Machine Learning Prediction of Pokemon Go Exergame Enjoyment

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***Abstract*—Physical inactivity is on the rise, with dire consequences such as obesity and many diseases. Exergames, which try to gamify physical activity, have been demonstrated to be an effective solution. For exergames to be effectively improve health, they have to be played for extended periods of time. However, prior work has found that while many players enjoy exergames initially, they often suddenly stop playing. For instance, nearly 85% of exergame players quit after a day, and 95% within 3 months. We believe that if timepoints at which a player stops enjoying an exergame can be predicted from objective data, mitigating action such as recommending a new exergame, can be taken to sustain the user engagement. In this paper, we explored whether player enjoyment of Pokemon Go can be predicted using machine learning analyses on location, step count, game usage and session statistics and weather data. We found that Bagged trees performed best overall, predicting player Exergame Enjoyment Questionnaire (EEQ) scores with a 74% accuracy.**

***Keywords—exergame, machine learning, enjoyment prediction** (key words)*

I. Introduction

Motivation: Physical inactivity and a lack of exercise have become increasingly prevalent in modern societies. Inactivity has been linked to many conditions, including obesity, cardiovascular disease and some cancers, and is a major contributing factor to many of the major health concerns in the United States. Physical inactivity also plays a role in heart disease, high blood pressure, diabetes, metabolic syndrome, and stroke. [1]. According to the Centers for Disease Control and Prevention, less than 52 percent of Americans aged 18 and over currently meet the government's physical activity guidelines for aerobic physical activity, meaning they do not get the required 150 minutes of moderate exercise (brisk walking) and 75 minutes of intense exercise (swimming or jogging) recommended in a week. Even worse, only 22 percent of the same group meet the physical activity guidelines for both aerobic and muscle-strengthening activity [2]. Statistics for the youth population in this country are not any better. The National Youth Fitness Survey had alarming findings that only 25 percent of U.S. youth aged 12-15 performed moderate-to-vigorous physical activity for at least 60 minutes each day [3].

Exergames, or electronic games that incorporate physical activity, present an opportunity to address physical inactivity. The American College on Sports Medicine defines an exergaming as technology-driven physical activities, such as video game play, that requires participants to be physically active or exercise in order to play the game. These game-based physical activities typically involve full body motion in order to participate in virtual sports, in group fitness exercise or other interactive physical activities. [4].

Mobile exergame applications have increased. *Pokémon GO* is a popular augmented reality mobile exergame in which players interact with the real world. *Pokémon Go* has millions of users. [7] and was selected for our study due to its popularity, which made it easier to find participants who had heard of the game before. Additionally, there were more resources for those who need help with the game. In Pokémon Go, the user travels around the real world that they can view through their phone. Certain locations in the real world correspond to event triggers in the game. As players approach a location various events occur from going to catch a Pokémon by swiping to throw a poke ball at it, to getting to a poke stop where you can stock up on resources such as poke balls and eggs. While playing, the player builds up better and better resources through the acquisition of things such as better poke balls, and the user seeks to raise the level and as collect as many Pokémon as they can.

Figure 1. Screenshot of Pokemon Go

Problem: A common issue in exergaming is that users quit the game, often unpredictably. For instance, nearly 85% of exergame players quitting after a day, and 95% within 3 months [1]. We hypothesize that machine learning analyses of mobile, game session and weather data can be used to accurately predict when a Pokémon Go player stops enjoying playing it so that mitigating action such as recommending a new exergame, can be taken.

Approach: In this paper, we investigate whether machine learning can be used to predict player enjoyment of Pokémon

Go (example screenshot shown in figure 1) from location data including frequently visited locations and in-game movement statistics, weather information including temperature, wind and rainfall, step count data, Pokémon Go app usage statistics such as how many times the user opened the Pokemon Go game, game session length statistics and prior exergaming experience. To generate a dataset suitable for machine learning, we conducted a data collection study of 39 participants. During enrolment, participants installed a data collection smartphone app on their phone and filled out a pre-questionnaire with questions about their demographics, and exergaming gaming experience and habits. They then played Pokémon go for one week while the smartphone app gathered step count, movement, weather, game session and usage statistics. Participants also filled out the Exergame Enjoyment Questionnaire (EEQ) [30] to report their levels of enjoyment of Pokémon Go. Machine learning analyses steps included feature extraction, correlation-based feature selection and comparison of various machine learning algorithms for the task of binary classification of enjoyment vs. no enjoyment based on EEQ scores. We found that Bagged trees performed best overall, predicting player EEQ scores with a 74% accuracy.

Prior work has explored machine learning prediction of player enjoyment of Just Dance [29] but not Pokemon Go. Another work that had a similar objective was [23], which investigated machine learning prediction of participation and attrition in free-to-play games. The authors examined variables such as the frequency of playing games, how often players participated with others, and how often players spent money on the app, among other things. [23]. They then trained machine learning models such as decision trees, vector machines, and logistic regression. [23] to predict game participation. Finally, Zhang et al [31] proposed a deep learning model to detect the unsatisfying experiences by classifying online reviews of virtual reality exergames using a deep learning method and find out the unmet psychological needs of users based on self-determination theory. This paper focused mostly on understanding unsatisfying experiences from the text in online reviews but did not analyze step count, sensor or weather data to predict exergame enjoyment.

Challenges: Machine learning detection of user enjoyment is challenging for several reasons including the fact that exergame enjoyment may manifest slightly differently in different users, which causes intra-class variability. Moreover, enjoyment class boundaries such as between enjoying and not enjoying may not be very distinct, causing fine-grained classification challenges.

Paper organization: is as follows. Section II describes our methodology including our data gathering study, questionnaires administered, data collection and feature extraction. Section III presents our results. Section IV discusses our findings and Section V is the conclusion of the paper.

II. Methodology

A. Data gathering study

Data for machine learning analyses was collected in study 18-0092 approved by the Worcester Polytechnic Institute IRB board. During enrolment, participants downloaded a data gathering application called ExergameMonitor developed for this study and available via the Google Play Store. Using the email provided, a link was sent out to users with the option to opt in to test the final application on Android phones.

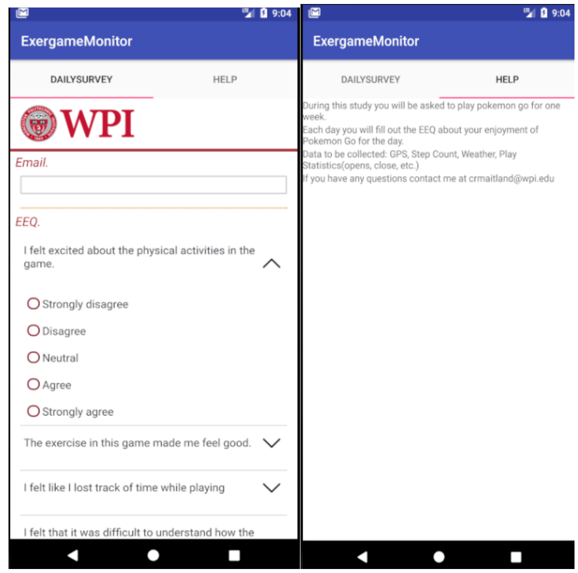

Figure 2: Screenshots of ExergameMonitor app

The ExergameMonitor application (example screenshot shown in figure 2) was written in Java and had application services broken up into the four types of data to be gathered (weather, play statistics, step count and GPS). GoogleFit was used to collect step count data while weather information was collected from OpenWeatherMap's REST API

Study participants played the game for one week. At the beginning of the week, users were asked to fill out a pre-study questionnaire. This contained information such as the participant's email, their experience level with exercise games, whether they enjoyed them or not, how much they have played them, and whether they had played Pokemon Go or other Geocaching game before. After filling out this form, the user played the exergame for one week. During this time, the user had the ExergameMonitor running. While doing so, the application collected GPS locations the player frequented and locations they visited while playing the exergame. It also recorded the temperature every hour, as well as the step count, while they played the exergame.

In addition, users filled out the Exergame Enjoyment Qualifier once a day. In this daily survey, players were asked to rate their experience playing the exergame on that day. This survey featured a Likert- based scale, where values are weighted with a score of 1 to 5, with one being "strongly disagree" and 5 being "strongly agree." A week after the initial survey was completed, the application communicated that the study was complete. After this point, machine learning was employed using classifiers to evaluate the enjoyment level of a participant.

B. Pre-questionnaire

The pre-questionnaire was used to collect information's on the demographics that would participate in the study. This asked which address they wanted to use so that we could establish their home location for GPS, as well as demographics questions. The pre-questionnaire is shown in table 1.

Table 1 Pre-Questionnaire

What is your Gender?
What is your Age?
What address would you like to be your home?
How much exercise would you say you get in a typical week?
Have you ever played a video game?
Have you ever played a game on your phone?
Do you consider yourself to have played an exercise game?
Have you played *PokemonGO*?
If you have, how long did you play?

C. Exergame Enjoyment Questionnaire (EEQ)

To quantify and compare player Pokemon Go enjoyment, study participants completed the Exergame Enjoyment Qualifier (EEQ) [30] at the end of each day. The EEQ is the first questionnaire specifically developed to assess and monitor exergame enjoyment. The EEQ combines elements of well-known and widely used questionnaires to assess physical activity enjoyment (i.e., PACES) and gameplay (i.e., Game Engagement Questionnaire (GEeQ), Game Experience Questionnaire (GExQ), and Immersive Experience Questionnaire (IEQ)) and adds new elements that are specifically relevant for exergaming. Using a Likert scale, as specified in the original EEQ questionnaire, each response to the EEQ's questions is given a score of 1 to 5, where for some questions, a 1 corresponded to highly agree while a score of 5 indicated disagreement. The Likert scale was reversed for other questions. All participants' responses were then summed to arrive at a total value of the responses. Table 2 shows the questions on the EEQ and response values.

Table 2 Exergame Enjoyment Questionnaire

Question	Response Values
I felt excited about the physical activities in the game.	1-2-3-4-5
The exercise in this game made me feel good.	1-2-3-4-5
I felt like I lost track of time while playing	1-2-3-4-5
I felt that it was difficult to understand how the game works.	5-4-3-2-1
I was focused on the game.	1-2-3-4-5
I felt that the game would have been more enjoyable without physical activity.	5-4-3-2-1
I felt that it was easy to familiarize myself with the game controls.	1-2-3-4-5
I felt emotionally attached to the game.	1-2-3-4-5
I consider playing the game "exercise."	1-2-3-4-5
I felt that the physical activity was too intense for me.	5-4-3-2-1
I did not feel a desire to make progress in the game.	5-4-3-2-1
I felt a strong sense of being in the world of the game to the point that I was unaware of my surroundings	1-2-3-4-5
I would rather not be exercising, even though the exercise was accompanied by game elements.	5-4-3-2-1
I felt that playing the game was beneficial for my physical well-being.	1-2-3-4-5
I felt that this game provided an enjoyable challenge.	1-2-3-4-5
I felt a sense of accomplishment from playing the game.	1-2-3-4-5
I felt that the game reacted quickly to my actions.	1-2-3-4-5
.I did not feel like I wanted to keep playing.	5-4-3-2-1
I would prefer that this physical activity was not accompanied by game elements.	5-4-3-2-1
I felt in control of the game.	1-2-3-4-5

D. Objective data collected during our study

GPS data was collected from the user's smartphone and used to determine the user's location and calculate movement statistics. The second piece of data was weather data collected from OpenWeatherMap, this returns numerous features such as wind, temperature, and rainfall. These were important pieces of information, because when talking about outdoor activities, weather can largely influence what happens. Precipitation can be reason for event cancellations and humidity and temperature are things which can highly effect how one exercises. The third piece of data was step count, provided by GoogleFit, and the final data stream was Pokémon Go usage data.

E. Features extracted

Several features believed to be predictive of player enjoyment and engagement with the game, were extracted including:

Step count features:
1. Step count while playing the exergame
2. Step count the day of the exergame

Weather features:
3. Average temperature the day of the exergame
4. Average humidity level on the day of the exergame
5. Average precipitation on the day of the exergame
6. Average wind conditions on the day of the exergame

Pokemon Go app usage features:
7. Earliest time the application was opened
8. Latest time the application was opened
9. Average lag time between exergame sessions
10. Number of times the application was started

Movement features
11. Distance traveled while playing the exergame
12. Furthest distance from home when playing the exergame

Game session statistics
13. Average length of session
14. Total time Pokemon Go was played on that day

Prior exergame experience feature:
15. Prior experience playing the exergame (response on a Likert scale)

To find distances covered, the Haversine formula is used. The Haversine formula tries to accommodate the spherical nature of the earth. The haversine formula is used to calculate the distance between two points on a sphere.

$$\mathrm{hav}\left(\frac{d}{r}\right) = \mathrm{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\,\mathrm{hav}(\lambda_2 - \lambda_1)$$

$$\mathrm{hav}(\theta) = \sin^2\left(\frac{\theta}{2}\right) = \frac{1-\cos(\theta)}{2}$$

Where φ is latitude, λ is longitude, r is radius, and d is distance between the points.

F. Participant recruitment

Study recruitment came from two primary sources: friends, and online forums and communities. Using these different populations ensured a diverse, representative pool of people. Both sources introduced participants from diverse backgrounds into the study, with different motivations for why they would play the game. Friends would be willing to go out of their way to help with the project. They most likely would play the game on their own and possibly for a longer period than other participants and not be in a hurry to finish it as quickly as possible. They might have limited knowledge of the game but would earnestly give it a try. There was also diversity within the friend group. Some friends were less motivated to participate in the study but agreed to because they were already playing the game as a company activity, and participating in the study was easy and simply expanded how they play the game. Online forums were the most interesting group to ponder. Websites such as Neoseeker and Gohub are filled with people who play the game regularly on their own time. Unlike the other two groups, these people are more diverse geographically and feature more experienced players. Other online forums used for recruitment were the WPI *Pokémon GO* group, as well as the Worcester *Pokémon GO* Discord server.

III. RESULTS

A. Participant demographics

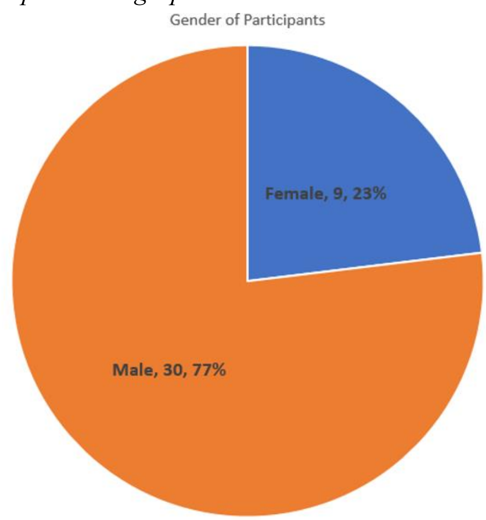

Figure 3 Gender Distribution of Participants

Figure 3 shows the distribution of gender of study participants. Of the 39 subjects who participated in this study, 9 were female and the remaining 30 were male.

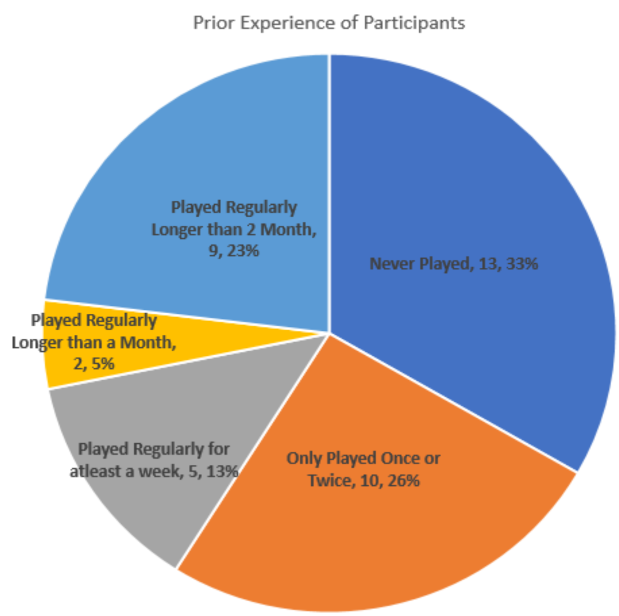

Figure 4: Prior Experience Distribution of Participants

Figure 4 shows the distribution of Exergame Experience. For this study, the majority (59%) of the participants had either never played the game before or had only played it once or twice. Included in this group, 13, or 33%, reported that they had never played the game and 10, or 26%, responded that they had played in the past, but only intermittently when they just tried it or played with a friend. 5, or 13% of participants responded that they had played the game for at least a week, while the smallest category was made up of 2 people (5%) who had played regularly for longer than a month. The largest category for regular players was made up of 9 players, representing 23% of the total group who reported playing regularly for longer than 2 months. Only broad conclusions can be drawn from the demographic data. First, most participants were not regular players of the game. Second of the 41% of players who reported they were regular players, the most (23%) reported being a regular player for more than 2 months.

B. Distribution of EEQ Scores

In theory, the possible range of EEQ scores is from 20 to 100. In the data we collected, the observed minimum was 45, with a maximum of 90. The observed mean demonstrated by our sample was around 71 as shown in figure 5.

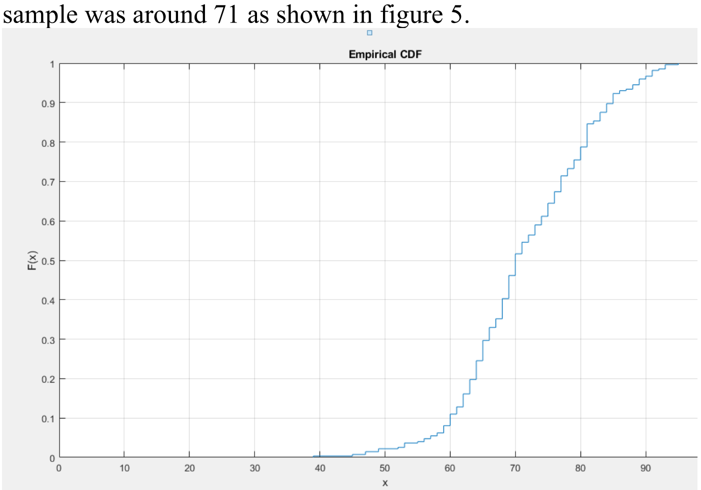

Figure 5: EEQ Scores CDF Plot

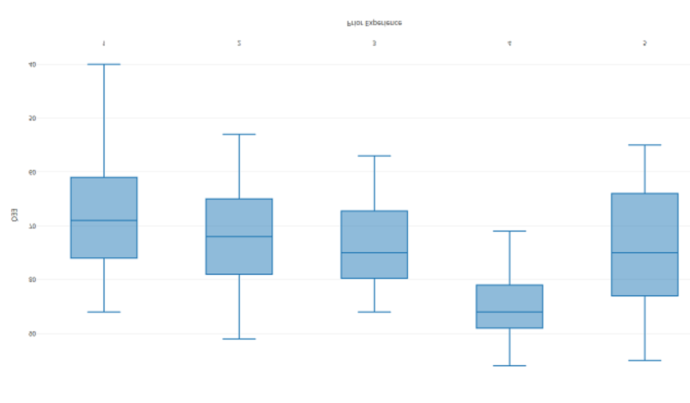

Figure 6: EEQ vs. Prior Experience

It is interesting to observe the relationship between the prior experience of participants and how they answer the EEQ as shown in figure 6. The mean EEQ of those who responded they had played for at least a month was 77, the highest EEQ. This makes sense, since a higher EEQ signifies enjoyment of the game and it makes sense that the more a player enjoys the game, the more likely he or she would play it regularly. It is also interesting to compare the medians for each category of regularity of play. In figure 6, we can see that as the experience of play increases, so too did the median EEQ. The only exception was in the jump to over 2 months played.

C. Player Step Count Distribution

In our data, the mean daily step count was 5,559.5. The data showed two peaks: participants who were less active and players who were highly active. The low activity users tended to hover below the 5,000-step mark, sometimes going over it. On the other hand, the high activity users achieved a little over 7,000 steps a day. Very infrequently the data showed players exceeding the 10,000 steps a day that are commonly recommended for a healthy lifestyle.

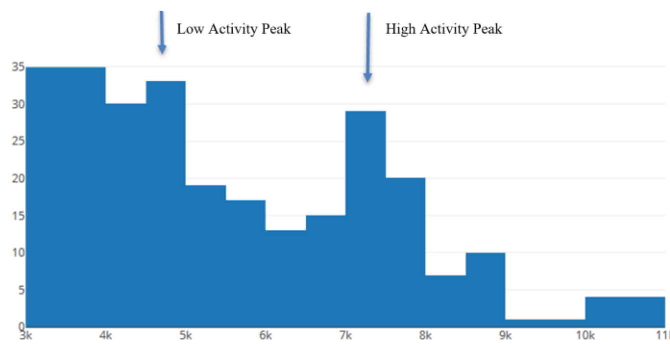

Figure 7: Daily Total Step Count

D. Feature statistics

Table 3 shows the distribution of all the statistics.

Table 3: Feature Statistics

Feature	Mean	Median	Standard Deviation
EEQ	72.0476	72	10.3042
Daily Total Steps	5595.2124	5181	1881.3048
Playing Steps	1389.2527	1265	679.7110
Distance Traveled	0.2064	0.016	0.2978
Distance Traveled From Home	0.3242	0.31	0.1129
Temperature	46.2868	41	12.2171

Precipitation	0.0732	0	0.3757
Wind	7.7271	8.1	5.8683
Humidity	55.4835	60	12.0213
Times App Opened	13.8095	14	3.0503
Time Played (mins)	72.9871	73.14	12.2478
Average Session Length (mins)	19.6520	20	2.9895
Earliest Open	10.2733	10.2982	0.9496
Latest Close	19.2417	19.2556	1.1461
Average Lag Time	178.4018	194.0182	27.8192

E. Correlation-based Feature selection

To determine which of these features are relevant, we utilized the P value derived from using the t-test. The cap on those values which are believed to be statistically significant is .05. Features with values lower than this are considered statistically significant, which means that they can predict the EEQ, while those with higher values than this are not and, thus, cannot be used to predict the EEQ.

Table 4: Feature Correlation to Exergame Enjoyment Score

Feature	P Value	Correlation Coefficient
Daily Total Steps	<.00001	-.6153
Playing Steps	<.00001	.5512
Distance Traveled	<.00001	.5654
Distance Traveled From Home	<.00001	.4451
Prior Experience	<.00001	.7012
Time Played	<.00001	.2318
Times App Opened	.02830	.6889.
Average Session Length	.04210	.2481
Latest Close	.17820	-.4210
Average Lag Time	.3162	-.2132
Earliest Open	.3817	.0041
Precipitation	.20173	-.1386
Temperature	.49377	.1937
Wind	.88421	-.0701
Humidity	.96650	.0083

F. Machine Learning Classification

Data pre-processing: To classify participants' EEQ scores 100 into enjoyment vs. not enjoying bins, it was necessary to divide EEQ scores, which ranged between 20 and 100 into 2 bins. We explored various binning approaches shown in table 5 below.

Table 5: Bins explored

Bins Used	
Mean	0-71, 71-100
Median	0-72, 72-100
Bin 20	0-20, 20-40, 40-60, etc.
Bin 10	0-10, 10-20, 30-40, etc.
Bin 5	0-5, 5-10, 10-15, 15-20, etc.

Median Bin		
Classification Model	Correctly Classified	Kappa Statistic
Fine Tree	61.2%	0.2240
Course Tree	63.4%	0.2605
Linear Discriminant	50.9%	0.0120
Linear SVM	52.0%	0.0316
Quadratic SVM	53.5%	0.0656.
Cubic SVM	57.5%	0.1483
Fine Gaussian SVM	55.7%	0.0931
Fine KNN	49.8%	-0.0062
Course KNN	52.0%	0.0234
Boosted Trees	61.9%	0.2360
Bagged Trees	62.3%	0.2449

Table 6: Classification results for various binning strategies

Mean Bin		
Classification Model	Correctly Classified	Kappa Statistic

Fine Tree	63.7%	0.2646
Course Tree	65.9%	0.3115
Linear Discriminant	57.5%	0.1183
Linear SVM	54.2%	0.0523
Quadratic SVM	59.7%	0.1767
Cubic SVM	60.8%	0.2119
Fine Gaussian SVM	55.7%	0.0431
Fine KNN	58.6%	0.1374
Course KNN	54.6%	-0.0181
Boosted Trees	64.8%	0.2802
Bagged Trees	66.3%	0.3149

Bin size 20		
Classification Model	Correctly Classified	Kappa Statistic
Fine Tree	65.2%	0.1899
Course Tree	71.8%	0.2235
Linear Discriminant	72.5%	.1494
Linear SVM	72.9%	0
Quadratic SVM	71.1%	.1648
Cubic SVM	58.6%	.0321
Fine Gaussian SVM	72.5%	-.0066
Fine KNN	57.5%	-.0584
Course KNN	72.9%	0
Boosted Trees	73.6%	.2789
Bagged Trees	74.4%	.2602

Table 6 shows the classification results for various binning strategies. Bagged Trees is the best performing machine learning classifier for users' enjoyment of the game. It achieved the highest percentage of accurate classifications of any of the classifiers for both the mean, median, and bin size of 20. It peaked in accuracy with a bin size of 20, giving it a correct classification rate of 74.4%.

IV. DISCUSSION

A. *Best performing machine learning classification algorithm*

Bagged trees performed best in classifying the data under multiple scenarios. With bins split around the mean, median, and with bin size of 20, it proved to be the most accurate classifier. Bagged trees peaked with a bin of size 20, where it could accurately predict 74.5% of the bins correctly. However, bin size also affects model performance and must be considered. With the mean and median as the cutoff for bins, the results were less accurate than with a bin of size 20. On the other hand, as the bin size decreased from 20 to 10 to 5, the results of the classifiers became more and more inaccurate. Other work on predicting enjoyment of Just Dance by Audibert et al [29] found that Naïve Bayes was the most accurate machine learning classifier type.

B. *Study Limitations*

The two main limitations of our study were:

1) *The relatively short timeframe over which individuals participated in the study (1 week):* Our study took place over a single week, which did not allow us to predict player behavior over longer periods of time. Because the purpose of the study is to impact player retention over the long term, this is certainly a limitation. Similarly, some features that were felt would be predictive do not vary much within a single week period. For example, humidity typically does not change much over one week in the winter but may affect results in the summer.
2) *The demographics of participants in our study may not be representative of the demographics of Pokémon 'go players:* Knowing the traits of all *Pokémon GO* players, such as the level of physical activity they get, would be useful to match participants and inform recruitment. It is important to recruit members who fit the target demographic for the game itself. As an extreme example, if people were recruited outside the games' target demographics, such as those with agoraphobia who would not be expected to go outside to play the game, it is hard to get data on the player base. They may rate it much lower than the average player would, and although this is valuable information, misses the general trends of users.

C. *Future Directions*

1) *Longer Duration Study*

Extending the study period to several months or one year would enable us to capture player's behavior better, especially how participants exhibit changes in behavior. This longer timeframe could better capture events such as when a user quits, and if they do quit what is the likelihood they start playing again, and if they do start playing again how is it different?

2) *Collect more data to get a representation especially lower EEQ values*

It would also be interesting to get more data on people who do not enjoy the game. During this study, the lowest EEQ score participants gave was a 45, while the theoretical EEQ score is 20. It would be interesting to explore EEQ scores in the 20-45 range.

3) Pokémon GO Gameplay Integration

It would be interesting to include features that capture Pokemon Go in-game play dynamics such as player accomplishments within the game. Part of what determines how much a player likes an exergame are the things that occur in the game. For example, it would be interesting to capture how many Pokémon the players caught, if they played with others or alone, or how often they went to the gym.

V. CONCLUSION

Physical inactivity is on the rise globally. Exergames are a promising intervention. However, many players enjoy the exergame initially but suddenly stop playing, often unpredictably. In this paper, we explored using machine learning to predict player enjoyment of Pokemon Go exergame from location, step count, weather and session statistics features. We conducted a data gathering study in which 39 participants played Pokémon go while a smartphone application recorded location, step count, movement, weather and session statistics features. We found that Bagged trees performed best overall, predicting player Exergame Enjoyment Questionnaire (EEQ) scores with a 74% accuracy. In future work, we intend to explore longer study durations, collect data from a more diverse and representative cohort and explore features extracted from in-game accomplishments.

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