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Enhancing game classification systems with machine learning: A comparative study on techniques and legal implications

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A B S T R A C T

This study conducted a thorough analysis of a dataset from a video game to reveal the relationship between game content, interactive features, and classification ratings. The project attempted to convert raw data into meaningful insights by employing Python for data processing and machine learning. The analysis uncovered strong relationships between content descriptors and ESRB ratings, indicating a market that strategically customizes game material to different demographic groupings. Moreover, the inclusion of interactive features such as 'Users Interact' and 'In-Game Purchases' suggests a transition towards gaming experiences that are more immersive and financially interactive. The highlight of this project was the creation of a web-based tool that can accurately forecast game classifications, utilizing advanced models such as XGBoost. The application offers developers and rating organizations a vital tool to achieve accuracy in game classification. The study's conclusions provide a detailed comprehension of console market dynamics, clarifying the present patterns and possible future developments in the gaming industry.

1. Introduction

The implementation of a machine learning-based program to accurately forecast game classifications shows great potential for game producers and rating organizations. Through the utilization of machine learning techniques, this program has the capability to examine different elements of game content, such as violence, profanity, and other potentially offensive material, to deliver age ratings that are more accurate and consistent. This would not only help developers ensure compliance with rating standards, but also assist rating organizations in improving the accuracy and dependability of their categorization systems. Research has shown that the prevalence of loot boxes in games and the potential parallels with gambling have raised concerns about the adequacy of current age rating systems (Hodge et al., 2022; Zendle, Meyer, et al., 2020) . Additionally, studies have highlighted the need for improved regulation of game content, particularly in relation to violence and hypersexuality, to better protect young players (Downs & Smith, 2010; Thompson & Haninger, 2001). Furthermore, the ethical implications of exploiting psychological research in video games underscore the importance of developing more robust and transparent classification methods (Søraker, 2016). The existing video game rating systems, such as the ESRB and PEGI, have been subject to scrutiny, with research emphasizing the need for more effective and reliable classification approaches (Dogruel & Joeckel, 2013; Felini, 2015). Moreover, the validation of movie, television, and video game ratings has been called into question, highlighting the necessity for enhanced accuracy and consistency in rating systems (Walsh & Gentile, 2001). The suggested program could mitigate these problems by incorporating machine learning techniques, which would enable a more data-driven and objective approach to game classification. By utilizing metadata models and sophisticated algorithms, the application can thoroughly analyze game material, considering elements such as substance usage, tobacco imagery, and

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aggressive priming, to produce age ratings that are more precise. In addition, the application has the potential to facilitate the establishment of a more uniform and clear method for categorizing games, which would be in line with the demand for enhanced regulation and policy in this field (Gentile et al., 2007; Grimes et al., 2023).

The objective of this study is to assess the performance and efficacy of machine learning techniques in improving game categorization systems. The study aims to examine the use of machine learning techniques for the purpose of selecting features and classifying games. The study seeks to enhance the precision, consistency, and dependability of game categorization systems by utilizing machine learning. The primary objective is to offer more accurate age ratings and content descriptors. The research will consist of comparing various machine learning methods and assessing their influence on the predicting capacities of game categorization systems. The primary objective of the project is to enhance the development of more reliable and evidence-based game classification methods, which will be advantageous for game producers, rating organizations, and consumers.

2. Literature Review

The categorization of video games based on their suitability for different age groups is a vital factor in ensuring that games are appropriate for players of various ages. Studies have demonstrated that video game age ratings have a substantial impact on the attitudes and actions of both parents and children (Azam, 2023; Shin & Huh, 2011). Nevertheless, there is compelling evidence indicating that players, especially older individuals, may disregard age classification systems when making decisions about which games to engage in (Hollett et al., 2022). This underscores the necessity for additional research on the efficacy of age grading systems and their influence on game choice. The subject matter of video games, namely regarding violence and vulgarity, has raised concerns within age rating systems. Research has indicated that games that are deemed appropriate for all age groups can nevertheless have violent aspects, whereas games intended for older audiences are more likely to include offensive language and explicit content (Ivory et al., 2009; Thompson & Haninger, 2001). This highlights the significance of precise and thorough age ratings to assist consumers in making well-informed decisions. Furthermore, researchers have investigated the influence of video game content on several facets of behavior and overall well-being. Research indicates that playing violent video games might result in heightened physiological arousal, including higher heart rate and blood pressure (Hasan, 2017). Furthermore, researchers have examined the impact of video games on pain response and tolerance. The results indicate that action-oriented games may influence how individuals perceive and tolerate pain (Raudenbush et al., 2009).

Moreover, researchers have investigated the age at which children are introduced to video games and have determined that the typical age of initial exposure is approximately 36 months (Tezol et al., 2022). The early exposure highlights the significance of strong age grading systems in protecting the welfare and growth of young players.

2.1 Games Rating System

The Entertainment Software Rating Board (ESRB) and the Pan European Game Information (PEGI) are two well-known and influential video game rating systems. The ESRB, founded in 1994, evaluates video games using age-specific symbols and content descriptors, which are shown on game boxes to provide information for consumers to make informed decisions (Haninger & Thompson, 2004). PEGI, which was founded in 2003, is a self-regulatory framework that assigns age ratings to video games. Its purpose is to assist consumers and safeguard young players (Azam, 2023). Nevertheless, studies demonstrate that players may disregard age classification systems while selecting games, indicating possible deficiencies in the efficacy of these systems (Hollett et al., 2022). Furthermore, there have been issues about the adherence to industry self-regulation standards, specifically with the proper labelling of loot boxes. This raises questions about the effectiveness of rating systems enforcement (Xiao, 2023).

2.2 Game Rating System and Machine Learning

Implementing machine learning in game categorization rating systems has the potential to significantly enhance the precision and efficiency of age ratings for video games. The existing age rating systems, such as the ESRB and PEGI, have faced criticism over their effectiveness and the necessity for enhancements (Dogruel & Joeckel, 2013; Xiao, 2023). Machine learning techniques can mitigate these concerns by offering a data-centric and unbiased approach to game classification. Machine learning can improve the accuracy and dependability of age ratings by examining different elements of game content, such as violence and other inappropriate material. This ensures that consumers obtain more reliable and informative classification information. Moreover, the ESRB age-based rating symbols and content descriptors have been recognized as crucial sources of information regarding game content, highlighting the importance of precise and dependable classification systems (Haninger & Thompson, 2004). In addition, a thorough examination of the content has shown a substantial presence of violent elements in certain video games that are classified as E. This emphasizes the necessity for improved methods of categorization, which can potentially be achieved through the utilization of machine learning techniques (Thompson & Haninger, 2001). Hence, the incorporation of machine learning into game categorization rating systems shows significant potential in overcoming the shortcomings of existing rating systems and guaranteeing responsible and age-appropriate material for players. This study is an extension of the previous study, "Prediction of the Digital Game Rating Systems Based on the ESRB" (Alomari, et al., 2019).

2.3 Legal Implications in Game Classification Systems

The convergence of video game content and legal regulation has become a matter of escalating significance as the gaming industry continues to expand. Game classification systems, such as the Entertainment Software Rating Board (ESRB) in North America, the Pan European Game Information (PEGI) in Europe, and the Computer Entertainment Rating Organization (CERO) in Japan, function as regulatory mechanisms to guarantee that video game content is accurately rated and appropriate for different age demographics. These systems are not only widely accepted as the norm in the industry, but they also have a vital function in legal frameworks that aim to safeguard consumers, especially minors, from being exposed to dangerous or unsuitable content (CERO, 2024; ESRB, 2024; PEGI, 2024).

2.4 Regulatory Frameworks and Industry Standards

The ESRB, founded in 1994, offers a uniform rating system that assists consumers, particularly parents, in making well-informed choices regarding the games their children engage with (ESRB, 2024). This regulatory entity assigns age and content classifications to video games based on their themes, language, violence, and other pertinent elements. PEGI and CERO, similar organizations, also carry out these responsibilities in their respective regions, while complying with local cultural norms and legal obligations (CERO, 2024; PEGI, 2024). The ratings issued by these organizations are legally binding in many countries, where the sale of games without a rating or the provision of games to underage individuals that are rated for mature audiences can lead to legal consequences.

2.5 Legal Challenges and Content Regulation

An important legal issue revolves around the portrayal of violence, sexual content, and gambling-like features in video games. Various studies have engaged in discussions regarding the influence of violent video games on behavior, resulting in legal measures and demands for more stringent regulations. The U.S. Supreme Court case Brown v. Entertainment Merchants Association (2011) invalidated a California law that aimed to prohibit the sale of violent video games to minors. The case highlighted the significance of protecting freedom of speech while acknowledging the necessity of regulating content responsibly (Brown, et al. v. Entertainment Merchants Assn. et al., 564 U.S. 786 (2011), 2011/08-1448). Another emerging legal obstacle pertains to the regulation of in-game purchases and treasure boxes. The inclusion of these characteristics, which frequently include actual currency, has sparked apprehension regarding their resemblance to gambling and the possible influence they may have on young participants (King & Delfabbro, 2019; Zendle, Cairns, et al., 2020). Countries such as Belgium and the Netherlands have implemented measures to categorize loot boxes as forms of gambling, thereby making them subject to strict regulatory oversight (Xiao et al., 2021; Zendle, Cairns, et al., 2020). The legal framework concerning these aspects is constantly changing, with continual discussions over safeguarding consumer interests and ensuring the ethical use of game monetization tactics (Hodge et al., 2022; King & Delfabbro, 2019).

2.6 The Role of Machine Learning in Enhancing Legal Compliance

Integrating machine learning techniques into game classification systems offers a promising chance to improve the precision and reliability of content ratings, therefore enhancing compliance with legal norms. Automated categorization systems employ machine learning algorithms to examine vast amounts of game data, detecting content that necessitates special ratings in accordance with industry norms and regulatory obligations (Penczynski, 2019). These technologies can assist regulatory bodies in enforcing content requirements more effectively and aid creators in comprehending the legal ramifications of their game designs by providing accurate and consistent classifications (Penczynski, 2019). Integrating instructional designers that possess pedagogical experience into automated game classification systems can improve the educational efficacy of computer-based simulation games (Sitzmann, 2011). In addition, the application of deep learning models, which are a type of machine learning algorithms that learn from data using artificial neural networks, can help determine the seriousness of content associated with internet gaming disorder. This showcases the adaptability of machine learning in different fields (Hong et al., 2023). The legal framework surrounding video games is constantly changing, considering factors such as intellectual property rights, accessibility, and the culture surrounding video games (Losavio & Losavio, 2014; Powers et al., 2015). The legal focus on video game accessibility highlights the importance of ensuring inclusivity in gaming experiences (Powers et al., 2015).

3. Methods

3.1 Data Collection

The dataset consisting of 4027 records about games, containing information such as game name, rating, content descriptors, interactive elements, console systems, and rating summary, will be acquired from the ESRB. The dataset will be gathered in a well-organized style to guarantee interoperability with machine learning methods.

3.2 Data Cleaning

The acquired dataset will undergo a meticulous cleaning procedure to rectify any discrepancies, missing values, or inaccuracies. Data cleaning encompasses the process of standardizing the format of entries, addressing missing data, and maintaining consistency in data representation.

3.3 Feature Engineering

The categorical variables such as content descriptors, interactive elements, and console systems will be transformed into binary columns for each game. This conversion will allow these variables to be represented as numerical features, which are more suited for machine learning techniques. This procedure will entail generating binary indications to determine whether specific content descriptors, interactive features, and console systems are present or absent in each game.

3.4 Development of Machine Learning Models

The classification assignment will involve considering various machine learning algorithms, including Support Vector Machines (SVM), Decision Trees, Random Forests, XGBoost, Gradient Boosting, BernoulliNB, KNN, and AdaBoost. The dataset will be divided into training and testing sets, with a substantial chunk assigned for training the models and the remaining amount used to assess their performance.

3.5 Model Training and Evaluation

The machine learning models will undergo training using the training dataset, and their performance will be assessed using the testing dataset. The models' classification performance will be assessed using evaluation measures such as accuracy, precision, recall, and F1 score.

3.6 Model Optimization

Hyperparameter tweaking and model optimization approaches will be utilized to improve the performance of the machine learning models. Cross-validation and grid search techniques can be employed to determine the most optimal model configurations.

3.7 Comparative Analysis

A comparative study will be performed to determine the most efficient method for game categorization using the ESRB dataset by evaluating several machine learning models. The performance, computational efficiency, and interpretability of the models will be evaluated to identify the most appropriate model for game categorization.

3.8 Results Interpretation and Reporting

The study's findings, which encompass the machine learning models' performance and the insights derived from the comparative analysis, will be interpreted and communicated. The final paper will offer suggestions for utilizing machine learning techniques to improve game categorization systems using the ESRB dataset.

4. Data Analysis

Utilizing Python for the analysis of video game data offers a chance to acquire significant information regarding game classification and content. This project seeks to analyze patterns and trends within a dataset of 4027 video game records received from the ESRB by utilizing Python's data analysis libraries and machine learning technologies. The dataset comprises game names, ratings, content descriptions, interactive aspects, console platforms, and rating summaries, making it a valuable resource for analysis.

The main goal of this data analysis is to reveal significant correlations and patterns within the dataset of video games. The project aims to utilize Python for the purpose of manipulating, cleaning, and analyzing data to convert the raw dataset into practical and useful insights. By harnessing Python's data analysis and machine learning skills, Authors can investigate the factors that impact game ratings, the frequency of various content descriptors, and the relationship between interactive features and game classifications.

Furthermore, the primary objective of this project is to create an internet-based application that uses the results of the data analysis to forecast precise game categorizations. The application intends to provide developers and rating organizations with a tool for more accurate and standardized game classification by incorporating the knowledge gained from Python-based data analysis. The application will utilize machine learning methodologies to augment the precision and dependability of age ratings, thereby aiding in the enhancement of game classification systems.

4.1 Game Rating

The dataset comprises 4027 games and offers a representation of the content maturity levels as indicated by the distribution of game ratings, as shown in Fig. 1.

T (Teen) - 1423 games: The group with the largest presence in the dataset signifies a substantial market demand for games targeting teenagers aged 13 and above. These games likely contain content that parents may consider inappropriate for children under the age of 13, such as light violence, occasional explicit language, or suggestive themes.

E (Everyone) - 899 games: The rating indicates a significant number of games that have been particularly created to appeal to people of all age groups, making it the second most common category. These games typically have content that is considered suitable for a wide range of people, including individuals of all ages, including children. The incorporation of these games highlights the industry's dedication to creating entertainment that is appropriate for every family member.

M (Mature) - 872 games: The number of 'M' rated games, which are designed for players aged 17 and older, is about the same as the number of 'E' rated games. The games may have aspects of extreme violence, gore, explicit sexual content, and/or the use of explicit language. The importance of this grade underscores a robust need for gaming experiences that specifically target mature audiences.

E10+ (Everyone 10 and older) - There are a total of 806 games available. Games falling under this particular group are considered suitable for those aged 10 and above. These media works may include a higher proportion of animated content, imaginative aspects, minor instances of violence, modest use of language, and/or little inclusion of provocative themes. The high prevalence of 'E' rated games indicates a purposeful emphasis on targeting the attention of pre-adolescent consumers in the gaming industry.

AO (Adults Only) - 27 games available. The analysis indicates that games rated 'AO', which are designed for individuals aged 18 years and older, have a low frequency of occurrence. These games may include prolonged portrayals of extreme violence, explicit sexual material, and/or the incorporation of real money gambling. The scarcity of these games can be ascribed to their specialized market, which could be due to limitations in distribution and restricted availability at retail outlets.

The distribution provides a thorough depiction of the gaming business, exhibiting a diverse array of content that caters to different age groups and individual preferences. The prevalence of 'T' ratings, in comparison to 'M' or 'AO' classifications, suggests that game developers may deliberately target a younger audience while including content that deals with mature themes. The high occurrence of 'E' and 'E10+' games indicates that a substantial portion of the market is focused on appealing to family-friendly and younger audiences. The rarity of 'AO' titles suggests that the creation of such content is infrequent, maybe due to commercial constraints and platform prohibitions.

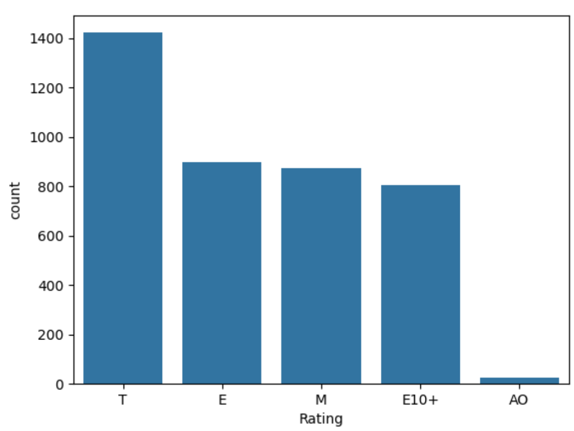

Fig. 1. Distribution of Game Rating in Games

4.2 Console Availability

The dataset, comprising 4027 games, exhibits a significant variation between various gaming consoles, as shown in Fig. 2. The PlayStation 4 has a substantial advantage, boasting a grand total of 2275 titles. This significant amount may suggest the console's huge market reach and broad appeal across the whole time of the dataset. Similarly, the Nintendo Switch possesses an extensive collection of 1929 games, demonstrating its dominant position in the gaming market. The Xbox One has a significant discrepancy, as it has the capacity to accommodate a total of 1193 games. It is important to mention that the PlayStation 5 and Xbox Series X|S, which are part of the most recent iterations of gaming consoles, now provide a very reduced assortment of games. The PlayStation 5 boasts a collection of 945 titles, but the Xbox Series X|S offers a smaller selection of 687 games. The scarcity of games can be ascribed to the recent entry of both systems onto the market. The Nintendo 3DS, PlayStation 3, Xbox 360, and Wii U, classified as legacy systems, provide restricted sales data, indicating their diminishing presence in the contemporary gaming business. The rise of cloud gaming platforms is demonstrated by the incorporation of 281 games on Google Stadia. The allocation of this console functions as a structure for examining the changing dynamics of the game industry's focus on platform-centricity.

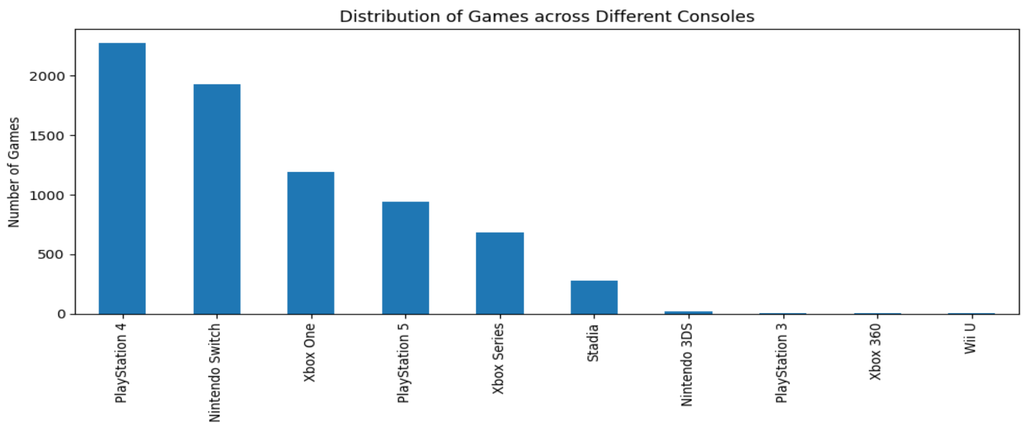

Fig. 2. Distribution of Games Across Different Console's

The dataset's heatmap in Fig. 3 offers a valuable and informative visual representation of the availability of games on different console platforms, as well as their link with ESRB ratings. This distribution focuses on the market penetration and game production patterns associated with each console, allowing for a more thorough understanding of the availability of games specific to each platform.

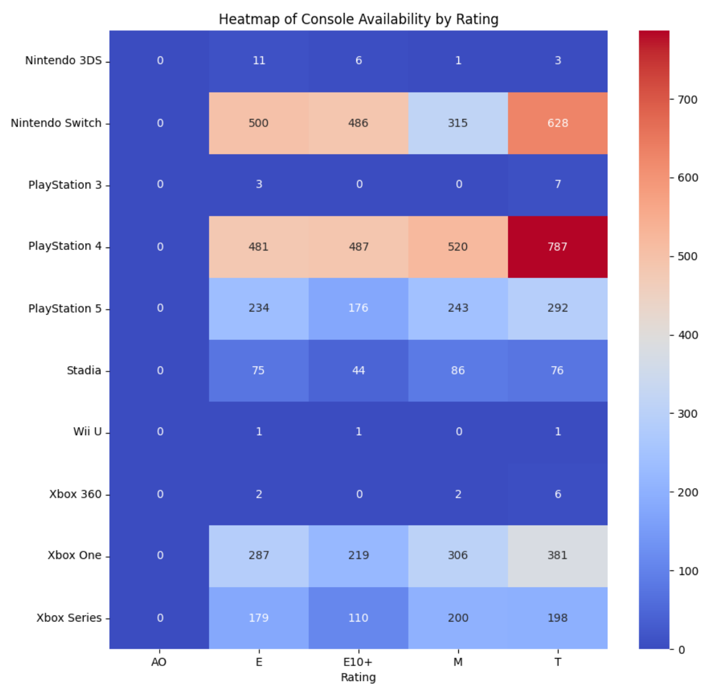

Fig. 3. Heatmap of Console Availability by Rating

The Nintendo Switch boasts a wide array of games spanning across many rating categories, with the 'Teen' (T) category having the largest quantity of titles. This suggests that the Switch has a broad appeal, catering to people of many age groups, including both younger and older demographics. The PlayStation 4 is specifically designed to appeal to an adult gaming demographic, as seen by its significant representation in the 'Teen' (T) and 'Mature' (M) categories.

The PlayStation 5 and Xbox Series consoles offer a diverse range of games that cater to different age groups, including 'Everyone' (E), 'Everyone 10+' (E10+), and 'Mature' (M) classifications. However, the quantity of accessible titles is not as broad. The scarcity of titles can be attributed to the recent launch of these platforms, indicating prospective opportunities for expansion in their respective collections.

The presence of titles from all ESRB categories on Google Stadia, albeit in smaller quantities, indicates the growing trend and potential growth of cloud gaming platforms. Gaming consoles such as the PlayStation 3, Xbox 360, and Wii U, which are no longer up-to-date, offer a restricted range of titles, which is indicative of their diminishing significance in the contemporary gaming sector.

The heatmap emphasizes the importance of understanding the correlation between console availability and ESRB ratings, as it influences game development strategies, market segmentation, and consumer choices. Distributing games across several platforms can offer stakeholders significant insights into the current dynamics of the gaming industry and allow them to anticipate future trends in game development and platform utilization.

4.3 Content Descriptors

The content descriptors in the dataset provide a contemplative viewpoint on the thematic makeup of video games, as shown in Fig. 4. Upon analyzing the dataset, it is evident that violence is the predominant characteristic, occurring a total of 1255 times. This discovery implies that violence is deeply integrated into the structure of games. The occurrence of fantasy violence and blood in game is clearly apparent, as demonstrated by the frequency of 1095 and 777 occurrences, respectively. This data highlights the gaming community's inclination towards narratives that incorporate innovative and confrontational components. The presence of the categories "Blood and Gore," "Strong Language," and "Language," with corresponding tallies of 627, 600, and 583, suggests that video games often contain mature and potentially explicit material, hence catering to an adult demographic. The depiction of sexuality in Suggestive Themes and Sexual Themes is tastefully conveyed, demonstrating a refined portrayal of mature content within the interactive medium. The infrequent usage of adjectives related to substance use, comedy, and sexuality, especially the notably limited mention of Sexual Violence, could indicate that the sector follows content sensitivity and regulatory standards. The aggregation of content descriptors displayed here is essential for understanding the thematic direction and content curation that are prevalent in the gaming environment.

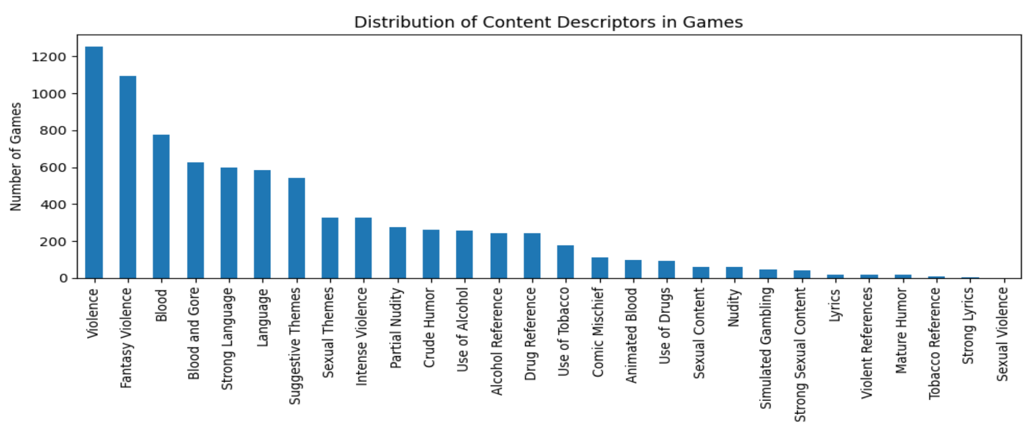

Fig. 4. Distribution of Content Descriptors in Games

The offered heatmap in Fig. 5 presents a comprehensive comparative analysis of content descriptors across various game ratings, yielding valuable insights into the thematic elements of video games. The data exhibits a conspicuous pattern in the distribution of content, aligning with the grading system of the Entertainment Software Rating Board (ESRB). This signifies the implementation of a tailored approach to guaranteeing the appropriateness and compatibility of information for diverse target audiences.

The inclusion of explicit portrayals of violence and blood in video games categorized as 'Mature' (M) and 'Teen' (T) is readily apparent, indicating a trend towards increasingly visually graphic and violent material in games intended for mature players. 'Fantasy Violence' is predominantly associated with video games that have been assigned a 'Everyone 10+' (E10+) rating. This rating signifies a nuanced differentiation that appeals to a younger demographic by combining elements of violence with imaginative and whimsical aspects. Conversely, the use of 'Strong Language' is primarily observed in the 'Mature' (M) category, hence reinforcing the mature classification of this rating.

The heatmap indicates that games with a 'Adults Only' (AO) rating contain a substantial quantity of 'Strong Sexual Content', while games with a 'Mature' (M) rating have a more moderate level of 'Sexual Themes' and 'Nudity'. This differentiation indicates a distinct division between content deemed suitable for mature audiences and content particularly designed for adult watching.

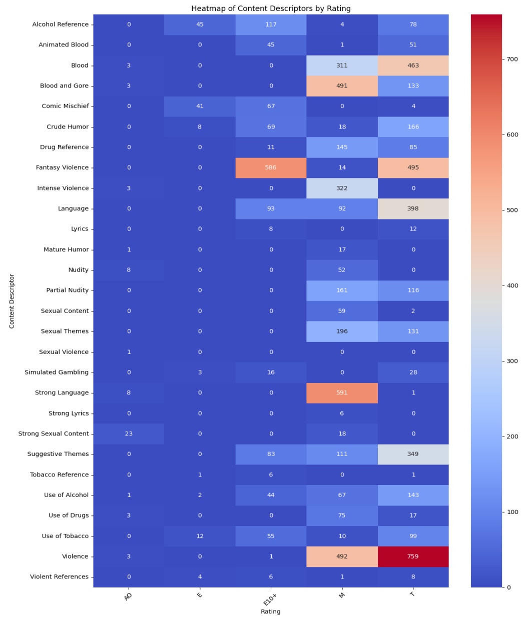

Fig. 5. Heatmap of Content Description by Rating

Moreover, the data indicates that 'Alcohol Consumption' and 'Drug Depictions' are present across several rating categories, with a higher occurrence in games classified as 'Mature' (M). This demonstrates that the industry acknowledges the presence of these elements in the actual world and integrates them into virtual environments, assuring their appropriateness for various age demographics.

The explicit correlation between the content descriptions and their accompanying game ratings underscores the gaming industry's commitment to regulated dissemination of content. This is also evident in the industry's adherence to societal standards and regulatory expectations, which ensures that the information provided aligns with the recognized criteria for each age group. The heatmap functions as a visual representation of the frequency of material and acts as a recognition of the meticulous content curation practices utilized in the gaming industry.

4.4 Interactive Elements

The inclusion of interactive elements in the dataset highlights the intricate and varied nature of modern gaming experiences, as shown in Fig. 6.

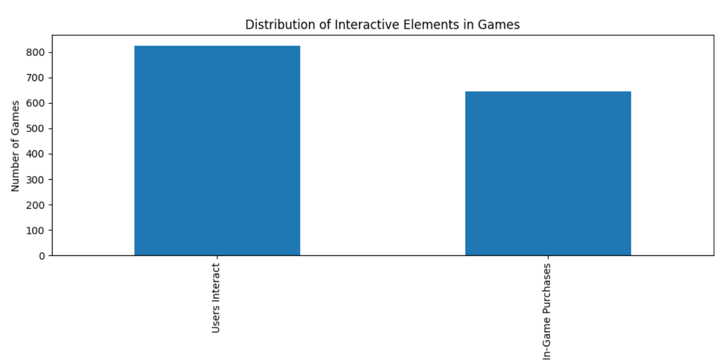

Fig. 6. Distribution of Interactive Elements in Games

The term “Users Interact” appears 825 times, referring to the wide range of social interactions facilitated by games, including both cooperative gameplay and competitive multiplayer situations. The existence of In-Game Purchases, which have been detected 646 times, provides proof of the dominant commercial methods that underpin the economic framework of the gaming industry. In this particular sector, the utilization of microtransactions and downloaded content has become a standard practice.

The presence of these interactive elements indicates the shift of the business from personalized experiences to lively, user-focused communities and economies. The transformation has significant implications for understanding user behavior, prioritizing game creation, and developing monetization strategies in the field of digital gaming.

The heatmap in Fig. 7 illustrates the spatial distribution of interactive elements in video games, categorized based on the ESRB ratings. The absence of 'In-Game Purchases' or 'Users Interact' in the 'Adults Only' (AO) category suggests that there is a scarcity of interaction or monetization elements inside this particular niche. Conversely, these characteristics are far more prevalent in games designed for a younger demographic, with 'Users Interact' being particularly noticeable in the 'Everyone' (E) and 'Teen' (T) categories. This indicates a purposeful emphasis on cultivating social ties and encouraging interactive experiences in games designed for a broader spectrum of age groups.

The integration of monetization strategies in video games, referred to as 'In-Game Purchases', becomes increasingly prevalent as the age of the intended audience rises, as evidenced by the consistent rise in usage from 'Everyone' (E) to 'Teen' (T) ratings. The industry's strategy for in-game economics may demonstrate its deliberate effort to tailor the inclusion of microtransactions to align with the financial means and level of involvement of different age groups.

Furthermore, the notable prevalence of the 'Users Interact' factor in all ratings, especially in the 'Teen' (T) category, emphasizes the gaming industry's shift towards more community-focused and socially driven gaming experiences. This move not only considers the social aspect of gaming, but also conforms to current game design trends that prioritize player interaction as a core component of the gaming experience.

The data indicates a purposeful integration of interactive elements, customized to match the expected level of growth and engagement of the target audience for each rating category. The heatmap provides significant insights on the present trends in game design and strategies to captivate players. This statement highlights the gaming industry's ability to adjust to evolving user expectations and habits.

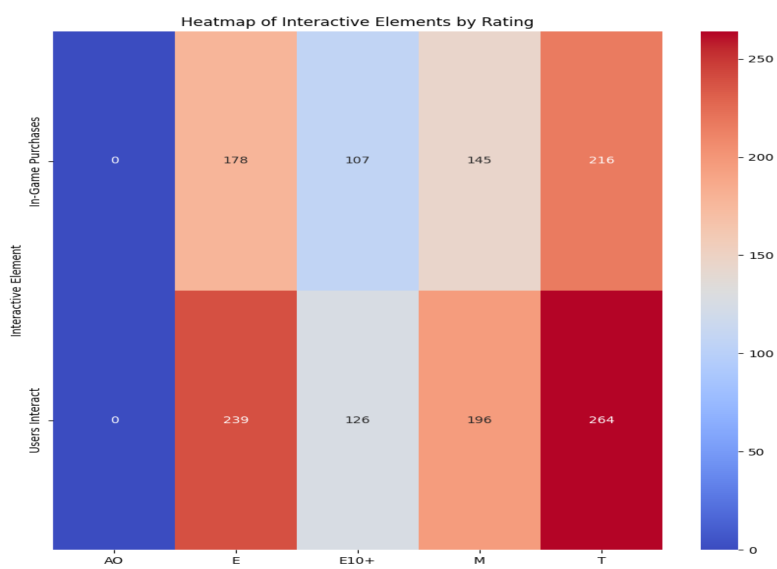

Fig. 7. Heatmap of Interactive Elements by Rating

4.5 Rating Prediction

This study aims to assess the efficacy of multiple machine learning classifiers in predicting video game ratings using distinct feature sets: content descriptors, text characteristics, and a hybrid of both. The dataset Authors have obtained is derived from an extensive video game database. It consists of diverse content descriptors such as violence and profanity, as well as textual summaries that provide descriptions for each game. Authors employ a variety of algorithms specifically designed for each type of feature to preprocess this data. To convert categorical content descriptors and text summaries into a viable format for machine learning models, Authors utilize a StandardScaler for the former and a TF-IDF Vectorizer for the latter.

Authors assess the efficacy of nine classifiers: Gradient Boosting, Logistic Regression, XGBoost, Random Forest, Support Vector Machine (SVM), Decision Tree, Bernoulli Naive Bayes, K-Nearest Neighbors (KNN), and AdaBoost. Every model is trained and validated using 80% training data and 20% testing data split. The performance measures consist of accuracy, precision, recall, and F1-score, which collectively offer a thorough assessment of the success of each classifier.

The classifiers are evaluated based on three separate feature sets:

- Content Descriptors Only: This refers to features that are specifically and directly relevant to the content of the game.
- Text Features Only: Characteristics obtained from written reports of the games.
- Combined Features: A merging of content descriptors and text features.

For every set of features, Authors utilize a pipeline that normalizes numerical data and transforms text data into a numerical representation using TF-IDF vectorization. This technique guarantees that each model is provided with input that optimally retains the informational richness of the original data.

The performance of each classifier is summarized in three tables, each corresponding to a distinct set of features.

- Table 1: Content Descriptors
- Table 2: Text Features
- Table 3: Combined Features

Table 1
Content Descriptors

Classifier	Accuracy	Precision	Recall	F1-Score
GradientBoosting	0.825	0.827	0.825	0.822
LogisticRegression	0.819	0.820	0.819	0.816
XGBoost	0.819	0.819	0.819	0.817
RandomForest	0.816	0.817	0.816	0.813
SVM	0.816	0.818	0.816	0.813
DecisionTree	0.816	0.819	0.816	0.813
BernoulliNB	0.811	0.822	0.811	0.811
KNN	0.811	0.810	0.811	0.808
AdaBoost	0.728	0.749	0.728	0.723

GradientBoosting demonstrates superior performance in all criteria (Accuracy, Precision, Recall, F1-Score), indicating its effectiveness in managing both numeric and categorical data commonly encountered in content descriptors.

Logistic Regression, XGBoost, and **DecisionTree** demonstrate comparable performance, with Logistic Regression and XGBoost significantly surpassing others in terms of Precision and F1-Score.

RandomForest and **SVM** have comparable performance but are somewhat surpassed by the leading performers.

Among the classifiers, **BernoulliNB** and **KNN** have the least effectiveness, while **AdaBoost** exhibits the lowest scores. This suggests that content descriptors alone may not offer enough information for these algorithms to accurately distinguish between different game types or characteristics.

Table 2
Text Features

Classifier	Accuracy	Precision	Recall	F1-Score
XGBoost	0.741	0.766	0.741	0.738
GradientBoosting	0.738	0.762	0.738	0.732
SVM	0.738	0.767	0.738	0.732
RandomForest	0.727	0.756	0.727	0.721
LogisticRegression	0.727	0.758	0.727	0.721
DecisionTree	0.667	0.688	0.667	0.663
BernoulliNB	0.640	0.706	0.640	0.642
KNN	0.605	0.677	0.605	0.621
AdaBoost	0.578	0.621	0.578	0.562

XGBoost demonstrates superior performance, showcasing its resilience with text-based features, closely trailed by **GradientBoosting** and **SVM**. These classifiers have high precision, indicating that they are dependable in their positive predictions.

Both **RandomForest** and **Logistic Regression** algorithms exhibit comparable performance, suggesting a satisfactory ability to process text input, while there is still potential for enhancement.

DecisionTree, **BernoulliNB**, **KNN**, and **AdaBoost** exhibit noticeably inferior performance metrics compared to their peers. This implies that relying solely on text features may present difficulties for these models to fully utilise without the inclusion of other types of data or the application of feature engineering techniques.

Table 3
Combined Feature.

Classifier	Accuracy	Precision	Recall	F1-Score
XGBoost	0.895	0.896	0.895	0.894
RandomForest	0.875	0.876	0.875	0.874
GradientBoosting	0.873	0.877	0.873	0.874
DecisionTree	0.857	0.859	0.857	0.857
LogisticRegression	0.851	0.856	0.851	0.851
SVM	0.823	0.825	0.822	0.820
KNN	0.821	0.8222	0.821	0.799
AdaBoost	0.707	0.739	0.707	0.699
BernoulliNB	0.655	0.723	0.655	0.658

Once again, **XGBoost** demonstrates its superiority by properly handling varied data formats. The integration of content descriptors and text features seems to greatly improve its performance.

RandomForest and **GradientBoosting** algorithms provide robust performance, demonstrating significant advantages when utilizing a combination of different types of features.

The **DecisionTree** and **LogisticRegression** models demonstrate significant enhancements when utilizing mixed features, suggesting that including diverse data types can offer these algorithms a more comprehensive understanding of the game material.

Support Vector Machines (SVM), **K-Nearest Neighbours (KNN)**, and **AdaBoost** demonstrate enhanced but still inferior performance when compared to the leading performers. **BernoulliNB** is the least effective when all the characteristics are combined, although it shows some improvement compared to employing only one type of feature.

The data indicates that the combination of content descriptors with text features results in a substantial enhancement in classifier performance across most parameters. **XGBoost** routinely surpasses competing classifiers in performance across all feature sets, demonstrating its versatility and resilience in processing both structured and unstructured data. The increase in performance measures from Table 1 to Table 3 for most classifiers highlights the importance of using a diverse range of data representation methods to improve classification accuracy and reliability. It also highlights the potential drawbacks of exclusively depending on a single sort of data feature, such as either content descriptors or text features, in order to achieve the best possible classification results. The integration of several data sources seems to offer a more comprehensive comprehension of the game material, enabling more precise predictions and classifications.

Online Application Development

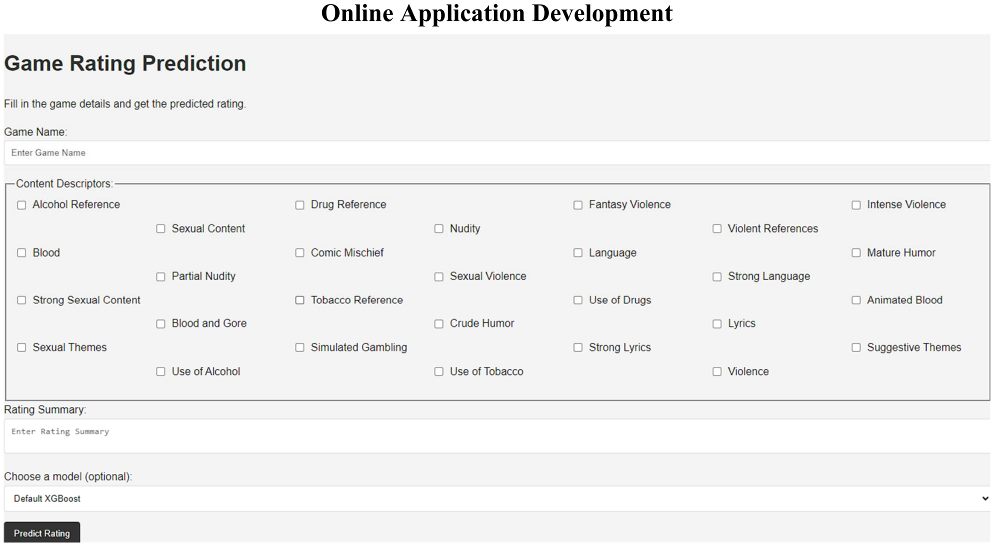

Fig. 8. Web Application Interface

4.6 Implementation of the Web Application Interface

The online application interface, as depicted in the provided screenshot, has been designed to offer a user-friendly and easy platform for users to forecast game ratings, as shown in Fig. 8. The system includes a user interface where users can enter the name of the game, choose appropriate content descriptors, provide a summary of the rating, and optionally select a machine learning model for prediction. The default model is configured as 'XGBoost', which is chosen because to its exceptional performance throughout the analysis stage.

4.7 Flask Web Framework

The application is built using Flask, a lightweight WSGI web application framework. It offers the essential capabilities for handling online requests, answers, and rendering HTML templates. The simplicity and versatility of Flask make it an ideal option for deploying machine learning models in a web environment that is ready for production.

4.8 User Input Handling

The Flask routes / and /predict handle the display of the home page and the prediction process, respectively. Upon form submission by the user, the /predict route manages the POST request, retrieves the form data using **request.form**, and proceeds to process it for prediction.

4.9 Data Preprocessing and Model Prediction

The user inputs are subsequently transferred to the **make_prediction** function, which is loaded from the ml module. This function utilizes the **prepare_input_data** function to create a feature vector from the input data that corresponds to the expected input structure of the model. The preprocessor is utilized to standardize and convert the input characteristics into a vectorized format, after which the designated machine learning model is employed to generate the prediction.

4.10 Displaying the Results

After making the prediction, the anticipated game rating is returned to the user through the **result.html** template. This template presents the predicted classification in a straightforward and succinct manner. In the event of an error occurring during the prediction process, the user will be presented with a suitable message instead.

4.11Application Hosting

The application has been launched successfully and can be accessed at **ml.3omari.com**, where it is publicly available for use. The deployment procedure entailed configuring the application to operate in a production environment with debug mode **disabled**, to guarantee stability and security.

5. Discussion

The extensive data analysis using Python's powerful machine learning tools has shown clear patterns and linkages within the video game dataset. The investigation found a clear association between content descriptors and the ESRB ratings, which has obvious implications for the classification systems employed by rating organizations. The inclusion of mature themes in games classified as 'Mature' (M) and 'Teen' (T) demonstrates a deliberate strategy by the gaming industry to match game content with the corresponding age groups, guaranteeing that the material complies with societal norms and regulatory guidelines. Moreover, the significant inclusion of 'Users Interact' and 'In-Game Purchases' in different rating categories highlights a deliberate change in focus towards developing gaming experiences that are more socially-oriented and economically complex. This indicates a widespread acceptance within the industry of business models that promote user involvement through community development and microtransactions. The machine learning results validate the data patterns, showcasing the efficacy of techniques such as XGBoost in identifying the subtle connections within the data. The built prediction program utilizes this data to create an automated tool that aids creators and rating agencies in accurately selecting appropriate game classes. This technology is a major advancement in incorporating machine learning into operational operations, offering improvements in both the precision and uniformity of game ratings. By utilizing the forecasting capabilities of these models, the application not only serves as a useful tool for stakeholders but also as a foundation for future study and development in the field of content categorization. The heatmap illustrating the distribution of games across various console platforms provides valuable insights into the current status and potential future direction of the industry, reflecting market dynamics. The PlayStation 4's dominance and the Nintendo Switch's great performance, in contrast to the limited game collections of newer consoles and the downfall of older systems, emphasize the fluctuation of platform popularity and market strategy. The combination of these discoveries, along with the comprehensive comprehension of the content and interactive components obtained from the machine learning study, offers a multi-faceted perspective of the gaming industry.

6. Conclusion

The project has effectively utilized Python's data analysis and machine learning to analyze and comprehend the intricate terrain of video game content and ratings. The web tool, which successfully predicts game classifications, is a notable technological achievement with practical implications for the gaming business. The strong association between content descriptions and ESRB ratings, together with the prevalence of interactive aspects, demonstrates the industry's progression towards creating material that is both captivating and suitable for its target demographic. Moreover, the examination of game distribution across different platforms has provided significant information on market penetration and the changing emphasis on platform-centricity, which is highly beneficial for industry stakeholders. This research not only provides an advanced technique for categorizing games, but also enhances the discussion on the appropriateness of material and the involvement of consumers in the digital era. The study establishes the foundation for further investigation, which could result in more sophisticated algorithms and a more profound comprehension of the complex dynamics involved in the realm of video games.

Integrating machine learning into game categorization systems not only improves the technical precision of these evaluations but also conforms to wider legal and ethical norms. To maintain a balance between creative freedom and consumer protection, it will be essential for the gaming industry to integrate new technologies with regulatory standards as it continues to innovate. This study seeks to further the ongoing discussion by showcasing the capability of machine learning to enhance the effectiveness and adherence to legal standards of game classification systems.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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