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PAPER

E-Sport Engagement Prediction Using Machine Learning Classification Algorithms

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ABSTRACT

In recent years, e-sports has experienced a rapid surge in popularity, attracting a vast and diverse audience. As this industry continues to evolve, understanding and predicting e-sport engagement becomes increasingly vital for stakeholders, including game developers, tournament organizers, sponsors, and marketers. Machine learning classification algorithms offer a powerful approach to analyse and forecast user engagement in e-sports, thereby enabling the industry to tailor experiences to individual preferences and behaviours. Thus, this study investigates the level of engagement classification technique of data mining using predictive modelling operations with four different classes, namely strongly agree, either agree or disagree, disagree, and strongly disagree. Machine learning algorithms, particularly classification models, have proven to be effective in analysing large and complex datasets related to e-sport engagement. This study applies statistical techniques to categorize users based on 59 attributes of 106 instances to predict the engagement levels. By training on historical user data, six classification algorithms from two groups, namely bayes and rules, have been used to identify patterns and trends that are indicative of different engagement levels, with the accuracy ranges from 76% to 92%. For feature selection, the result shows that participating in activities, enjoying exchanging ideas, and playing with like-minded gamers were the top three ranking dimensions contributing to the level of engagement. Machine learning classification algorithms have the potential to revolutionize how e-sport engagement is understood and optimized. By analysing diverse data points and leveraging advanced predictive techniques, machine learning algorithms enable stakeholders to tailor e-sport experiences to individual preferences and behaviours, ultimately enhancing user engagement and satisfaction.

KEYWORDS

e-sport engagement, machine learning, classification algorithms, prediction, user engagement

1 INTRODUCTION

The trend of e-sports continues to grow and gain popularity, especially among the younger generations. As e-sports become more popular, understanding what

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contributes to e-sports engagement is increasingly important. Predicting e-sport interaction engagement classification using machine learning algorithms has revolutionized the way we understand and enhance gaming experiences. By leveraging advanced machine learning algorithms, we can now predict and optimize user engagement in e-sports, leading to more personalized and immersive interactions [1]. Machine learning algorithms identify and anticipate engagement levels with surprising accuracy by utilising a varied variety of data points such as demographic profile, player behaviour in terms of frequency, physical conditions, social relationships, surroundings, and user preferences. As the e-sports business evolves, machine learning for engagement categorization will surely play a critical part in determining the future of gaming, providing unmatched insights and possibilities for both players and industry stakeholders [2]. Predictive e-sport interaction engagement based on machine learning algorithms has emerged as a game-changing development in the world of online gaming. E-sport platforms may now apply advanced machine learning algorithms to anticipate user behaviours, personalise game experiences, and increase overall engagement. Machine learning can efficiently categorise user behaviours and preferences by utilising classification techniques such as decision trees, support vector machines, and neural networks, allowing for the delivery of personalized information and suggestions [3]. This novel strategy not only improves the game experience for players but also provides enormous opportunity for e-sports firms to maximise user engagement and build long-term commitment. As machine learning advances, the use of predictive analytics in e-sports requires a new age of personalized gaming interactions, ushering in a new era of personalised gaming interactions [4]. This unique strategy not only revolutionises the way gamers interact with e-sports but also increases their overall engagement by using the power of data-driven insights. As a result of the convergence of machine learning and e-sports, the gaming community is entering a new era of increased player involvement and unparalleled opportunity. This dynamic interplay of technology and enjoyment highlights the boundless possibilities of using machine learning for e-sport interaction engagement and categorization.

2 RELATED WORKS

This section discusses related works with the study of e-sport engagement as the subject of the analysis, which focuses on the classification technique of predictive modelling operations represented in a data mining environment.

2.1 E-sport engagement

Investigating factors influencing e-sport engagement provides insights into user behavior within the gaming community. Understanding why users engage or disengage helps in tailoring experiences to meet their preferences [5]. Understanding why users engage or disengage helps in tailoring experiences to meet their preferences. E-sport engagement often extends beyond gameplay to community interactions. Studying factors influencing engagement helps in fostering a sense of community, facilitating discussions, and creating a more interactive and engaging environment [6]. User retention is crucial for the long-term viability of e-sport platforms, and understanding the factors that influence engagement allows for the creation of successful retention tactics that reduce churn while keeping users actively connected [7]. Furthermore, considering the aspects that influence engagement enables personalised experiences and targeted marketing initiatives. Platforms may target certain user groups with content, promotions, and communication depending on their interests and behaviours. Based on the elements impacting engagement, e-sport platforms and stakeholders may make educated commercial decisions [8]. This involves allocating resources, developing features, and strategizing to meet user expectations. Exploring the user behaviour and optimising the game experience are both served by identifying the elements that determine the amount of e-sport participation. This research is important for the growth and sustainability of e-sports. The significance of this research extends to the growth and sustainability of the e-sports industry, providing actionable insights for stakeholders and contributing to the overall positive impact of e-sports on global entertainment and social dynamics.

The sustained growth and viability of the e-sports sector is dependent on maintaining an active and engaged user base. Factors that influence engagement are critical for long-term success. Competitive advantage is gained by e-sport systems that successfully exploit information regarding engagement elements. When compared to rivals, they may differentiate themselves by providing a greater user experience and community participation. Users who are satisfied and engaged are more likely to become loyal consumers [9]. The research of engagement variables improves user happiness by encouraging loyalty and advocacy within the gaming community. E-sports have a big societal impact because they influence how people connect and interact. Addressing the aspects that influence involvement helps to foster healthy social dynamics in the gaming community.

2.2 Factors affecting user engagement

A variety of elements, including e-sport game design, community dynamics, technology, and individual preferences, all have an impact on the amount of e-sport involvement [10]. Identifying the characteristics is critical for e-sport platforms, game developers, and the gaming community. Game design related to the quality of gameplay significantly impacts the level of e-sport engagement [11]. Moreover, e-sports games that offer a balanced and challenging experience maintain player interest and engagement. Playing with like-minded gamers can also help improve communication within a team, as everyone is on the same page. This can lead to more efficient strategies and game plans, as well as higher levels of success. In addition, playing with like-minded gamers can also create a sense of companionship or friendship within a team, which can help to build a strong team bond and create a positive environment [12]. Eventually, playing with like-minded gamers has the potential to greatly influence the level of e-sport engagement. For any team to have success in the competitive gaming scene, having the right team dynamic and chemistry is essential. By finding like-minded players to play with, teams can create a strong foundation and foster an environment of motivation and dedication, while also improving communication and team cohesion. Forum and discussion platforms that facilitate communication among players contributed to the high level of e-sport engagement.

2.3 Application of classification machine learning algorithms in e-sport engagement

Predictive e-sport interaction engagement based on machine learning algorithms has emerged as a game-changing development in the world of online gaming. E-sport platforms may now apply advanced machine learning algorithms to anticipate user behaviours, personalize game experiences, and increase overall engagement [7]. These systems can efficiently categorise user behaviours and preferences by utilising classification techniques such as decision trees, support vector machines, and neural networks, allowing for the delivery of personalized information and suggestions. This novel strategy not only improves the game experience for players but also provides enormous opportunity for e-sports firms to maximise user engagement and build long-term commitment [13].

By leveraging advanced machine learning algorithms, we can now predict and optimize user engagement in e-sports, leading to more personalized and immersive interactions. These algorithms utilize a diverse range of data points, including demographic profile, player behavior in terms of frequency, physical conditions, social relations, environment, and user preferences, to classify and predict engagement levels with remarkable accuracy. One of the key advantages of machine learning in e-sport engagement prediction is its ability to incorporate a wide range of input variables [14]. Demographic profiles, player behavior, physical conditions, social dynamics, environmental factors, and user preferences all contribute to an individual's engagement with e-sports. By training machine learning models on such multidimensional data, we gain a comprehensive understanding of the factors influencing engagement, enabling more precise predictions and targeted interventions. Furthermore, machine learning algorithms can adapt and improve over time, enhancing their predictive capabilities as they are exposed to new data [15]. This adaptive nature is particularly valuable in the dynamic e-sports environment, where user behaviors and preferences constantly evolve. By continuously learning from new data, classification algorithms can refine their predictions and strategies, ensuring that e-sport experiences remain engaging and relevant to users.

It is important to note that the application of machine learning in e-sport engagement prediction raises important ethical considerations. While these algorithms offer valuable insights, there is a need to prioritize user privacy and data security. Responsible usage of personal data and transparent communication with users are essential to building trust and ensuring ethical practices in e-sport engagement prediction [16].

3 METHODOLOGY

E-sports are becoming increasingly popular, and the industry has seen rapid growth in recent years. With this growth, it is important to understand how to predict the level of engagement of players in e-sports. Machine learning classification algorithms can be used to predict e-sports engagement for this study gathered using an online survey (google form: https://forms.gle/AHWeyRHWsgAA8KQL7). This section discusses the research methodology used to develop a machine learning classification algorithm to predict e-sports engagement, as shown in Figure 1.

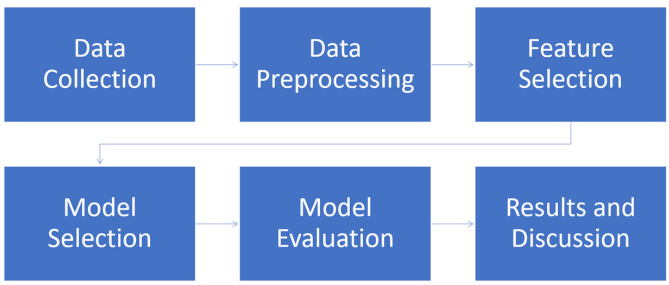


Fig. 1. Research methodology

The research methodology used for this project was composed of six parts: data collection, data preprocessing, feature selection, model selection, model evaluation, results, and discussion.

3.1 Data collection

The data used in this study was collected from a questionnaire distributed among random users via Google Form. The data contained player characteristics such as age, gender, game interests, and amount of time spent playing. It also contained game-specific information, such as physical circumstances, social relationships, surroundings, and user preferences, to accurately categorise and anticipate interest levels as shown in Figure 2.

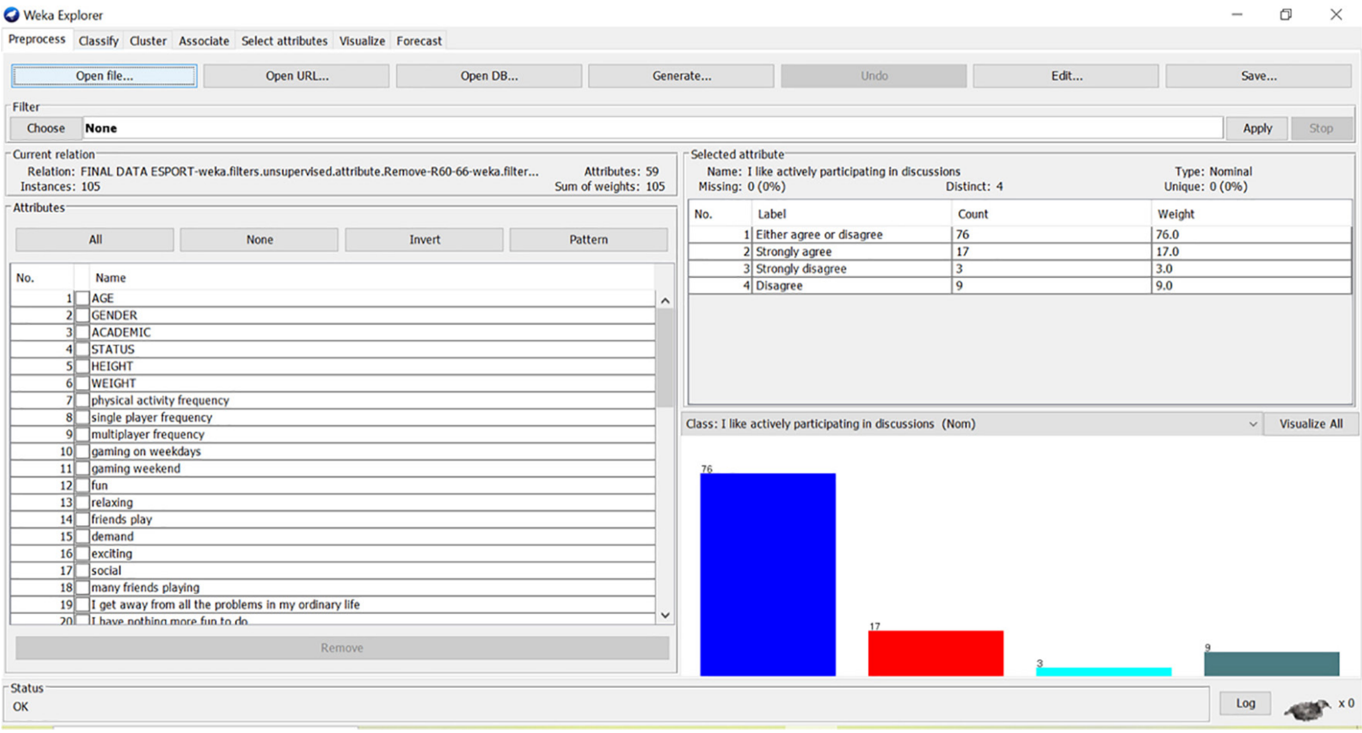


Fig. 2. Screenshot of preprocess tab that contains information about attributes, number of records, data type and label for each dimensions

3.2 Data preprocessing

Data preprocessing is an important step in any machine learning project. It involves cleaning and preparing the data in such a way that it can be used to train a model. In this study, we selected the criteria and features that should be considered for data preprocessing in a study of e-sport engagement prediction using machine learning classification algorithms. The first step in data preprocessing is to select and prepare the data for use in this study. This includes selecting the appropriate dimensions, such as a demographic profile, frequency of playing, physical conditions, and user preferences attributes. Once the data set is selected and the features are chosen, the data needs to be cleaned and prepared. This involves removing any missing or incorrect data points, filling in missing data points, and normalizing the data. This ensures that the data is consistent and ready to be used in the study.

3.3 Feature selection

The next step in data preprocessing is feature selection. This involves selecting the most relevant features to use in the study. It is important to select only the features that are likely to be predictive of e-sports engagement. This includes features such as demographic profiles (gender, age, height, weight, status of working, and level of education), physical conditions which refer to different types of pains in the body when playing e-sports, and frequencies of playing during the weekdays or over the weekends. In order to successfully predict e-sports engagement, we have to consider a range of features that can influence engagement. These include demographics (such as age, gender, and level of education), frequency of playing, physical condition, and engagement pattern. Each of these features can provide valuable insight into a player's engagement with e-sports.

In order to rank the dimensions of e-sport engagement, we need to identify which features are most important. This can be done by examining the correlation between each feature and engagement. For example, if a player's age is strongly correlated with higher engagement levels, then this feature should be given a higher ranking. Similarly, if a player's nationality or physical condition is correlated with lower engagement levels, then these features should be given a lower ranking. Once the features have been ranked, we used a machine learning classification algorithm to build a model that can accurately predict e-sports engagement. Feature selection is an important step in predicting e-sports engagement using machine learning classification algorithms. By ranking the dimensions of e-sports engagement according to their correlation with engagement levels, we can more accurately build models that can predict engagement. This can be an invaluable tool for understanding the factors that influence player engagement and performance.

3.4 Model selection

For model selection, before the data is ready to be used in the study, it is important to split the data into training and testing sets. Once the data was collected, it was preprocessed and cleaned in order to ensure accuracy and consistency. The data was then split into training and testing sets in order to ensure the accuracy of the model. This ensures that the model is trained on a representative sample of the data and that it is tested on a separate set of data. This helps to ensure that the model is not overfitting and is generalizing the data correctly. The model was developed using various machine learning classification algorithms from two selected groups of machine learning classification models. Two groups of classification algorithms selected were Bayes and Rules groups. All active models were trained and tested to identify the highest accuracy and fit with the dataset.

3.5 Model evaluation

There are a variety of classification algorithms available, such as logistic regression, support vector machines, and random forests. Each algorithm has its own strengths and weaknesses, so we should carefully consider which one is best suited for their particular application. The model was then tested and evaluated using various metrics, such as accuracy, precision, and recall.

3.6 Interpretation of results and findings

The model results and feature importance to understand which factors are most influential in prediction e-sport engagement were interpreted, and patterns or insights revealed by the models were examined. Practical significance of identified factors and how they contribute to the engagement predictions were discussed. The performance of different classification algorithms was compared, and the key findings for e-sports industry stakeholders were discussed.

Data preprocessing is an important step in any machine learning project, especially when it comes to predicting e-sports engagement using machine learning classification algorithms. It is important to select the appropriate data set and features, clean and prepare the data, and engineer the most relevant features. Finally, the data should be split into training and testing sets to ensure that the model is generalizing the data correctly. In summary, the data for this study was collected from various sources and then pre-processed and cleaned. The model was then developed using various machine learning classification algorithms and evaluated using various metrics. This research demonstrates the potential of using machine learning classification algorithms to predict e-sports engagement.

4 RESULTS AND DISCUSSION

The result of the study indicates the effectiveness of machine learning classification models in analyzing the e-sport engagement dataset. Machine learning methods, particularly classification models, have proven useful in analysing big and complicated datasets linked to e-sport participation. To forecast involvement levels, this study uses statistical approaches to categorise people based on 59 parameters from 106 cases. Six classification algorithms from two groups, bayes and rules, were trained on historical user data to detect patterns and trends indicative of different involvement levels, with accuracy ranging from 76% to 92%.

4.1 Feature selection

Identifying and selecting the relevant features that contribute most to predicting engagement levels was important to understand which dimensions are driving the predictions, promoting transparency and trust in the selected machine learning algorithms.

Table 1. Feature selection (select attribute) function

=== Attribute Selection on all input data ===

Search Method:
    Attribute ranking.

Attribute Evaluator (supervised, Class (nominal): 59 I like actively participating in discussions):
    Information Gain Ranking Filter

Ranked attributes:

0.76139	**55 I often participate in activities**
0.73182	**54 I enjoy exchanging ideas**
0.37579	**53 I enjoy playing with like-minded gamers**
0.34567	41 SR connect and be part of the community
0.3238	45 SR sharing the experience

(Continued)

Table 1. Feature selection (select attribute) function *(Continued)*

0.32288	39 SR chance to meet others with similar interests
0.31665	43 SR get a sense of camaraderie mutual trust OR friendship
0.30669	38 SR enjoy interacting with others
0.29886	47 SR bonding moments
0.29061	44 SR chance to bond
0.27503	57 I enjoy playing esports gaming when I am with others
0.27162	56 I love playing esports gaming with my friends
0.27137	58 Playing esports gaming is more fun when played together
0.26127	48 SR social setting
0.24052	42 SR interacting and get to know others
0.22752	40 SR social outlet
0.2029	46 SR having good time
0.18912	27 back pain
0.17192	8 single player frequency
0.166	51 I am able to speak comfortably about my personal values and beliefs
0.15804	25 Shoulder pain
0.15176	10 gaming on weekdays
0.14849	32 foot pain
0.14709	26 neck pain
0.13396	23 hours of Overwatch esports content
0.13141	9 multiplayer frequency
0.12867	52 I am tolerant of and try to learn about others beliefs and values
0.12811	28 hip pain
0.11875	35 Nervousness
0.1108	49 There is a direct relationship between my personal values and my daily actions
0.11055	50 Prayer meditation quiet personal reflection more important in my life
0.09914	30 knee pain
0.09787	29 hand pain
0.09666	11 gaming weekend
0.0738	36 Irritation
0.06594	33 Headache
0.06557	37 Sleep problems
0.06513	3 ACADEMIC
0.06486	31 leg pain
0.06162	4 STATUS
0.06159	34 Stomach ache
0.06124	24 Esports videogame playing frequency
0.02281	17 social
0.02158	7 physical activity frequency
0.01874	18 many friends playing
0.01696	21 I become restless and irritated when not playing
0.01509	20 I have nothing more fun to do
0.01302	2 GENDER
0.01271	12 fun
0.012	22 I do not have to think about all the worries in my ordinary life
0.01025	15 demand
0.00936	16 exciting
0.00507	13 relaxing
0.00382	14 friends play
0.00195	19 I get away from all the problems in my ordinary life
0	5 HEIGHT
0	6 WEIGHT
0	1 AGE

Selected attributes:
55, 54, 53, 41, 45, 39, 43, 38, 47, 44, 57, 56, 58, 48, 42, 40, 46, 27, 8, 51, 25, 10, 32, 26, 23, 9, 52, 28, 35, 49, 50, 30, 29, 11, 36, 33, 37, 3, 31, 4, 34, 24, 17, 7, 18, 21, 20, 2, 12, 22, 15, 16, 13, 14, 19, 5, 6, 1: 58

The result of feature selection (select attribute) highlights three dimensions that are particularly influenced by the e-sport engagement levels dominated by participating in activities, as shown in Table 1. Active participation in e-sport-related activities emerges as a top contributor. This could include participation in tournaments, events, or community activities. This findings is also similar to research conducted by Abbas and Jasim [17], which reported that since the rise of e-sports, there has been an immense growth in the number of people actively engaged in the community. From casual players to professional gamers, the scope of e-sports has grown exponentially, and the level of engagement has followed suit [18]. Tournaments and events are one of the most popular forms of e-sports activity and have long been a staple of the e-sports community. Players have the opportunity to showcase their skills in a competitive environment, while also connecting with other players from around the world. Participation in tournaments and events can drive high levels of engagement, as players feel a sense of belonging and accomplishment from their participation [19].

Furthermore, community activities are also a major contributor to e-sports engagement levels. This could include participating in forums, online courses, or other activities that involve interacting with other members of the e-sports community. These activities provide an opportunity for players to connect with other like-minded individuals that ranked third in feature selection results, learn new skills, and share their knowledge and experiences. This sense of community and collaboration can be a powerful motivator for high levels of engagement, which is also supported by Kim and Kim [20].

Interactive content has also become increasingly important for driving engagement levels in e-sports. This could include live streaming, video tutorials, or even interactive games. These types of activities can provide a much more immersive experience for players, as they are actively engaging with the content rather than simply viewing it passively [21]. This findings is also similar to the study done by Loat [22]. Interactive content has the potential to drive high levels of engagement and interest, as players are actively engaging with the content and developing a deeper connection with the e-sports community. Players who actively participate in tournaments, events, and community activities are more likely to have a higher level of engagement and involvement in the e-sports community [23]. Additionally, interactive content can provide a more immersive and engaging experience for players, which can help drive higher levels of engagement. Ultimately, this combination of active participation and interactive content can be a powerful combination for driving high levels of engagement in e-sports.

The second top dimension contributing to the e-sport engagement was enjoying exchanging ideas that influence the level of e-sports engagement. A recent study of e-sports engagement revealed that the exchange of ideas is an essential part of any successful e-sports team or tournament [24]. This exchange of ideas involves discussing strategies, analyzing opponents' moves, and discussing the best way to play any given e-sports game [25]. This exchange of ideas allows teams to stay competitive and remain engaged in the e-sports scene [18]. The exchange of ideas is important for many reasons. First, it allows players to stay engaged in the game and keep up with the competition. By discussing strategies and analyzing opponents' moves, players can stay up-to-date on the latest trends in the game [26]. This knowledge can be used to make better decisions in-game and stay ahead of the competition. Exchanging ideas can also help foster a sense of community within the e-sports scene. By discussing strategies and tactics with other players, players can build relationships and form a bond that can help motivate them to do better. This sense of community can also help players stay engaged in the game even if they do not perform. By talking to other experienced players, players can gain insight into the game that they may not have been able to get elsewhere [27]. This can be especially helpful for newer players who may not have the same level of knowledge as more experienced players.

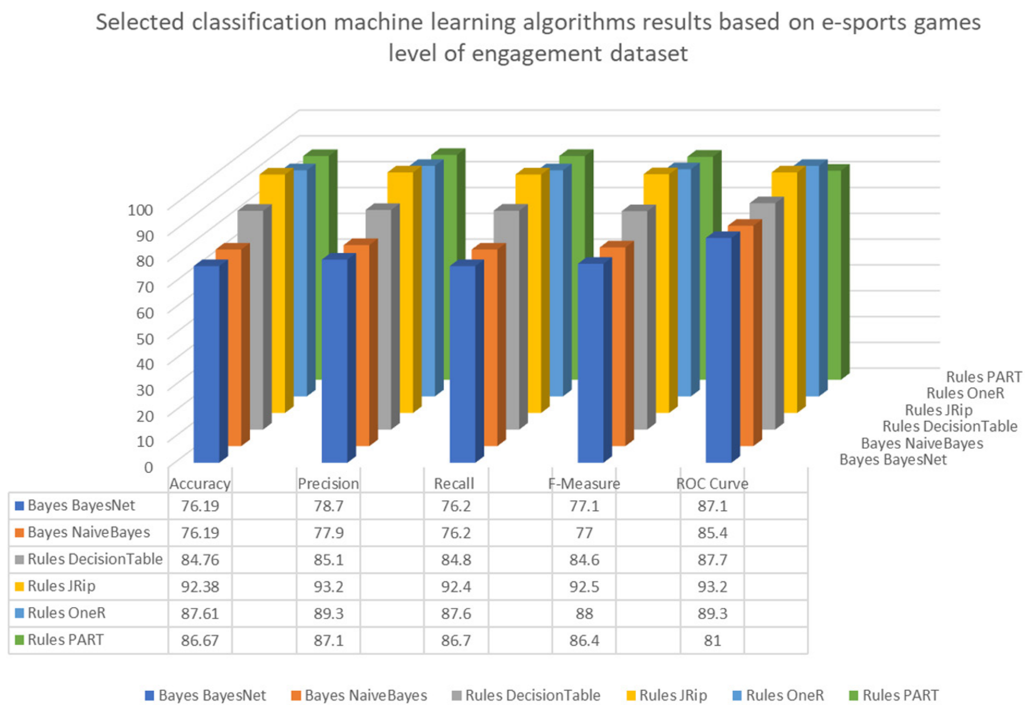
The third dimension in the rank of e-sport engagement is playing with like-minded gamers. This finding is also similar to research conducted by Otu [28] that claimed having the right team dynamic and chemistry is essential for any team to reach their potential and be successful in the competitive e-sport gaming scene. Building a team of players that have the same mindset and goals can help create a strong foundation for any team in e-sports games [25]. Creating a team of like-minded players can help foster an environment of motivation and dedication, as well as provide an opportunity for team members to learn from each other and grow. Having a team of players that all have the same goals and ambitions can help create a cohesive unit that can work together towards a common goal.

4.2 Classification machine learning algorithms

The study affirms that classification models, specifically six algorithms from the Bayes and rules groups, have proven effective in handling large and complex datasets related to e-sport engagement. The choice of these models suggests a diverse approach, considering the strengths of each algorithm type. The dataset comprises 106 instances with 59 attributes. This indicates a comprehensive set of information collected for each user. The richness of the dataset is crucial for training accurate and robust machine learning models. The primary goal of the study is to predict engagement levels. By training on historical user data, the models achieved accuracy ranging from 76% to 92%. This suggests a high degree of success in predicting engagement levels, showcasing the potential practical application of the developed models. The reported accuracy ranges (76% to 92%) indicate a strong performance of the classification models, as shown in Table 2 and Figure 3, respectively. The variability in accuracy may be attributed to the inherent complexity of predicting engagement levels, which can be influenced by diverse and dynamic factors. The use of both Bayes and rule groups of classification algorithms demonstrates a balanced approach. Each group has its strengths, with Bayesian models being probabilistic and rule-based models providing interpretable decision rules. The combination allows for a more comprehensive analysis. The findings have practical implications for e-sports platforms and communities. Understanding the key dimensions that drive engagement can inform strategies to enhance user experience, foster community interaction, and tailor content to meet the preferences of different user segments.

Table 2. Classification machine learning algorithms results

Group	Bayes		Rules			
Model	BayesNet	NaiveBayes	DecisionTable	JRip	OneR	PART
Accuracy	76.19	76.19	84.76	92.38	87.61	86.67
Precision	78.7	77.9	85.1	93.2	89.3	87.1
Recall	76.2	76.2	84.8	92.4	87.6	86.7
F-Measure	77.1	77.0	84.6	92.5	88.0	86.4
ROC Curve	87.1	85.4	87.7	93.2	89.3	81.0



	Accuracy	Precision	Recall	F-Measure	ROC Curve
Bayes BayesNet	76.19	78.7	76.2	77.1	87.1
Bayes NaiveBayes	76.19	77.9	76.2	77	85.4
Rules DecisionTable	84.76	85.1	84.8	84.6	87.7
Rules JRip	92.38	93.2	92.4	92.5	93.2
Rules OneR	87.61	89.3	87.6	88	89.3
Rules PART	86.67	87.1	86.7	86.4	81

Fig. 3. Selected classification machine learning algorithms results.

Based on results shown in Table 2 and Figure 2, respectively, in terms of accuracy, JRip has the highest accuracy at 92.38%, indicating the proportion of correctly predicted instances. DecisionTable and PART also demonstrate strong accuracy, surpassing 84%. For precision, measuring the accuracy of the positive predictions made by the model also shows that JRip has the highest precision at 93.2%, indicating a low rate of false positives in its predictions, while DecisionTable, OneR, and PART also exhibit strong precision scores. The precision of a predictive model measures the accuracy of the positive predictions it makes and is an important factor in determining the level of e-sports engagement. The higher the precision, the more reliable the predictions, allowing players and teams to make better decisions [29]. DecisionTable, OneR, and Part all exhibited strong precision scores, but JRip had the highest precision at 93.2%. This indicates that JRip is the most accurate model for predicting e-sports engagement. JRip is a rule-based machine learning model that uses a series of "if-then" rules to identify patterns in a dataset and make predictions [30]. The rules are created by analyzing a data set and then combined to form a set of rules that can accurately identify patterns. This allows JRip to make accurate predictions, as it is able to identify patterns in a dataset and correctly assess the level of e-sports engagement.

For recall (sensitivity) that measures the ability of the model to capture all positive instances, it is depicted that JRip has the highest recall at 92.4%, indicating that it effectively identifies a high proportion of actual positive instances. DecisionTable, OneR, and PART also demonstrate strong recall values. OneR utilizes a single decision tree to evaluate the data and determine the most likely outcome [31]. This method of evaluation is highly accurate when determining positive instances, making it a top choice for e-sports engagement. Similarly, PART utilizes a series of decision trees to evaluate the data and determine the most likely outcome.

Meanwhile, the F-Meaure value represents the harmonic mean of precision and recall, providing a balanced measure of the model's performance. As a result, JRip has the highest F-measure at 92.5%, indicating a good balance between precision and recall, and also DecisionTable, OneR, and PART also exhibit strong F-measure values.

The high F-measure values of these models indicate that they are able to accurately identify relevant data points while also minimizing false positives [32]. This is important in e-sports, where data accuracy is essential for success. Moreover, for the ROC curve, JRip has the highest ROC curve score at 93.2%, indicating its ability to maintain a high true positive rate while controlling false positives. DecisionTable, OneR, and BayesNet also show competitive ROC curve scores.

In summary, JRip consistently achieves the highest scores across all metrics, suggesting it is a strong performer in terms of accuracy, precision, recall, F-measure, and ROC curve. For Decision Table, OneR and PART also demonstrate strong performance across multiple metrics, making them competitive choices for the given problem. Bayes group, which represented by BayesNet and Navie Bayes, is outperformed by other models, especially in terms of ROC curve scores, while at the same time achieving reasonable accuracy, precision, and recall. These results collectively provide a comprehensive assessment of the models' performance, aiding in the selection of the most suitable classification algorithm for the specific task at hand. It's important to consider the specific requirements and priorities of the problem when choosing a model, as different metrics may be more or less important depending on the context. Additionally, these results may guide further optimization or fine-tuning of the models for improved performance.

5 CONCLUSION, RECOMMENDATION AND FUTURE WORKS

As for conclusion, exchanging ideas is an important part of the e-sports scene. It can help players stay engaged in the game, foster a sense of community, and learn from others. As e-sports continues to grow in popularity, understanding what contributes to e-sports engagement is increasingly important, and the exchange of ideas is an important part of this. The third in the rank was playing with like-minded gamers dimension. The world of e-sports has seen tremendous growth over the past decade. With the rise of competitive gaming, more and more players are looking to get involved in the competitive scene and become professional gamers. However, one of the biggest challenges for many players is finding like-minded gamers to play with. The high precision of JRip means that it can be used to accurately assess player and team performance in e-sports. By using JRip, players and teams can accurately predict the level of engagement and make more informed decisions about their performance. This could be beneficial for both players and teams, as it allows them to make better decisions and improve their game. The F-measure value is a valuable metric for evaluating the performance of a model in predicting e-sports engagement. JRip has the highest F-measure value at 92.5%, indicating a good balance between precision and recall. DecisionTable, OneR, and PART also provide strong F-measure values ranging from 81.2% to 89.2%, making them suitable for predicting e-sports engagement.

For recommendation, adapting models to account for the rapidly changing landscape of e-sports, including new game releases and evolving player behaviors dimension, should be taken into consideration to discover the dynamic nature of e-sports. Furthermore, the unique characteristics and features of different e-sports platforms and games should be considered when developing the predictive models.

The future works related to e-sport engagement prediction study showcase a multidisciplinary approach, incorporating machine learning, data analytics, and insights from user behavior analysis. The field is evolving rapidly, with a focus on developing more accurate and personalized engagement prediction models while addressing ethical considerations and industry-specific challenges. The industry is moving towards real-time engagement predictions, enabling platforms to adapt content or interactions dynamically during live broadcasts. Personalization is becoming a key focus, with studies aiming to tailor content and recommendations based on individual user preferences and engagement history. Integration of AI-driven features within games and streaming platforms to enhance engagement and create more interactive and personalized experiences. Increased collaboration between researchers and the e-sports industry to implement and validate predictive models in real-world settings, leading to practical applications.

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