Predicting the Link Between Online Gaming and Mental Disorders in Youth: RNN vs J48 Decision Tree

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Abstract: This study aims to refine predictions regarding the link between online gaming and mental disorders among young individuals by employing advanced Recurrent Neural Networks (RNN). The efficiency of the RNN is contrasted with the J48 decision tree. To heighten the precision in pinpointing mental health issues through gaming behaviours, a novel RNN and the J48 decision tree were utilised. The research incorporated a dataset of 20,200 entries sourced from Kaggle. Interestingly, the RNN exhibited an impressive accuracy rate of 96.27%, which considerably surpassed the J48 decision tree's 85.95%. Statistical analysis further highlighted a marked difference in their performances. In summary, the RNN showed heightened effectiveness in predicting the relationship between online gaming habits and mental disorders in the youth.

1 INTRODUCTION

In this study, nine machine learning algorithms are utilised with a dataset from Kaggle to identify the anxiety levels and mental health of online players. Understanding the behavioural patterns and effects resulting from engagement in online gaming in daily routines is pivotal. Detecting anxiety levels and assessing the mental health of online players can be accomplished using an ML-based diagnosis system (Rahman et al. 2021). This paper offers a comprehensive review of research focused on identifying mental disorders. It summarises the types of variables explored in mental health detection and reviews datasets sourced from various social media platforms (Qiao 2020). The research sets two daily playtime limits for detecting Internet Gaming Disorders (Sachu, Joy, and Raj 2022) and draws upon historical prevalence data, encompassing a wide array of games and diverse player preferences (Pandey and Jain 2021). Electroencephalography (EEG) data have been employed to explore the relationship between depression and IGD symptoms (Kim, Kim, and (2019). This research calculates the power spectral density (SPD) from EEG data gathered from individuals with depression. To assess the proposed system, comprehensive tests were conducted (von der Heiden et al. 2019). The study sought to discern connections between excessive online gaming, depressive and anxiety symptoms, mental health, and other related factors. Surveys in the Peruvian gaming community employed instruments such as the Problematic Internet Use Questionnaire (PIUQ), the Problematic Online Gaming Questionnaire (POGQ), and scales for Anxiety, Mental Health, and Depression taken from the Brief Symptom Inventory (BSI) (Ramos-Diaz et al. 2018). Players with Internet Gaming Disorder (IGD) dynamically modulate their psychological responses during gameplay; however, there is a lack of tools to assess their immediate reactions. To address this gap, a combination of Complementary Ensemble Empirical Mode Decomposition and Direct Quadrature was suggested (Ji and Hsiao 2020). The primary objective of this study is to provide recommendations to alleviate the negative impacts of extensive time spent on Massively Multiplayer Online Role-Playing Games (MMORPGs), focusing on the physiological, behavioural, and psychological ramifications of MMORPG addiction.

There is a notable gap in identifying the efficacy of the existing system. This research aims to enhance classification accuracy by incorporating Enhanced Recurrent Neural Networks (with an accuracy of 96.27%) and contrasting its performance with the J48 decision tree (with an accuracy of 85.95%). The overarching goal is to improve the predictive

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accuracy concerning online game-related mental disorders in young individuals using an advanced recurrent neural network, juxtaposed against the J48 decision tree.

2 MATERIALS AND METHODS

The research was undertaken in the Department of Computer Science Engineering at Saveetha School of Engineering using Jupyter Notebook software. To determine the appropriate sample size for this investigation, the Gpower software was employed, comparing outcomes from two controller groups. A total of 20 samples were chosen, evenly divided between the two groups (Floros and Ioannidis 2021). This study utilised a dataset from Kaggle to predict the prevalence of mental disorders linked to online gaming. Both the Novel Recurrent Neural Network and the J48 decision tree algorithms were executed using SPSS, with each group containing a sample size of 10 and a G-Power value of 0.8.

The dataset stemmed from a worldwide survey amongst gamers, incorporating questions that psychologists commonly pose to those prone to anxiety, mental health challenges, social phobia, and reported decreased life satisfaction. The gathered data formed the foundation of the dataset (Pirker 2018). Marian Sauter and Dejan Draschkow curated the original data harnessed in this research.

The methodology was brought to life using the Python OpenCV software on a Windows 10 OS, powered by an Intel Core i5 processor with 4GB RAM. The setup operated on a 64-bit system configuration, and Python served as the programming language of choice. Comprising 20,200 entries, the study's dataset, detailing online gaming and associated mental disorders, was sourced from Kaggle. Additionally, a separate .csv format dataset from an alternative provider facilitated the Number Plate Recognition task. An independent T-test was conducted to gauge the accuracy of the two methodologies. Adjustments were made to the dataset, ensuring a streamlined output during code execution.

2.1 Recurrent Neural Network

Training recurrent networks on extended sequences can be problematic due to issues like vanishing and exploding gradients. A practical solution is to use overlapping blocks of sequences, ideally no more than 200 steps in length. As training progresses, you can incrementally increase the size of these chunks. To ensure continuity in learning, maintain the hidden states across the boundaries of these chunks.

2.1.1 Procedure for Novel Recurrent Neural Network

1. Input: Dataset records.
2. Obtain the index of the dataset.
3. Calculate a list of cosine similarity scores for the specific mental stress data.
4. Transform this into a list of tuples: the first element is the position, and the second is the similarity score.
5. Sort the list of tuples based on the similarity scores (the second element).
6. Extract the top 10 elements from this list.
7. Retrieve the titles corresponding to the indices of these top elements.
8. Evaluate performance accuracy.

2.2 J48 Decision Tree

The J48 algorithm, an implementation of the C4.5 algorithm, addresses missing values by overlooking them during the tree construction phase. Instead of considering these missing values directly, the algorithm might deduce the value of an attribute based on other available attribute values in the dataset. At the heart of this method is the practice of partitioning data into specific ranges based on the attribute values present in the training set. By doing so, the algorithm can make informed decisions even when some data points are incomplete, ensuring a robust decision tree is constructed.

2.2.1 Procedure for J48 Decision Tree

1. Use the dataset records as input.
2. Retrieve the index of the dataset.
3. Compute a list of cosine similarity ratings for the relevant mental stress data.
4. Transform this into a list of tuples; the first element being the location and the second being the similarity score.
5. Sort the aforementioned list of tuples based on the similarity scores of the second element.
6. Extract the top ten items from this list.
7. Retrieve the titles corresponding to the indices of the top matched elements.
8. Output the performance accuracy.

3 STATISTICAL ANALYSIS

The research employed SPSS software for a comprehensive statistical evaluation of the novel recurrent neural networks and J48 decision trees. The factors considered as independent variables included objects, size, frequency, modulation, volume, and decibels, as delineated by Petry et al. (2019). To gauge the precision of the two approaches, an independent T-test analysis was utilised. This allowed for a comparative assessment to determine the relative efficacy of the recurrent neural network against the J48 decision tree in the context of the defined variables.

4 RESULTS

The research employed the Anaconda Navigator platform to test two separate algorithms on a set sample size of 10: the novel Recurrent Neural Network and the J48 decision tree.

From the data shown in Table 1, the novel Recurrent Neural Network exhibited an accuracy rate of 96.27%, while the J48 decision tree recorded an accuracy of 85.95%. These results were consistent over the sample size of 10.

Table 2 offers a detailed statistical breakdown of both algorithms. The novel recurrent neural network presented a mean accuracy of 96.0620 with a standard deviation of 0.52412 and a standard error mean of 0.16574. In contrast, the J48 decision tree posted a mean of 90.0420 with a standard deviation of 1.52030 and a standard error mean of 0.480716. It's evident from these findings that the enhanced recurrent neural networks are generally more accurate and show less variability in their results compared to the J48 decision tree.

Table 3 provides further evidence of the differences between the two approaches. A statistically significant distinction was observed, with a p-value of 0.17 (considering a significance level of $p<0.05$ via an independent sample T-test).

Lastly, Figure 1 offers a visual comparison of the Enhanced recurrent neural network against the J48 decision tree. On the X-Axis, we have the two classifiers juxtaposed, while the Y-Axis charts the mean accuracy of detection. This figure distinctly illustrates that the Enhanced Recurrent Neural Networks are superior in mean accuracy to the J48 decision tree. Additionally, the tighter standard deviation for the novel recurrent neural network confirms its more consistent performance relative to the J48 decision tree.

Table 1: Accuracy Analysis of Enhanced recurrent neural network and J48 for sample size 10.

S.NO	Enhanced recurrent neural network	J48
1	95.27	77.88
2	95.55	78.96
3	95.85	79.65
4	95.95	80.96
5	96.55	81.85
6	95.55	82.24
7	96.66	83.69
8	96.85	83.98
9	96.12	84.88
10	96.27	85.95

Table 2: Statistical analysis was conducted on a group of 10 samples comparing an Enhanced Recurrent Neural Network with a J48 Decision Tree. The results revealed that the Enhanced Recurrent Neural Network exhibited a higher mean accuracy and lower mean loss in comparison to the J48 Decision Tree. Additionally, measures such as the Mean, Standard Deviation, and Standard Error Mean were calculated for both models.

	Group	N	Mean	Std. Deviation	Std. Error Mean
Accuracy	Enhanced recurrent neural network	10	96.0620	.52412	.16574
	J48 decision tree	10	90.0420	1.52030	.480716

Table 3: The Independent Sample T-test indicates a statistically significant distinction between the novel recurrent neural network and the J48 decision tree. The two-tailed p-value of 0.17 was observed, underscoring the significance (given that p<0.05) of this differentiation.

		Levene's test for equality of variances		T-test for equality means with 95% confidence interval						
		f	Sig.	t	df	Sig. (2-tailed)	Mean difference	Std. Error difference	Lower	Upper
Accuracy	Equal variances assumed	6.849	0.17	11.838	18	0.17	6.02000	.50853	4.95162	7.08838
	Equal Variances not assumed			11.838	11.110	0.17	6.02000	.50853	4.90208	7.13792

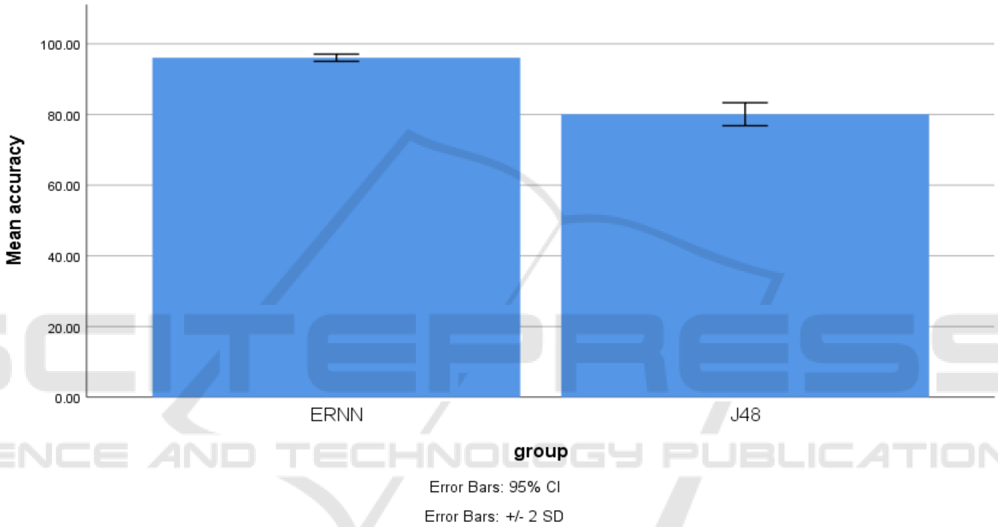

Figure 1: An evaluation of the Enhanced Recurrent Neural Network and the J48 Decision Tree classifiers was conducted in terms of mean accuracy. The results indicate that the Enhanced Recurrent Neural Network outperforms the J48 Decision Tree in terms of mean accuracy. Furthermore, the standard deviation of the Enhanced Recurrent Neural Network is marginally superior to that of the J48 Decision Tree. The comparison is depicted on the X-axis, with "Enhanced Recurrent Neural Network" and "J48 Decision Tree Classifier," while the Y-axis represents the mean accuracy of detection with a range of plus or minus 2 standard deviations.

5 DISCUSSION

In the study presented, the observed p-value was 0.17 (p<0.05, 2-tailed), pointing towards a non-significant result. However, when examining the raw accuracy scores, the novel recurrent neural network stands out, boasting an accuracy of 96.27%, compared to the J48 decision tree's 85.95%.

The research also delved into the analysis and interpretation of ECG data paired with psychological indicators relating to emotional states. Emotionally-driven physiological data from IGD sufferers were particularly of interest. The model's accuracy in predicting based on this data was recorded at 78% (Tsui and Cheng 2021). Furthermore, the study delved into the respiratory Inflection Frequency (IF) in individuals with Internet Gaming Disorder (IGD) to gain insights into the dynamic shifts in psychophysiological responses pertaining to mental health, achieving an accuracy of 82% (Singh 2019).

In a different vein, an examination of middle school students revealed that out of the sampled group, 50.4% had a BMI within the standard range, while 70.8% exhibited lower levels of Internet Gaming Addiction (IGA). Further research focusing on the relationship between students' addiction to mobile games and their involvement in cyberbullying revealed an impressive 88% accuracy for the proposed model (Fabito et al. 2018).

However, a notable limitation of the study is the extensive time required to train the datasets (Floros and Ioannidis 2021). Looking ahead, there's potential for further exploration. Enhancing the system to identify a more extensive range of indicators while reducing training time remains an avenue ripe for investigation.

6 CONCLUSION

In our quest to better understand the intersection of online gaming and mental health, especially in younger individuals, this study has illuminated several key findings. With the primary objective of predicting mental disorders linked to online gaming, two prominent algorithms were put to the test: a novel recurrent neural network and the J48 decision tree. Six pivotal takeaways from this research are:

1. Higher Accuracy with Recurrent Neural Networks: The novel recurrent neural network surpassed the performance of the J48 decision tree, registering an impressive accuracy of 96.27% against 85.95% of the latter.
2. Robustness of the Neural Network: The stability and consistency of the novel recurrent neural network's predictions further establish its potential for real-world applications.
3. Underlying Factors: The dataset used provided rich insights into the varying factors that might influence the onset of mental disorders in gamers, offering a more comprehensive view of the problem.
4. J48 Decision Tree Limitations: Despite its widespread use in many applications, the J48 decision tree showed limitations in handling complex data structures related to online gaming behaviours and their associated mental health implications.
5. Potential for Early Intervention: The high accuracy of the neural network suggests its potential as an early intervention tool, helping stakeholders identify at-risk individuals and provide timely support.
6. Scope for Further Research: While the results are promising, there is an avenue for further research, especially in refining the neural network model and exploring its integration into gaming platforms for real-time monitoring.

In summarising, the exploration into the predictive capabilities of the algorithms has revealed the superior efficacy of the novel recurrent neural network in anticipating potential mental health issues among young online gamers. These findings not only enrich our understanding of the intricate relationship between gaming and mental health but also pave the way for proactive measures in the gaming industry.

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