator

Indicator	w (weight)	Statement
Salience	15	I feel addicted to playing online games
		I always fill my time by playing online games
		I cannot afford not to play online games for a day
Tolerance	12	I am challenged to increase the games level
		I am obsessed with getting the rewards when I win online games
		I made new friends from online games
Mood modification	17	I feel that playing online games is a stress reliever.
		I can express myself in online games because I feel bored
		I can divert emotional feelings

Indicator	*w* (weight)	Statement
Withdrawal	10	I get angry easily when kept away from online games.
		I am often restless when the intensity of online games is reduced /when I do not play games
		I feel so empty when I am not playing online games.
Relapse	8	I feel that no activity is more fun than playing online games
		I am always attracted to playing online games often becausefriends invite me
		I can not be separated from playing online games
Conflict	18	My parents often scold me for playing online games too much
		I do not have time to study, because I too often play online games
		I do not interact with the social environment / prefer to be alone
Problems	20	I lost track of time because I played online games too much
		My eyes are nearsighted because of the online games' intensity
		I often forget to eat because I am too engrossed in online games

Based on research conducted by (Lemmens et al., 2009), applying seven indicators to measure the severity of game addiction, namely salience, tolerance, mood modification, withdrawal, relapse, conflict, and problems. In this study, data were obtained from a questionnaire with 857 respondents who were junior high school adolescents with an age range of 14-16 years. Three questions represent a value of the indicator, each question worth 1 to 5. A value of 1 indicates "strongly disagree", 2 indicates "disagree", 3 indicates "neutral", and values 4 and 5 indicate "agree" and "strongly agree". So that each indicator has a value in the range of 3-15, and each indicator has a weight value determined by an expert in the field of psychology as a parameter in decision-making; the higher the weight, the clearer the brush indicator will be in determining the severity of game addiction. Fill in the questions in the questionnaire with each indicator shown in Table 1.

The indicators in the research are explained as follows.

1. Salience (A): playing games is a priority activity for someone, and it dominates their thoughts, feelings and behaviour.
2. Tolerance (B): a person plays games more often than usual and with a gradually increasing period.
3. Mood modification (C): playing games is someone's escape when they have a bad mood.
4. Withdrawal (D): unpleasant emotions or effects when there is a reduction in gameplay time.
5. Relapse (E): a tendency to return to playing games as in previous patterns.
6. Conflict (F): social interaction effects of game addicts on individuals in their environment.
7. Problems (G): problems caused by game addiction.

3. Methods

This research consists of three main steps: TOPSIS-FCM and KELM classification. The TOPSIS-FCM method is used to determine class labels on data. Meanwhile, the KELM method is used to classify data. The research steps are illustrated in Figure 1.

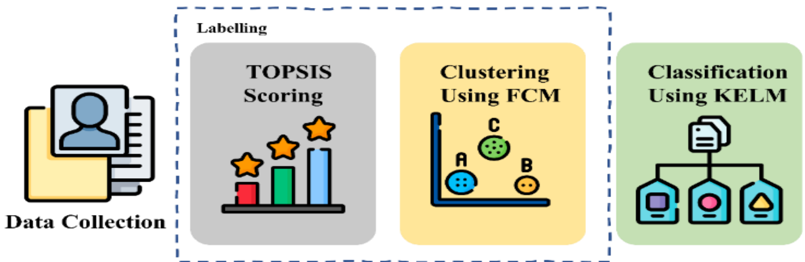

Figure 1. Graphical abstract of research.

Game Addiction

Playing games at a reasonable time has a good effect on teenagers. Based on previous research, playing games can improve brain rotation performance. In addition, playing games with appropriate portions can improve short-term memory, players' visual abilities, analytical abilities, and decision-making abilities (Podlogar and Podlesek, 2022). Game addiction is a mental health problem where sufferers experience dependence on games characterized by impaired control over games so that they can shift to other more important priorities such as academic needs, social needs and even health (Jin et al., 2021).

Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)

The technique for Order of Preference by Similarity to the Ideal Solution (TOPSIS) is an effective method for taking multi-variables with limited alternatives (Dutta et al., 2021). The main principle of the TOPSIS method is to find the best alternative closest to the ideal solution based on the specified criteria. The TOPSIS method has simple calculations and can be implemented in various fields (Chen, 2019). With simple calculations, TOPSIS can effectively provide an assessment based on several criteria for decision-making. In TOPSIS, each criterion has a weight that represents how influential the criteria are on the decision. TOPSIS implementation relies on the proposition that the best solution is the shortest distance from the Positive Ideal Solution (PIS) and the farthest distance from the Negative Ideal Solution (NIS) by using the Euclidean distance calculation (Nguyen et al., 2022). This study used the TOPSIS method to provide a score based on the research variables. Scoring is determined based on the weight given by an expert in psychology. Furthermore, the label determination of game addiction severity level by grouping the scores based on the clustering method FCM.

Fuzzy C-Means (FCM)

Clustering is an unsupervised machine-learning technique for identifying cluster labels in a dataset based on data points without a target—the clustering process groups data with adjacent values in the same category. The data in the same category shows similar characteristics (Sarker, 2021). One clustering method that uses the membership function concept in fuzzy is Fuzzy Clustering Means (FCM). FCM is a clustering method sensitive to noise, outliers and cluster size (Askari, 2021). FCM divides the dataset into c clusters, with each data having a membership function value. The membership function plays a major role in fuzzy logic because it represents data values between 0 and 1 mapped to degrees of membership in the input space (Zhu et al., 2019). The first step in the clustering process using FCM is to randomly determine the partition matrix $U(n, c)$, where n is the number of data and c is the number of clusters. $U(n, c)$ partition matrix is used to determine the centre point in each cluster with Equation 1.

$$c_j = \frac{\sum_{i=1}^{m} (u_{i1})^2 x_{ij}}{\sum_{i=1}^{m} (u_{i1})^2} \tag{1}$$

where xij is the i-th input data and the j-th variable. Then update the partition matrix $U(n, c)$ in each iteration until the cluster results in the p siteration are the same as the results of the $(p - 1)$ iteration, with Equation 2.

$$u_{ij} = \frac{D(x_i,\ c_j)^{\frac{-2}{w-1}}}{\sum_{j=1}^{k} D(x_i,\ c_j)^{\frac{-2}{w-1}}} \tag{2}$$

where $D(xi, cj)$ is the Euclidean distance between xi and cj, and w is the weight of the power, which is determined to be equal to two. The final result of the $U(n, c)$ partition matrix is used to determine clusters, where the nth data cluster is the maximum column index for each row (Azam et al., 2021). Cluster results show labels of game addiction severity in the data. The data is then used as learning data in the classification process.

Kernel Extreme Learning Machine (KELM)

Huang first introduced Extreme Learning Machine (ELM) by applying the concept of a feed-forward neural network to train a single hidden layer feed-forward neural network (SLFN) (Wang et al., 2017; Ye and Wang, 2020). In contrast to the feed-forward neural network method, which updates the weights in each iteration, the SLFN network training in ELM uses the Moore-Penrose generalization method, which can optimize weights previously determined randomly at the beginning of one step (Chouikh et al., 2021). Weight optimization with Moore-Penrose, which is only done in one step, makes the ELM method have lower computational costs and shorter training times than conventional neural networks (Bai et al., 2022; Cai et al., 2020).

Handling problems with the ELM method can be overcome by developing the ELM method, namely the Kernel Extreme Learning Machine (KELM) method. The mapping using the activation function $g(x)$ in the basic ELM hidden layer is changed to the kernel function $k(x)$ mapping data into a higher dimension to separate data between classes properly. The KELM method was inspired by the Support Vector Machine (SVM) kernel method, which obtained better results, so ELM tried to combine it with the kernel (Novitasari et al., 2020).

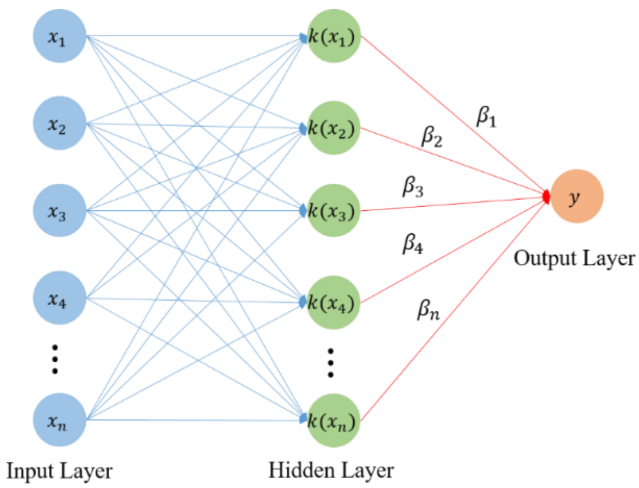

Figure 2. KELM Architecture

In Figure 2, the kernel function in the hidden layer can smooth data and simplify classification problems with better effectiveness. The Radial Basis Function (RBF) is a kernel function with only one hyperparameter, simplifying model configuration and training costs (Tang et al., 2021). The RBF kernel function is suitable for low dimensional and high-dimensional data, so it is ideal (Shi et al., 2018). The functional equivalent of the RBF kernel is shown in Equation 3.

$$K(x, y) = e^{-\gamma\|x-y\|^2} \tag{3}$$

where x and y represent sample data, while γ is a unique hyperparameter (Jahed Armaghani et al., 2020).

4. Results

The first stage in this research is to add the points for each question on each indicator so that each indicator has a value ranging from 3 to 15 to determine the data label. The higher the value on the indicator, the higher the possibility that the child will experience game addiction. The next step is to score using the TOPSIS method based

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on the weights specified in Table 1 so that the values of each student are obtained as in Table 2. Scoring in the TOPSIS method aims to provide an assessment according to the level of influence of indicators on the severity of playing games so that the labelling process according to the category determined by the expert in the field of psychology.

Table 2. Scoring Data using TOPSIS

Resp ID	A	B	C	D	E	F	G	Score
1	6	4	6	7	6	5	7	0.252
2	6	6	5	6	5	6	9	0.310
3	5	7	8	6	7	7	6	0.304
4	6	5	6	7	6	5	6	0.233
5	10	8	6	8	11	6	11	0.456
6	7	15	15	5	11	13	3	0.525
7	7	4	3	5	6	3	7	0.208
8	6	6	5	6	5	7	8	0.300
9	7	6	7	8	6	9	7	0.366
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
857	6	5	5	4	6	4	10	0.304

Based on the score in Table 2, clustering is carried out using the FCM method to determine the threshold for each label. This study will divide the severity level of game addiction into three clusters: mild, moderate, and severe. So the value of c in the FCM method is determined equal to three. The FCM method aims to find the data's midpoint for each cluster. The data will be labeled according to the shortest distance from the score to the cluster midpoint. The cluster center values and labeling results in applying the FCM method are shown in Table 3.

Table 3. Scoring Data using TOPSIS

<table>
<tr><th>Resp ID</th><th>A</th><th>B</th><th>C</th><th>D</th><th>E</th><th>F</th><th>G</th><th>Score</th><th>Pusat Cluster</th><th>Cluster</th></tr>
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<tr><td>6</td><td>7</td><td>15</td><td>15</td><td>5</td><td>11</td><td>13</td><td>3</td><td>0.525</td></tr>
<tr><td>14</td><td>10</td><td>10</td><td>10</td><td>6</td><td>8</td><td>8</td><td>6</td><td>0.439</td></tr>
<tr><td>25</td><td>15</td><td>15</td><td>14</td><td>6</td><td>9</td><td>13</td><td>15</td><td>0.795</td></tr>
</table>

Based on Table 3, data with a score close to the cluster 1 center point, namely 0.068, is labeled with the mild class category. Data with a score close to the cluster 2 center point, 0.293, is categorized as a moderate class. Meanwhile, a score close to 0.537 is categorized as a severe class. The results of data distribution by cluster are shown in Figure 3.

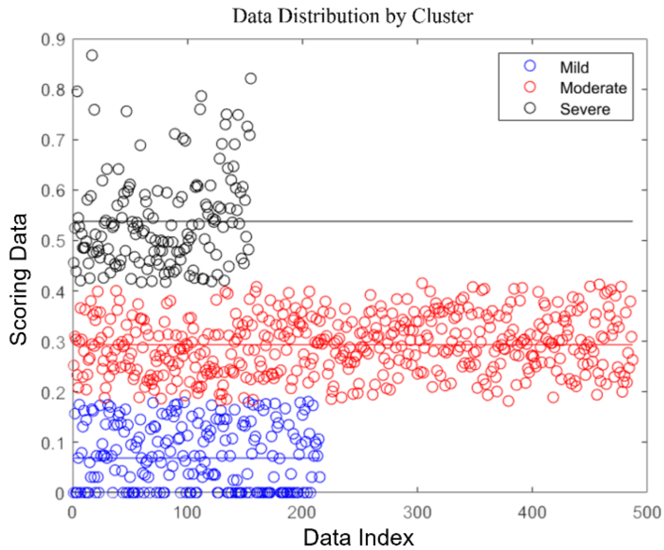

Figure 3. Data distribution by cluster

Each cluster's center line shows the cluster's center point so that data with a point adjacent to the cluster center shows a data label. Each class has 215 data for the mild and 487 for the moderate classes. Meanwhile, in the severe class, there were 155 data. Visualization of the average value of variables in each class is shown in Figure 4.

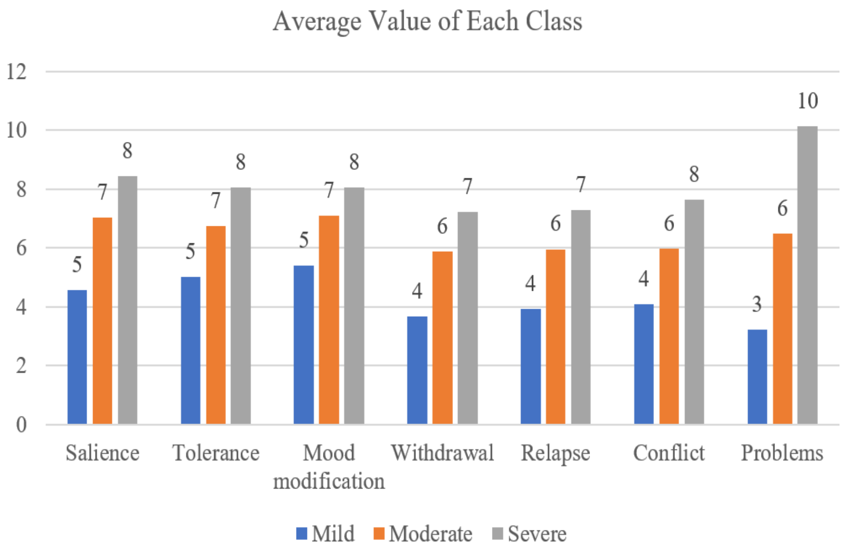

Figure 4. Visualization of the average value of variables in each class

Based on Figure 4, the average score in the mild class ranges from 3 to 5. Meanwhile, the moderate and severe classes have values of 6 to 7 and 7 to 10. Furthermore, the data will be classified using the KELM method. The data is divided into training and testing data using k-fold cross-validation with k equal to 5. There are 771 training data and 86 testing data. The model formed using training data will then be evaluated using data testing. Evaluation is done by using a confusion matrix. Classification is carried out using the basic ELM method to determine the best method. The comparison results are shown in Table 4.

Table 4. Comparison result

Evaluation Matrices	ELM	KELM
Accuracy (%)	90.59	95.34
Sensitivity (%)	91.42	97.43
Spesificity (%)	90.28	92.80

Based on Table 4, the ELM and KELM methods perform well in classifying game addiction data. KELM is superior to ELM. The difference in accuracy between the ELM and KELM methods reaches almost 5%. The results of the evaluation using the confusion matrix are shown in Table 5.

Table 5. Confusion matrix

		Predicted Class		
		Mild	Moderate	Severe
Actual Class	Mild	20	2	0
	Moderate	0	48	0
	Severe	0	2	14

Based on Table 5, it can be seen that there are 20 data in the Mild class which are correctly predicted to be Mild class, 48 data in the moderate class are correctly predicted, and 14 data in the severe class are correctly predicted to be Mild class. In the moderate class, 4 data are classified in the wrong class, namely in 2 data, which should be mild class data which should be predicted as a moderate class, and 2 data in the severe class which are predicted to be a moderate class. It indicates a less strict boundary between the moderate class and the other classes, so the class with the score for the mild class and the severe class is closer to the data points in cluster 2. Table 3 shows that the accuracy, sensitivity, and specificity values are 95.34, 97.43, and 92.80. In future research, it is expected to improve accuracy by adding an imbalance data handling method.

5. Discussion

Treatment can be determined at each level based on the identification results of the severity of playing games. In the early stages, students will be given education about the positive and negative impacts of playing games so that a child can consider the decisions they will make in playing games. At a moderate level, it can be done with several therapies to change students' mindsets about gaming behavior and help students carry out other activities to reduce flight mood or student problems in games. At the severe level, it is necessary to further investigate students' clinical condition by considering the risk factors. So that handling steps can be carried out effectively based on students' matters. In future research, it is expected to consider several external factors that can influence students to tend to play games. Some of these treatments can be done to reduce game addiction in students to increase academic achievement.

In this study, automatic labeling and classifying data on adolescent game addiction were carried out using the TOPSIS-FCM and KELM methods. The results of this study are expected to form a Game Addiction Identification System to help treat children who are addicted to games so that they can improve student academic achievement.

Based on the study results, the TOPSIS-FCM method was used to label the data obtained. Data with a score close to the cluster 1 center point, 0.068, is labeled with the mild class category. Data with a score close to the cluster 2 center point, 0.293, is categorized as a moderate class. Meanwhile, a score closes to 0.537 is categorized as a severe class. From 875 data, each class has 215 data for the mild and 487 for the moderate classes. Meanwhile, in the severe class, there were 155 data. Furthermore, classification is carried out by comparing the ELM and KELM methods to form a game addiction identification system. The ELM and KELM methods have good performance in classifying game addiction data. KELM is superior to ELM. The difference in accuracy between the ELM and KELM methods reaches almost 5%.

Treatment can be determined at each level based on the identification results of the severity of playing games. In the early stages, students will be given education about the positive and negative impacts of playing games. At a moderate level, this can be done by reducing student moods or problems in games. At the severe level, it is necessary to carry out further investigation regarding the clinical condition of the student.

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