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Article

From Play to Prediction: Assessing Depression and Anxiety in Players Behavior with Machine Learning Models

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Abstract

In today's society, depression and anxiety pose significant challenges for individuals across various age groups, emphasizing the need for timely identification to facilitate effective treatment and prevent future complications. However, current methods of assessing mental health often rely on self-reporting, which can be biased and tedious. This paper explores the potential of utilizing artificial intelligence for continuous, unobtrusive monitoring of mental well-being through the analysis of gameplay log data in a multi-genre game involving 64 participants with Machine learning algorithms, specifically the NuSVC model, achieved 93.75% accuracy, 94.44% precision, 93.75% recall, and a 93.72% F1-score for identifying depression, while the GBM classifier attained 93.75% accuracy, 95.45% precision, 93.75% recall, and a 91.67% F1-score for detecting anxiety. These findings highlight the potential of using game-based behavioral data as a potential indicator of mental health status and offering an innovative approach for diagnosis that reduces the burden on healthcare systems and makes mental health support more accessible to those reluctant to seek help through conventional means.

1. Introduction

The rapid pace of life has a significant impact on people's mental health, leading to adverse effects in modern society. The COVID-19 pandemic has significantly affected people's mental health [1], [2]. However, the full extent of this impact is still not completely clear. Researchers have looked at survey data from around the world to measure levels of anxiety and depression before and during the pandemic [3], [4], [5]. Their findings show that rates of depressive disorder and anxiety disorders have increased compared to before the pandemic [1], [2], [5]. This rise has been seen in both men and women and across different age groups [6]. Moreover, Social distancing and lockdowns are not just temporary inconveniences; they are likely to create profound and long-lasting impacts on individuals' mental health, even after finishing this COVID-19 regularization [7], [8]. Therefore, it underscores the need for a tool that can identify the DA, as similar situations may repeat or be utilized in post-situations like the current one.

Based on World Health Organization (WHO) reports, approximately 5% of adults, which equates to around 280 million individuals, are affected by depression, with a prevalence rate of 4% among men and 6% among women, indicating that women are 50% more likely to experience this condition. Additionally, 4% of the population suffers from anxiety disorders, making these two issues the most prevalent mental health concerns worldwide. Despite the existence of treatments for these disorders, only one in four (25%) individuals has access to any form of care. Besides, their social and financial conditions exacerbate treatment issues in low- and middle-income countries. Significant barriers hinder people from accessing treatment, such as insufficient investment in mental health-related services, inadequate trained professionals, and social stigma [9], [10]. In light of this growing concern, psychologists and psychiatrists are actively seeking new ways to improve the diagnosis and treatment of these mental health issues. The Institute for Health Metrics and Evaluation (IHME) data on the Global Burden of Disease in 2019 highlights that the prevalence of depression and anxiety exceeded that of other mental disorders [11]. Figure 1 provides a visual representation of this trend.

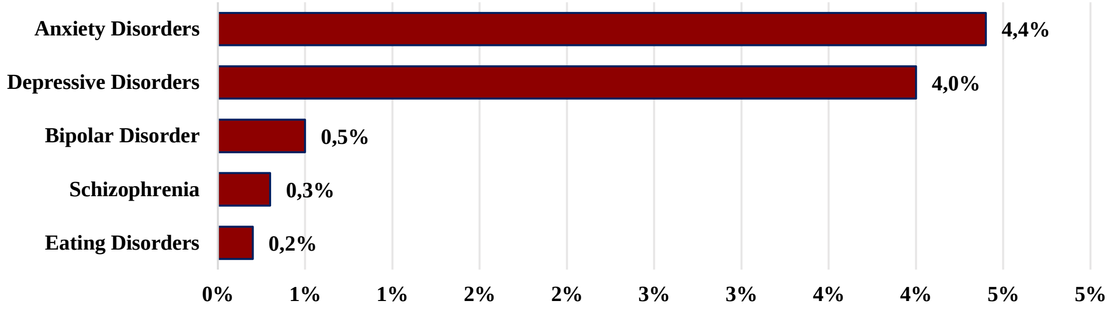

Figure 1. The prevalence of predominant mental illnesses

Research indicates that 34% of adolescents worldwide, aged 10 to 19 years, are at risk of developing clinical depression [12]. Moreover, The American Psychological Association (APA) has reported a significant increase in the trend of major depression among young people and adolescents [13]. Figure 2 illustrates the percentage of individuals who experienced anxiety or depression for the first time, which hindered them from continuing their regular daily activities [14].

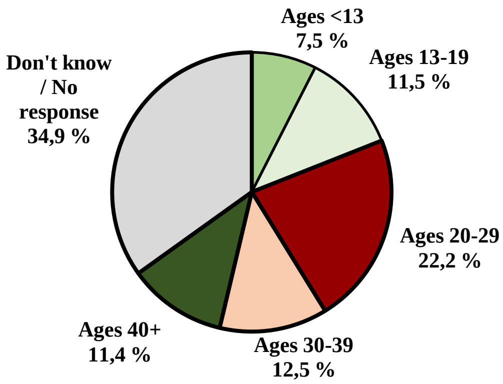

Figure 2. The global percentage of individuals who first experienced anxiety or depression affected their daily activities

Depression and anxiety are not just considered significant mental health problems, but they are also seen as possible symptoms before they are associated with other disorders and dysfunctions, including attention deficit hyperactivity disorder (ADHD), insomnia, substance abuse, suicidal thoughts, and eating disorders that can lead to problems like obesity [15], [16], [17], [18], [19], [20]. Furthermore, these conditions can exacerbate learning difficulties, hinder career advancement, and compromise psychological well-being [21], [22]. Consequently, timely identification of these disorders is vital and is a fundamental first step in tackling and enhancing society's overall health and well-being. According to the data provided by The Gallup Organization Ltd, illustrated in Figure 3-A and Figure 3-B, the prevalence of severe and chronic anxiety or depression presents a significant and pervasive issue on a global scale [23]. This figure illustrates that mental health issues are a significant and global problem affecting individuals regardless of their race, nationality, or beliefs. Many countries are grappling with this fundamental issue, and there is a pressing need for more accessible platforms to help people identify their mental health conditions.

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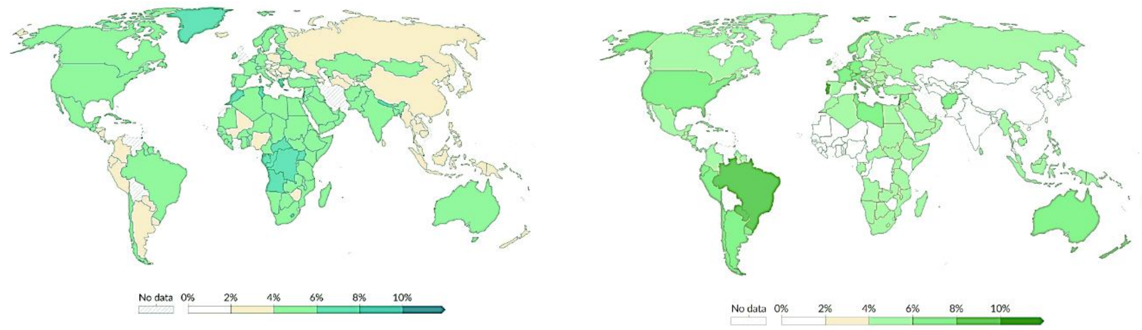

Figure 3. The worldwide distribution of depression (A) and anxiety (B)

The primary method for evaluating psychological states typically involves using questionnaires and interviews, during which individuals provide self-reports regarding their mental well-being and behaviors. Although this method is still common, there's a growing interest among computer scientists and psychologists in finding new ways to automate the assessment process. This change is motivated by the drawbacks of self-reporting, which can give rise to several issues, such as:

- **Lack of Clear Choices:** Some surveys force individuals to make binary choices, as seen in some Myers–Briggs Type Indicator (MBTI) assessments [24]. This inflexible format can be challenging as people may feel torn between options, influenced by their surroundings, or changes in mood [25].
- **Limited Self-understanding:** People's self-perception can differ from how others see them. For instance, an individual labeled as "happy" or "calm" may not recognize this characteristic, suggesting a lack of self-awareness [26].
- **Bias in Presentation:** In environments such as job interviews where evaluations are crucial, people may often feel compelled to conceal their authentic selves and present an idealized image instead; for instance, they may avoid showing their depression and anxiety in order to get a job as an airplane pilot. This inclination to showcase a favorable persona can lead to a distorted portrayal stemming from a fear of scrutiny or potential embarrassment [26], [27].
- **Boredom and Fatigue:** Long surveys can potentially overwhelm participants with many questions, leading to respondent frustration and generating rushed or arbitrary responses. As a result, this diminishes the accuracy and reliability of the assessment [27].
- **Limitations in speaking about DA:** In many cultures, freely discussing DA is hindered by societal barriers such as gender biases or cultural taboos. Figure 4 shows how individuals in certain countries or categories struggle to share information about their experiences with DA [23].

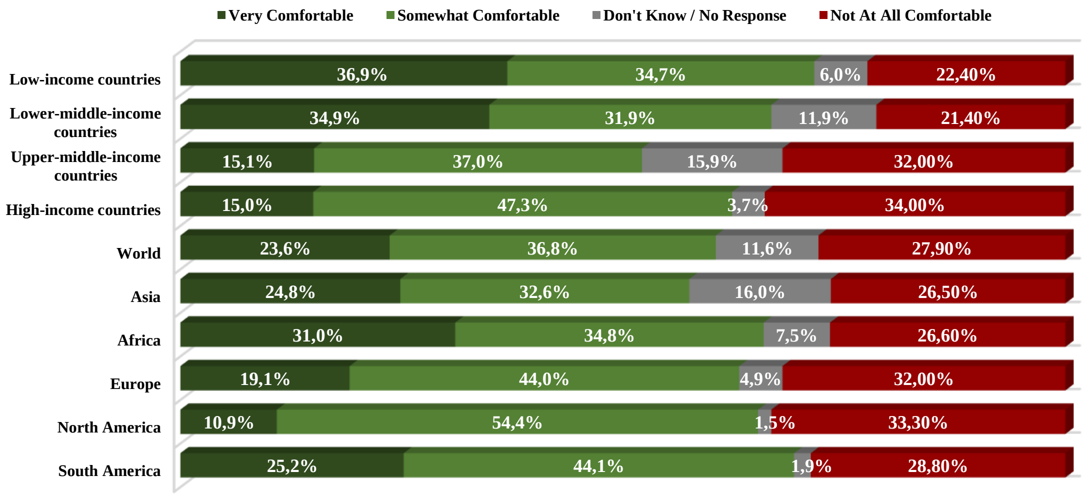

Figure 4. The result of a survey that was taken from people in about their comfort level in openly discussing feelings about DA.

Researchers have proposed various alternative methods to address the limitations of traditional self-reporting assessments. These include behavioral monitoring, analysis of social media activities, examination of preferences, and the use of game-based assessments (GBAs) [28], [29], [30], [31]. Indirect approaches have shown promise in providing valuable insights into an individual's psychological traits, personality, and underlying issues, offering a potential solution to the challenges of self-reporting. Serious games and gamification elements have found diverse and impactful applications. For instance, ReWIND, a serious role-playing game, is an example of how game elements can help mitigate and decrease psychological problems, such as reducing anxiety levels [32]. Furthermore, serious games and gamification techniques have been employed for personality assessment and offering personalized recommendations, cognitive enhancement, physical and sports activities, and maintaining the player's motivation as well as the exploration of psychological patterns [33], [34], [35], [36]. In our recent studies [28], [37], we introduced a multi-genre game and used statistical inference to detect DA and psychological patterns, yielding promising results that aligned well with established psychological definitions.

In this paper, our goal is to utilize a more extensive player base and various data science methods to showcase how games can be used indirectly to gauge and predict individuals' levels of DA. Using games as assessment tools, we can collect broader data samples from participants over an extended period. This enables us to gain more comprehensive insights into these psychological phenomena, unlike the limited scope of conventional questionnaires. Furthermore, our approach involves placing players in scenarios that require them to respond and make decisions to overcome challenges. This not only enhances the robustness of the evaluation process but also mirrors their real-life behaviors and cognitive processes. Moreover, this approach not only seeks to improve the accuracy of mental health assessments but also aims to make evaluations more accessible and engaging for individuals who may be reluctant to seek help through conventional means. Ultimately, this research aspires to contribute to the development of effective tools for early identification and intervention in mental health issues, thereby enhancing overall societal well-being. The research questions we want to answer in this paper are presented below:

- How can gameplay data be effectively utilized to predict levels of depression and anxiety in players?
- What specific gameplay behaviors are most indicative of mental health status, and how do they differ between individuals with and without depression or anxiety? How do players' emotional responses during gameplay correlate with their reported levels of depression and anxiety?

- In what ways can serious games be designed to enhance the accuracy of mental health assessments compared to traditional self-reporting methods?

2. Related Works

A biomarker is a measurable indicator of some state or condition that can be detected, monitored, and reproduced during laboratory and scientific evaluations. Research has been exploring the potential use of data from commercial off-the-shelf digital games as digital biomarkers for assessing and modeling mental health and health decline. The argument is that natural interactions with digital games can offer valuable data, identifying five categories of digital biomarkers: behavior, cognitive performance, motor performance, social behavior, and affect. Researchers delve into the types of gameplay-generated data, their relevance to mental health modeling, and their potential as digital biomarkers, suggesting that game data could be harnessed for population screening and prevalence estimations, providing a non-intrusive method for assessing mental health at scale [38].

To examine previous studies on identifying DA and other psychological facets, research is categorized according to the methods utilized. One standard methodology involves employing statistical analysis techniques to characterize and understand how games can differentiate between various psychological aspects [39]. For instance, Mandryk and Birk [40] explored the relationship between gaming activity and well-being indicators using statistical inference techniques and Beck Depression Inventory (BDI-II) questionnaires, finding that play frequency and platform preferences were associated with depression scores, and platform preference were linked to anxiety levels. [28] suggest using games to identify behavioral patterns associated with DA, using statistical tools like correlation, linear regression, ANOVA, and others, and demonstrating significant links between game-related parameters and DA.

Moreover, gamified questionnaires with text-based games or role-play models can make assessments enjoyable and reduce self-reporting issues [41], [42]. Advanced techniques like machine learning develop predictive models for evaluating mental health, reducing assessment time and the potential for cheating. Common methods include SVM, logistic regression, random forests, decision trees, and neural networks [43]. Aggarwal and Goyal [44] developed a system combining game and player data with self-esteem measures, showing the Decision Tree classifier achieved 84.71% accuracy. Salmani et al. [45] found the KNN model achieved the highest accuracy in a study on serious games. Vaanathy et al. [46] applied machine learning to predict DA, with SVM achieving 93.48% accuracy for depression and KNN 91.44% for anxiety.

Other notable studies include Heller et al. [47], which used gameplay data to create diagnostic models for ADHD and DA. The developed models showed high accuracy in predicting ADHD diagnoses based on gameplay, with F-measure values of 78% for the inattentive type and 75% for the combined type. Additionally, the models demonstrated accuracies of 71% for anxiety disorders and 76% for depressive disorders when compared against diagnoses by child/adolescent psychiatrists. Some Research conducted in this field in 2015 and 2017 demonstrated that SVM achieved about 70% accuracy, and a separate study in 2017 focusing on depression identification reported an SVM accuracy of 79% [43].

Aggarwal et al. [48] used machine learning on PUBG player data, predicting ADHD and GAD with 81.81% and 84.9% accuracy, respectively. Li et al. [49] introduced using pupil-wave signals in VR to assess DA, achieving better performance than other methods. Voinescu et al. [50] showed that VR-based tests effectively predicted DA symptoms. Finally, Maskeliūnas et al. [51] used EEG, ECG, EMG, gaze tracking, and physical activity monitoring to improve assessment results.

One of the recent works presents a validation study of a psychometric test incorporated within a video game aimed at assessing executive functions in children aged 5 to 12. Employing contemporary psychometric techniques, the research evaluates the test's reliability and factor structure using methods such as Cronbach's Alpha and Exploratory Factor Analysis. The results demonstrate good internal consistency and support a two-factor model fit. These findings underscore the significance of gameplay testing for enhancing the efficacy of the assessment tool, enabling modifications to improve reliability. This methodology provides valuable insights for developers of serious games in creating and validating educational measurement instruments [52].

3. Methods and Material

3.1 Game Design

As part of our research, we have crafted a multi-genre mobile game using the Unity game engine. This game has three unique gameplay experiences: memory-based challenges, survival shooter game, and graph traversal, all designed for mobile devices.

In the memory-based game, the player is presented with a grid of numbered cards for just five seconds to memorize (Figure 5-A). Once the time is up, the cards flip over, and the player must then recall the numbers and locations to match pairs through trial and error (Figure 5-B). To intensify the challenge, we incorporated a countdown timer to encourage quick thinking and evaluated players' performance in different difficulty levels, ranging from easy to complex. The difficulty level is determined by the number of cards and the time allowed for their matching. We selected this game concept based on research findings indicating that individuals with depression often struggle with short-term memory issues [53], [54].

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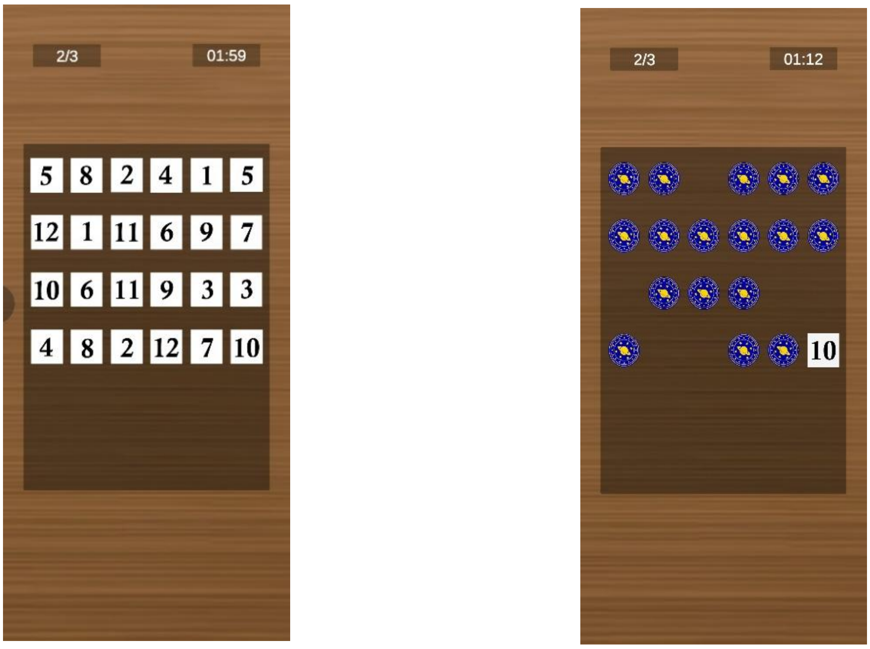

Figure 5. A) Five seconds are allotted to memorize the numbers B) Players make guesses and try to remember the matching card pairs before the time runs out.

We selected the survival shooter genre for our study due to its fast-paced, high-pressure gameplay, which presents an ideal setting to examine the effects of depression and anxiety on players. This genre allows us to observe how individuals with these conditions navigate stressful situations, make quick decisions, and adapt to unpredictable changes compared to those without [28], [55]. Additionally, the survival shooter genre frequently incorporates elements of unpredictability and sudden changes in gameplay dynamics. This feature allows us to assess how individuals with DA adapt to unexpected situations and shifts in their environment, mirroring real-life scenarios that demand flexibility and adaptability. In this game, players maneuver a spaceship by tilting their mobile device left or right and tapping the screen to shoot. The goal is to endure for 180 seconds to achieve victory successfully. Furthermore, three lives are granted to mitigate the intensity of the game. If players fail three times, they have the option to surrender, as in the other games we mentioned. Figure 6 shows a view of this game.

The design of our game aims to maintain a balance between challenge and manageability, ensuring that the stress experienced is not overwhelming; mostly regarding the time objective to survive, this game was specially designed in order not to be both easy and hard to achieve those players could overcome after several tries. Moreover, excessive violence did not exist in our game; there are simple animations for explosions, and we do not show harmful details. By incorporating specific design elements, such as minimizing graphic violence and allowing players the autonomy to stop playing at any time, we aim to create an engaging experience that fosters positive emotional regulation rather than exacerbating mental health issues by putting enormous pressure on players.

Figure 6. A view of our shooter survival game includes enemies, perks, and asteroids.

The next game presents a unique challenge that involves exploring all the nodes on a graph, beginning from a specified starting node. This game operates under a set of special rules that add complexity and strategy to the gameplay. For instance, when a player chooses a direction to move in, the game automatically visits all possible nodes in that direction until the player encounters a cell that blocks further movement. Additionally, once a cell has been visited, it transforms into an inaccessible block, preventing the player from revisiting it. In some levels where there are two starting points, the game becomes even more challenging. Both nodes move simultaneously when a command is issued, requiring the player to strategize carefully to avoid obstacles and navigate the graph efficiently. To provide a clearer understanding of the game dynamics, we have included visual representations of two different levels in Figure 7. The primary objective of the game is to discover a path that successfully navigates through all the nodes while adhering to the constraints imposed by the game's rules. This must be accomplished within a given timeframe, adding an element of urgency and excitement to the gameplay. Players must employ strategic thinking and quick decision-making to overcome the challenges presented by the game's unique mechanics and constraints.

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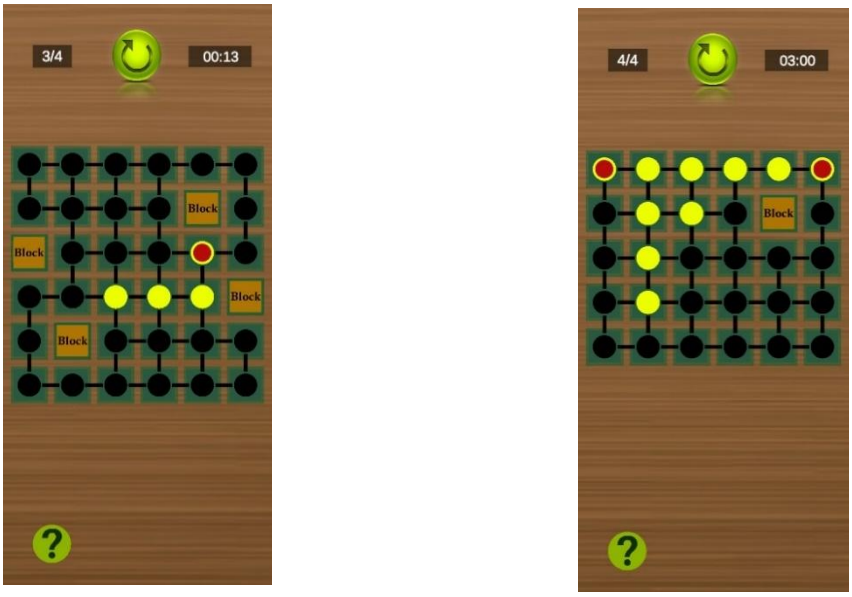

Figure 7. Two distinct levels in the graph traverser game: Level A has one starting point, while Level B has two starting points.

In our game design, we incorporated a feature specifically aimed at testing players' tendency to give up easily. After the timer runs out, players are presented with an option: they can choose to keep playing and continue their efforts, or they can use a "give up" button to proceed directly to the next level. By providing players with this choice, we aim to understand their choice for perseverance or their tendency to avoid challenging situations [56], [57], [58]. In all of our games, players are given the option to either view the tutorial before starting games or to dive directly into the game and gain experience through trial and error. We have incorporated this feature to establish a distinct differentiation between individuals with and without depression or anxiety. This approach allows us to observe how players with different levels of DA behave when presented with the choice to seek guidance or to learn by doing. Figure 8 illustrates this approach, showcasing the tutorial for the graph traverser game.

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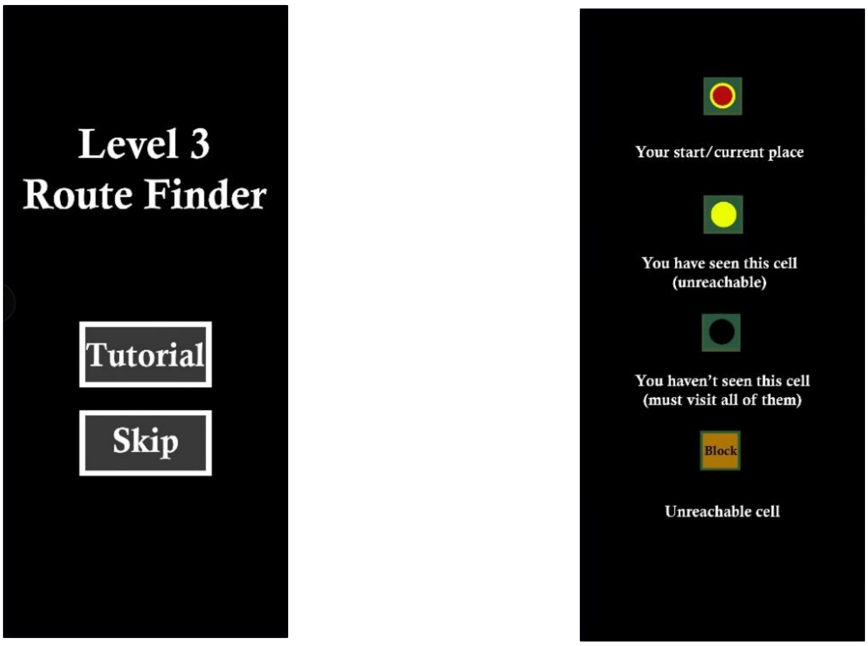

Figure 8. The tutorial of the graph traverser game.

3.2 Data

In our experiment, we had a total of 83 individuals participated. In this study, we randomly assigned half of the participants to complete the DA questionnaires first, followed by playing the game, while the other half began with the game and then completed the questionnaires. This approach was implemented to minimize biases. Furthermore, all participants were informed that they were part of a research experiment and had the option to share their data with us or decline. Upon completion of the game, each player was given the choice to transmit their data to our server. This was done by providing them with a "send" button, which they could click if they wished to share their data. In the end, 64 participants decided to send their gameplay log data to us and provided their formal consent through the research form for the utilization of their data in this experiment. Additionally, they completed the BDI-II and Beck Anxiety Inventory (BAI). These inventories are among the most globally recognized tools for identifying depression and anxiety [59]. These assessments comprise a total of 42 questions, with 21 questions addressing each disorder. Respondents are required to select from multiple-choice options, each assigned a rating from zero to three. These questionnaires are tailored for individuals aged 13 to 80 [60]. The list of 21 signs considered for each Beck Depression and Anxiety assessment is outlined in Table 1 and Table 2. At the conclusion of the experiment, participants were offered the option to receive their results privately via email. The email contains a disclaimer indicating that the results obtained from the application of the BAI and the BDI-II are solely for experimental purposes. We strongly advise that individuals seek consultation with a qualified health professional for more accurate diagnoses, should it be necessary.

Table 1. The symptoms investigated in the BDI-II Questionnaires

BDI-II	
Sadness	Loss of Interest
Pessimism	Indecisiveness
Past Failure	Worthlessness
Loss of Pleasure	Loss of Energy
Guilty Feelings	Changes in Sleeping Pattern
Punishment Feelings	Irritability
Self-Dislike	Changes in Appetite
Self-Criticalness,	Concentration Difficulty
Suicidal Thoughts or Wishes	Tiredness or Fatigue
Crying	Loss of Interest in Sex
Agitation	

Table 2. The symptoms investigated in the BAI Questionnaires

BAI	
Hands trembling	Numbness or tingling
Shaky	Feeling hot
Fear of losing control	Wobbliness in legs
Difficulty breathing	Unable to relax
Fear of dying	Fear of the worst happening
Scared	Dizzy or lightheaded
Indigestion/discomfort in the abdomen	Heart pounding or racing
Faint	Unsteady
Face flushed	Terrified
Sweating (not due to heat)	Nervous
Feelings of choking	

The BDI-II and BAI scores can range from zero to 63, with higher scores indicating a more severe condition. Some studies have suggested dividing individuals into four distinct groups based on their scores to categorize them. The cut-off scores for BDI-II are shown in Figure 9-

A, and those for BAI are available in Figure 9-B. The threshold illustrated in these two figures is derived from the standard cut-off recommended by prior research efforts [60], [61], [62], [63].

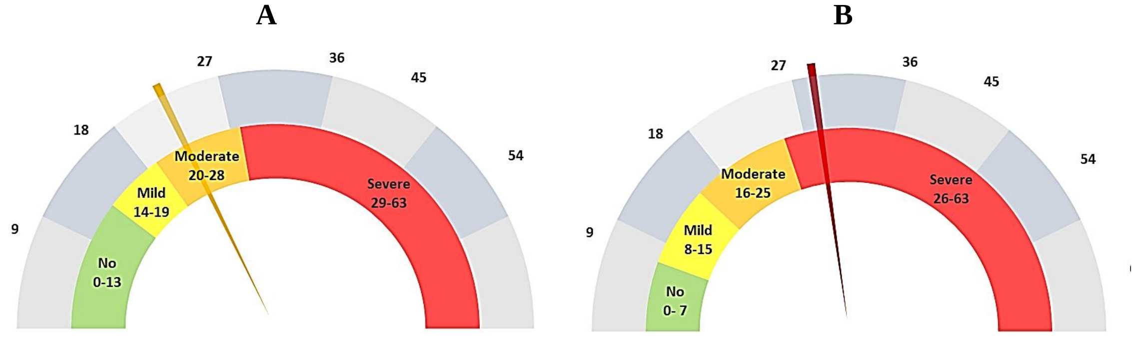

Figure 9. The standardized cutoff scores of BDI-II (A) and BAI (B)

Prior to conducting this experiment, we followed several steps to ensure the accuracy of our games and experiments. Initially, we carried out a trial test at the E-learning and Multiagent Laboratory of the University of Tehran. In this phase, we had a total of 15 participants. We utilized their feedback and data analysis to refine our work, address any bugs, and select more effective games for our experiment. The subsequent phase was thoroughly outlined in our previous paper [28], where we employed comprehensive statistical analysis to identify significant differences and trends that provide a scientific foundation for this study. For this experiment, we selected our participants from the higher education students of the University of Tehran and IT departments of Sapco company, representing a diverse age range from 19 to 63 years. In this sample, older individuals show greater susceptibility to DA, as illustrated in Figure 10.

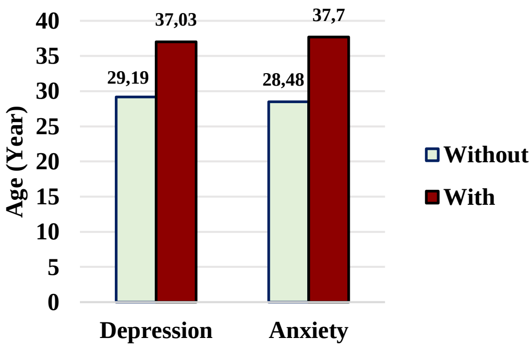

Figure 10. The average age of people with and without DA in this sample

Based on the standard cut-offs we demonstrated in Figure 9, We decided to categorize individuals into two groups based on the sample size for our classification purpose. According to the thresholds, individuals with "No" or "Mild" levels of disorder (scoring below 20 on the BDI-II and below 16 on the BAI) are considered to be without disorders, and those with scores in the "Moderate" to "Severe" range are placed in the disorder group. Notably, some of the demographics related to our experiment are shown in Table 3. Based on this table, individuals with and without DA are nearly balanced, which mitigates issues such as class imbalance and its effects on machine learning algorithms.

Table 3. Demographics of Our Players

Category	Subcategory	Count	Percentage (%)	Category	Subcategory	Count	Percentage (%)
Field of Work	Computer Related	28	43.75	**Prefered Game Device**	PC	25	39.06
					Mobile	29	45.31
	Other Fields	36	56.25		Console and Other	10	15.63
Occupation	Students	35	54.69	**Weekly Playtime (H/W)**	More than 7	15	23.44
	Workers	29	45.31		1 to 7	43	67.19
					Not Playing	6	9.38
Gender	Female	19	29.69	**DA**	With	31	48.44
	Male	45	70.31		Without	33	51.56

The data we extracted from the log files, a combination of JSON and text-based description format, yielded approximately 127 features or columns. This extensive dataset allowed us to conduct a thorough analysis and explore the rich information contained within the logs of the player's behavior during our experiment

3.3 Model Selection

We have performed a binary classification task to differentiate individuals with and without high levels of DA disorders. To gain a deeper understanding of this condition, we carried out distinct model selection processes for depression and anxiety. Our primary goal was to pinpoint the most robust and distinctive models. In our pursuit of machine learning, we have utilized a wide range of techniques to identify the most effective ones for predicting players' DA conditions. This involved not only the algorithms previously used but also additional techniques that we believed held promise for our research. By taking this comprehensive approach, we were able to explore a wide range of machine learning capabilities and ensure the identification of the most accurate and reliable models for predicting the presence or absence of DA among the individuals in our study. The selected models include:

- Linear Discriminant Analysis (LDA) Classifier
- Nu Support Vector Classification (NuSVC)
- Logistic Regression Classifier
- Random Forest Classifier
- Gradient Boosting Machine (GBM)
- Support Vector Machine (SVM)
- Multi-Layer Perceptron (MLP)
- AdaBoost Classifier
- Gaussian Naive Bayes (NB)
- Extreme Gradient Boosting (XGB) Classifier
- Extra Tree Classifier
- Decision Tree Classifier
- K-Nearest Neighbors Classifier
- Passive Aggressive Classifier

In our quest for the most powerful and efficient features, we utilized a comprehensive approach to the feature selection process. Our methodology entailed the exploration of various techniques, such as correlation-based feature selection, univariate feature selection, backward feature elimination, and tree-based feature importance, to ensure the identification of the most impactful features for our analysis. By conducting this comprehensive feature selection process, we aimed to increase the reliability and optimize the performance of our ML algorithms by identifying and incorporating the most impactful variables. We utilized a grid search approach with a wide range of alternative parameters alongside our feature selection efforts.

Furthermore, we implemented a cross-validation strategy, utilizing a five-fold train-test split. This enabled us to train our models on 80% of the data and rigorously test them on the remaining 20% in each round, ensuring a more generalized and reliable performance. By adopting this approach, we were able to learn from a larger volume of data and mitigate the risk of overfitting, ultimately delivering models with greater robustness. To assess the performance of our models, we calculated a set of metrics, including accuracy, precision, recall, and F1-score. We also leveraged confusion matrices and comparative analyses between training and testing results to identify and address potential issues, such as overfitting or other problems that could compromise the models' effectiveness.

4. Results

Upon conducting extensive research on the games and analyzing the obtained logs, we accumulated 64 tabular row records. These records were then utilized as input for machine learning algorithms to identify behavioral patterns within our data. We divided our evaluation process into two parts to ensure a comprehensive and insightful analysis. This approach allowed us to tailor our methods for each of the DA disorders, thereby enabling us to derive optimal scores based on the available data and the inherent intricacies involved in assessing human behavior and personality through indirect evaluation methods. The performance results of the most effective algorithms are presented in Table 4 for Depression and Table 5 for Anxiety.

Table 4. The result of the best algorithms for depression

Model	Accuracy	Precision	Recall (Sensitivity)	F1-score
NuSVC	93.75%	94.44%	93.75%	93.72%
Logistic Regression	87.5%	87.5%	87.5%	87.5%
LDAC	81.25%	85.00%	83.33%	81.17%
Logistic Regression	81.25%	81.74%	81.25%	81.17%
NuSVC	81.25%	86.36%	81.25%	80.56%

Table 5. The result of the best algorithms for anxiety

Model	Accuracy	Precision	Recall (Sensitivity)	F1-score
GBM	93.75%	95.45%	91.67%	93.07%
LDAC	81.25%	81.75%	81.25%	81.18%
GBM	81.25%	83.34%	85.00%	81.18%
Passive Aggressive	81.25%	88.46%	75.00%	76.81%
NuSVC	81.25%	88.46%	75.00%	76.81%

The NuSVC model demonstrated remarkable performance, achieving an accuracy of 93.75%, a precision of 94.44%, a recall of 93.75%, and an F1-score of 93.72% in identifying depression. Similarly, the GBM classifier recorded an accuracy of 93.75%, a precision of 95.45%, a recall of 93.75%, and an F1-score of 91.67% in detecting anxiety. Notably, both models exhibited a specificity of 100%. We have presented the confusion matrix for NuSVC and GBM, the most successful algorithm for predicting Depression and Anxiety, in Figure 11 to understand our model's performance thoroughly.

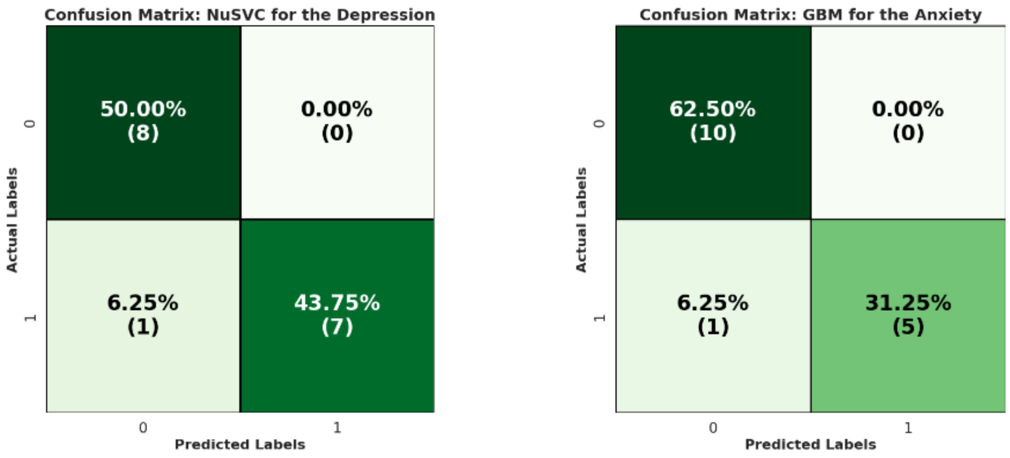

Figure 11. The confusion matrix of the best ML algorithms for Depression and Anxiety.

As per the indicated methodology, our approach encompasses a range of feature selection methods and their corresponding feature counts. Our assessment of the Random Forest feature's significance reveals varying levels of effectiveness among individual features. Figure 12-A and Figure 12-B depict the most notable features.

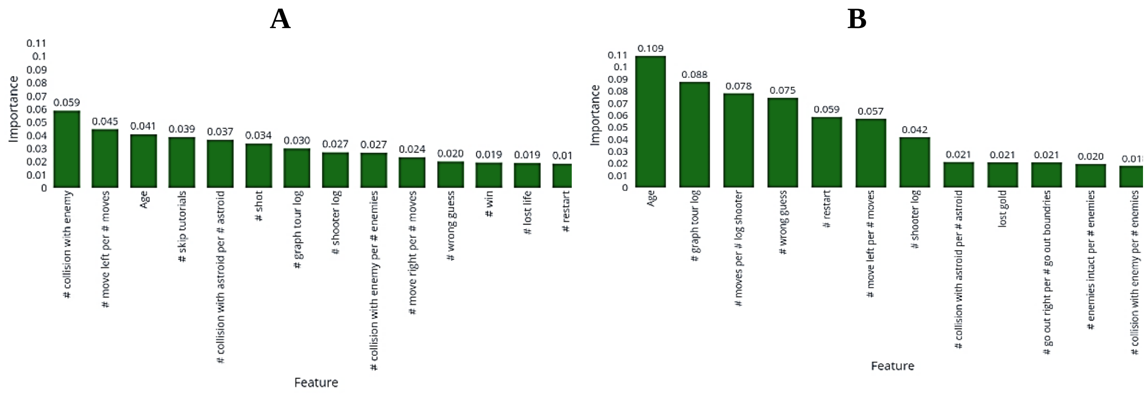

Figure 12. The Random Forest-based feature importance for Depression (A) and Anxiety (B)

It is essential to contextualize, compare, and establish a baseline to gain a comprehensive understanding of the outcomes of our research. Our examination, depicted in Table 6, juxtaposes our results with previous research endeavors relevant to our study, enabling us to discern the extent of our progress and the value added to our research objectives.

Table 6. Comparing our results with previous work

Research	D/A	Algorithm	Accuracy
Our Research	Depression	NuSVC	**93.75%**
	Anxiety	GBM	**93.75%**
[46]	Depression	SVM	**93.00%**
	Anxiety	K-NN	**91.44%**
[33]	Anxiety	DT	**84.90%**
[32]	Depression	AdaBoost, J48,	**71.00%**
	Anxiety	RandomForest	**76.00%**

5. Discussion

Our research endeavor centered around the creation of a multi-genre game designed with the primary objective of analyzing player behaviors. Through this innovative approach, we aimed to develop a model capable of accurately predicting the presence or absence of depression and anxiety (DA) among players. In our search for the most effective model, we explored a wide range of settings for our classification task. This comprehensive approach allowed us to attain promising results, enabling us to categorize individuals into two distinct groups, with or without disorder. By leveraging the power of game-based behavioral analysis, our study has taken a significant step forward in the realm of indirect mental health assessment. The insights gained from this research showed the potential to enhance the way of identifying mental health concerns, ultimately leading to more effective interventions and improved well-being for individuals struggling with depression and anxiety. To get a better understanding, we showed a summary of our method, as can be seen in Figure 13.

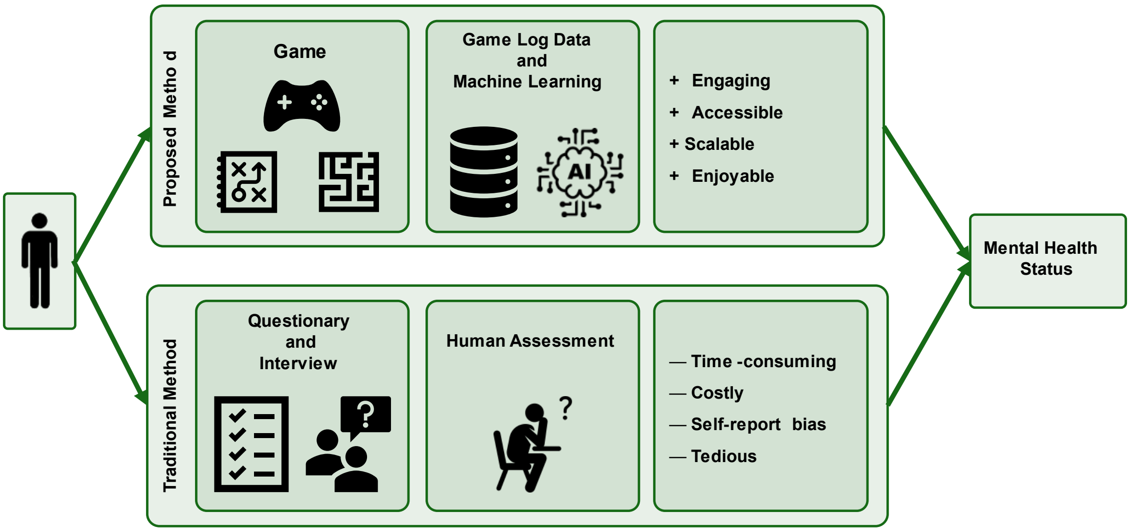

Figure 13. A summary of our Method versus the traditional approach

By delving deeper into the mechanics and design of these games, we can develop powerful tools that significantly enhance the accuracy and efficiency of evaluating mental health conditions. By making mental health assessment more accessible, engaging, and effective, we can empower people to take proactive steps towards maintaining their well-being and seeking timely interventions when necessary. This approach provides an engaging method for gathering samples over extended periods and across various moods of individuals, avoiding monotony and intrusiveness. Furthermore, it allows us to expose the participants to real-world scenarios, observe their reactions, and simulate infrequent events.

Our previous work [28] found a solid correlation and statistical difference between player behavior and the DA. Based on the results of this research endeavor, as seen in Table 3 for Depression and Table 4 for Anxiety, we achieved a promising result. Consequently, a model like the one we utilized with a considerable sample size and a game with more extended gameplay and design can be considered for experimentation as an alternative for detecting mental health disorders. Compared to previous studies, the findings listed in Table 5 mark a significant advancement in our research. To visually represent our progress, we have incorporated bar charts in Figure 14 to compare the outcomes.

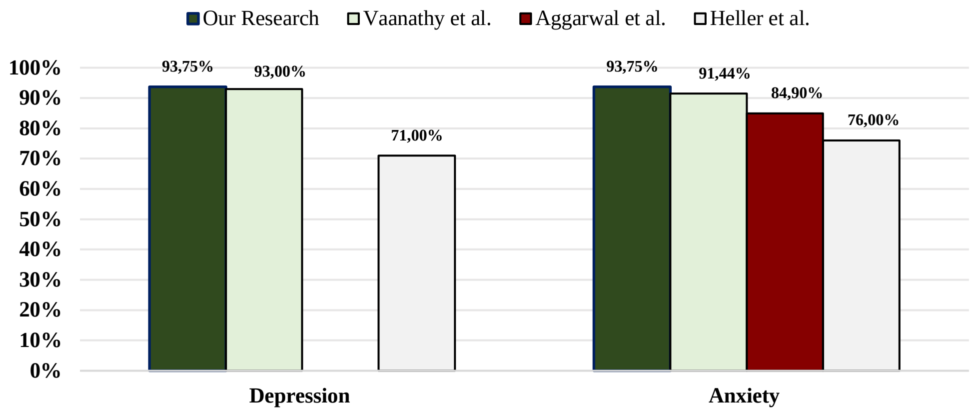

Figure 14. Comparing our results with others.

Within this realm, the absence of a reliable baseline due to the utilization of various games makes it difficult to draw accurate comparisons. Even subtle alterations in the games, including the colors employed, can potentially impact the mental states of participants, yielding divergent outcomes. Consequently, it is unreasonable to directly compare the two studies, as they do not adequately account for these variations nor sufficiently address the diverse experiences and challenges encountered by individuals across different cultures. Such comparisons may introduce biases into the analysis.

For future work, we aim to involve a more significant number of participants to re-evaluate and validate our findings. Additionally, we plan to examine our results across different game genres to enhance the robustness of our conclusions. By exploring various game genres, we can identify which types of games are most effective for psychological assessment. Furthermore, we intend to explore the potential of games in addressing a broader spectrum of psychological issues, including the detection and differentiation of individuals with Bipolar Affective Disorder (BAD), who may be susceptible to both DA [64]. Our objective for further research is to investigate the interplay between BAD and DA through our serious game approach for identification. This research is essential to overcome some of the limitations we have encountered and to refine our results.

To enhance the generalization and robustness of our model, we should consider conducting this experiment multiple times with a larger sample size and collaborating with additional psychologists and health professionals in clinical settings. This approach would help us develop a reliable diagnostic tool. It is important to acknowledge that in both our current research and prior studies [28], we focused primarily on assessing the feasibility of this method using diverse approaches, and we aimed to provide a fresh perspective on evaluating mental health. However, our current findings are limited in scope and do not yet address real-world assessment practices. As such, we recognize the need for additional demonstrations and experiments, which we have identified as a common limitation inherent in this type of research.

One important point to note is that several methods exist for identifying various aspects of mental health, including both quantitative and qualitative approaches. This paper primarily emphasizes using quantitative methods, such as questionnaires, for several reasons. Firstly, quantitative approaches provide a consistent global tool for assessing these conditions, allowing the same settings to be applied in different situations. This perspective makes our examination more robust and easier to replicate. Considering this advantage, using an expert to evaluate individuals' levels qualitatively might undermine this consistency. Secondly, we aim to develop a machine learning algorithm. Since utilizing quantitative data is more straightforward, our algorithm can effectively understand the relationship between parameters. Therefore, we have chosen to prioritize quantitative methods over qualitative ones for the time being. However, we acknowledge the importance of investigating qualitative and interview-based approaches in our future work.

6. Conclusion

This study investigated the feasibility of using artificial intelligence to monitor mental well-being and detect depression and anxiety by analyzing gameplay log data in a multi-genre game. Our findings underscore the significant potential of leveraging game-based behavioral data for mental health assessment. By involving 64 participants who completed the BDI-II and BAI and analyzing their gaming interactions, we achieved promising results indicating that machine learning algorithms and serious games may hold significant potential for the identification of mental health conditions, particularly in the area of depression and anxiety (DA). The NuSVC model achieved a 93.75% accuracy, 94.44% precision, 93.75% recall, and a 93.72% F1-score for identifying depression. Similarly, the GBM classifier attained 93.75% accuracy, 95.45% precision, 93.75% recall, and a 91.67% F1-score for detecting anxiety. These high-performance metrics highlight the robustness and reliability of our approach, suggesting that game-based behavioral data can serve as a strong indicator of mental health status.

One key advantage of our method is its unobtrusive nature. Traditional mental health assessments often rely on self-report questionnaires, which can be biased and cumbersome for individuals. In contrast, our approach leverages naturalistic data collected during gameplay, enabling continuous and passive monitoring without interrupting the user's daily activities. The practical implications of this research are far-reaching. Integrating mental health monitoring tools into gaming platforms can provide early identification and timely intervention for mental health issues. This is particularly important in today's society, where the prevalence of depression and anxiety is rising. Yet, many individuals are reluctant to seek help due to stigma or lack of access to healthcare services. Our approach can make mental health support more accessible, especially for younger populations, who are more inclined to engage with digital games. Furthermore, our method's scalability makes it a valuable tool for real-world applications. Limited resources and high demand often strain mental health services. By embedding mental health assessment algorithms into popular gaming platforms, we can extend the reach of these services to a larger audience without significantly increasing costs, alleviating the pressure on healthcare systems.

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