Sentiment Analysis of User Reviews on the Game GTA V Using Support Vector Machine

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Abstract— **This study explores user sentiment toward the game Grand Theft Auto V (GTA V) by analyzing 101,540 user reviews collected from Steam and Kaggle. The reviews were processed using standard text preprocessing techniques including case folding, tokenization, stopword removal, and stemming. The TF-IDF method was used to convert text into numerical vectors, and sentiment classification was conducted using the Support Vector Machine (SVM) algorithm. The model was evaluated with accuracy, precision, recall, and F1-score as performance metrics. Results show that 88.8% of reviews are positive, while 11.2% are negative. The SVM model achieved an accuracy of 94.2% and an F1-score of 94.2%, indicating high reliability. Wordcloud analysis highlights key aspects valued by users such as graphics, story, and gameplay, while negative sentiment is often associated with technical issues like lag and bugs. This study demonstrates the effectiveness of combining TF-IDF and SVM for sentiment classification in the gaming domain, and it offers a scalable approach for understanding public opinion in digital platforms.**

Keywords— *GTA V, sentiment analysis, support vector machine, TF-IDF, user review*

I. INTRODUCTION

In today's digital landscape, video games have evolved far beyond their original role as a source of leisure. They now represent a dynamic component of contemporary culture, lifestyle, and digital social interaction [1]. The gaming industry has emerged as a crucial segment of the digital economy, fostering interactive environments where players engage in creative pursuits, establish online communities, and express their perspectives through user-generated content [2].

One prominent example of this transformation is Grand Theft Auto V (GTA V), an open-world title developed by Rockstar Games. Since its release, GTA V has achieved remarkable commercial success and is recognized among the best-selling games globally [3]. The game has garnered extensive feedback from players via multiple online platforms, with Steam—one of the leading digital game distribution services—serving as a primary outlet for user reviews and ratings [4].

The abundance of user-generated reviews introduces a key analytical challenge: how to efficiently extract and interpret public sentiment from large-scale textual data. To address this, sentiment analysis leveraging Natural Language Processing (NLP) and machine learning algorithms has been widely employed. These methods classify opinions into sentiment categories, typically positive or negative, and have demonstrated efficacy across various fields [5][6].

For example, Decision Tree models optimized using Particle Swarm Optimization (PSO) have been applied to analyze GTA V Roleplay reviews [7], while comparative studies between Naïve Bayes and Support Vector Machine (SVM) have explored sentiment trends in film reviews [8]. Likewise, SVM has proven effective in analyzing tourist opinions from platforms like Google Reviews [9]. Moreover, Steam has been highlighted as a credible repository for understanding user sentiment in the gaming domain [4].

Despite the extensive application of sentiment analysis in sectors such as cinema and tourism, limited attention has been given to large-scale sentiment classification in open-world video games like GTA V. The complexity of GTA V reviews—spanning technical performance, gameplay, storyline, and community interaction—demands a scalable sentiment analysis framework, which has been underexplored in prior studies. This study introduces a hybrid approach utilizing SVM in conjunction with Term Frequency–Inverse Document Frequency (TF-IDF) to assess player sentiment toward GTA V. The ultimate objective is to construct a computational sentiment map that offers actionable insights for developers seeking to refine product quality and elevate user experience.

A dedicated Related Work section has been added to provide a structured overview of existing studies. Prior works are organized based on method and application domain, including sentiment analysis using Support Vector Machines (SVM) in gaming contexts [10], hybrid approaches combining Particle Swarm Optimization (PSO) and Decision Tree for classifying game reviews [11], [12], and Naïve Bayes-based models applied to sentiment detection in mobile applications [13], [14]. In addition to these conventional machine learning algorithms, recent studies have also explored deep learning

techniques for sentiment analysis [15], although such methods typically require larger training datasets and higher computational resources. Distinct from these prior studies, the present work focuses on large-scale user-generated reviews from open-world games, with a particular emphasis on Grand Theft Auto V (GTA V).
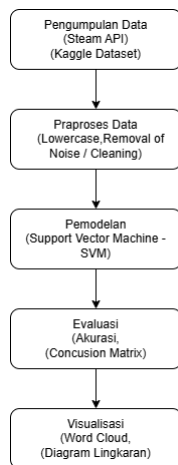
II. MATERIALS AND METHODS

Figure 1. Research flowchart
Source: Author's documentation.

A. Dataset

This research leverages user-generated reviews of *Grand Theft Auto V* (GTA V) as the principal data source. To ensure both breadth and representativeness, the dataset was compiled from two primary origins.

The first dataset was obtained from Kaggle, a well-known platform for public data repositories. This particular collection comprises English-language reviews of GTA V sourced from the Steam platform, spanning from June 27, 2023, to February 7, 2024. It encompasses over 52,000 entries, each containing the review text, timestamp, and a sentiment label derived from Steam's native recommendation system—explicitly categorized as either "Recommended" (indicating positive sentiment) or "Not Recommended" (indicating negative sentiment) [10].

To enrich the dataset and include more up-to-date user feedback, additional reviews were gathered through web scraping techniques. This complementary data acquisition covered the period from February 8, 2024, to March 23, 2025. The scraping process was carried out using the official Steam API in conjunction with Python-based tools such as requests and BeautifulSoup, enabling systematic and policy-compliant data extraction.

Upon consolidating both data sources, the final dataset comprised 101,540 review entries. Each entry includes the review content, posting date, and sentiment classification—either positive or negative—assigned using a hybrid approach that combines manual inspection with semi-automated labeling. This extensive dataset provides a solid foundation for

evaluating user sentiment and identifying emerging opinion trends regarding the quality and reception of GTA V.

B. Data Preprocessing

Text preprocessing is a foundational component of sentiment analysis, aimed at transforming unstructured textual input into a format suitable for machine learning models. Raw textual data typically contains noise and inconsistencies, such as punctuation, stop words, or variations in case, which must be addressed to ensure analytical precision.

The preprocessing pipeline in this study incorporated several key procedures:

- **Lowercasing:** All review texts were transformed into lowercase to maintain consistency across tokens and prevent redundancy caused by case-sensitive mismatches (e.g., "Game" and "game" treated as different tokens).
- **Character Filtering:** Non-alphabetic elements—including punctuation, numbers, and special symbols—were removed, as they contribute minimal semantic value and may distort the learning process. This filtering step helps to streamline the textual data.
- **Stopword Elimination:** Function words such as "is," "the," and "and," which typically carry limited contextual meaning, were excluded using the standard English stopword list provided by the Natural Language Toolkit (NLTK). This process aims to retain only the most informative terms.
- **Tokenization:** Each review was decomposed into individual word units (tokens) through the word_tokenize() function in NLTK. Tokenization enables precise text manipulation and facilitates further analysis at the word level.
- **Stemming:** Word stems were extracted to normalize inflected or derived terms. For example, "playing," "played," and "plays" were all reduced to their root form "play" using the Porter Stemmer algorithm. This normalization step reduces dimensionality and improves generalization in model training.

All preprocessing operations were implemented using the Natural Language Toolkit (NLTK) library in the Python programming environment. The resulting corpus—cleaned and standardized—served as the foundation for the subsequent feature extraction phase, which utilized the Term Frequency–Inverse Document Frequency (TF-IDF) technique to quantify textual information.

To enrich the preprocessing outcomes, word cloud visualizations were also constructed for both sentiment classes. These graphical representations illustrate the most prominent terms found in positive and negative reviews, offering an intuitive overview of recurring lexical patterns. The word clouds corresponding to each sentiment category are displayed in Figure 2 and Figure 3.

Figure 2. Word cloud of positive reviews
Source: Author's visualization using Google Colab.

Figure 3. Word cloud of negative reviews
Source: Author's visualization using Google Colab.

The word cloud visualizations (Figure 2 and Figure 3) provide an intuitive portrayal of lexical distributions in user reviews. Beyond merely depicting term frequency, these graphics subtly reveal the emotional undertones embedded in user sentiment. The relative size and positioning of each word reflect its prominence, thereby enabling rapid identification of dominant themes and linguistic trends within the corpus.

In the positive sentiment word cloud, frequently occurring terms such as "graphics," "fun," and "story" suggest user appreciation for Grand Theft Auto V's visual aesthetics, entertainment value, and narrative structure. Conversely, the negative sentiment visualization is dominated by terms like "bug," "lag," and "crash," underscoring widespread dissatisfaction with technical performance issues.

These visualizations offer a concise yet comprehensive overview of perceived strengths and shortcomings in the game. Moreover, they serve as strategic indicators for developers by highlighting areas that require optimization. The prevalence of technical complaints in the negative sentiment cluster, for example, may inform future development efforts aimed at performance enhancement.

In sum, word clouds function not only as visual summaries but also as qualitative instruments that enhance the interpretability of sentiment analysis. Their insights reinforce the preprocessing outcomes and contribute to the robustness of subsequent analytic stages, including TF-IDF-based feature extraction and classification using Support Vector Machines (SVM).

C. Feature Extraction (TF-IDF)

Following the preprocessing stage—which included normalization, stopword elimination, and stemming—the next critical step involved transforming the textual reviews into a numerical format amenable to machine learning algorithms. For this purpose, the Term Frequency–Inverse Document Frequency (TF-IDF) technique was employed as the core feature extraction method.

TF-IDF is a statistical weighting scheme designed to quantify the significance of a word within a particular document relative to its occurrence across a broader corpus. It consists of two principal components:

- **Term Frequency (TF):** Quantifies how often a term appears in a single document, indicating its contextual relevance within that document.
- **Inverse Document Frequency (IDF):** Measures the rarity of a term across the entire corpus. Rare terms are assigned higher weights, reflecting their discriminative potential in sentiment analysis.

By combining these two components, TF-IDF assigns greater weight to terms that are both frequent within individual documents and relatively rare across the corpus, thereby emphasizing contextually meaningful words while down-weighting ubiquitous, less informative ones.

Each review was subsequently transformed into a high-dimensional feature vector, where each dimension corresponds to the TF-IDF weight of a particular term. The resulting matrix is sparse, as most words do not occur in every document. This sparse matrix serves as the input for the classification algorithm used in the sentiment analysis.

In this study, TF-IDF vectorization was implemented using the TfidfVectorizer class from the Scikit-learn library in Python. The following hyperparameters were configured to optimize feature extraction:

- stop_words='english': Removes standard English stopwords to reduce noise.
- max_df=0.85: Excludes terms that appear in more than 85% of documents, as such terms offer limited discriminatory power.
- min_df=5: Filters out terms occurring in fewer than five documents, reducing the influence of outliers.
- ngram_range=(1,1): Restricts the representation to unigrams (single-word tokens) for computational efficiency and interpretability.

These settings facilitated the generation of a refined and noise-reduced numerical representation of the review texts, thus improving the model's capacity to learn meaningful sentiment patterns.

To classify user sentiments, this study adopted the Support Vector Machine (SVM) algorithm with a linear kernel. SVM was selected for its well-documented performance in text classification tasks and its proficiency in handling high-dimensional, sparse data—such as TF-IDF feature vectors.

SVM operates by constructing an optimal hyperplane that maximally separates two data classes—in this case, positive and negative sentiments. The optimal hyperplane is the one that achieves the widest possible margin between the classes, enhancing the model's generalization ability to unseen data.

The model training was conducted using the TF-IDF feature matrix, with implementation carried out via the LinearSVC module from Scikit-learn. To ensure reproducibility, a fixed random_state parameter was applied.

The dataset was split into training and testing subsets using an 80:20 ratio through the standard train_test_split method.

The selection of SVM was also influenced by its computational efficiency and robust performance in large-scale natural language processing tasks. Once trained, the model was used to generate sentiment predictions for the test set, which were then evaluated using various performance metrics in the subsequent analysis phase.

D. Model Evaluation

The evaluation phase was designed to measure the performance of the sentiment classification model in accurately differentiating between user reviews with positive and negative sentiment. This assessment was conducted on the test subset, comprising 20% of the total dataset, which had been previously separated using the standard train–test split technique.

Model performance was analyzed using a **confusion matrix**, which tabulates the number of true positives, true negatives, false positives, and false negatives by comparing predicted sentiment labels against their actual counterparts. This matrix serves as the foundation for computing several key evaluation metrics, each offering distinct insights into model behavior:

- **Accuracy:** Represents the proportion of total correct predictions relative to all predictions made. It offers a general measure of the classifier's overall effectiveness.
- **Precision:** Quantifies the proportion of predicted positive instances that are actually positive. A higher precision indicates a lower false positive rate.
- **Recall (Sensitivity):** Reflects the model's ability to correctly identify all actual positive instances. This metric is crucial in applications where false negatives are particularly undesirable.
- **F1-Score:** Denotes the harmonic mean of precision and recall, offering a balanced evaluation metric, especially valuable in cases involving imbalanced class distributions.

In the context of this study—sentiment classification of user reviews for *Grand Theft Auto V (GTA V)*—these evaluation metrics provide a holistic understanding of model performance. **Accuracy** offers a macro-level view of the classifier's ability to produce correct predictions. **Precision** and **recall**, in contrast, furnish more nuanced insights into how reliably the model distinguishes sentiment polarity. The **F1-score** serves as a critical indicator of balance between precision and recall, particularly in datasets where one sentiment class may be more prevalent than the other.

Collectively, the evaluation process grounded in the confusion matrix and its associated metrics is essential not only for quantifying classification performance but also for identifying potential shortcomings in the model. Such analysis lays the groundwork for subsequent refinements, whether through data augmentation, algorithmic optimization, or enhanced feature engineering strategies.

III. DISCUSSION AND RESULTS

This study successfully performed sentiment classification on a total of 101,540 user reviews pertaining to the video game *Grand Theft Auto V (GTA V)*, obtained from both the Steam platform and publicly available datasets on Kaggle. The classification process employed the Support Vector Machine (SVM) algorithm, which was paired with Term Frequency–Inverse Document Frequency (TF-IDF) for feature representation. This methodological combination demonstrated high effectiveness in capturing semantically meaningful and context-relevant terms from user-generated content, thereby enhancing the model's discriminatory power.

Prior to model training, an exploratory data analysis (EDA) was conducted to investigate the initial distribution of sentiment labels. The results of this analysis indicated a pronounced skew toward positive sentiment, with favorable reviews significantly outnumbering negative ones. This distribution suggests that the majority of users expressed satisfaction with their gameplay experience, reinforcing the perception of *GTA V* as a well-received and engaging title within the gaming community.
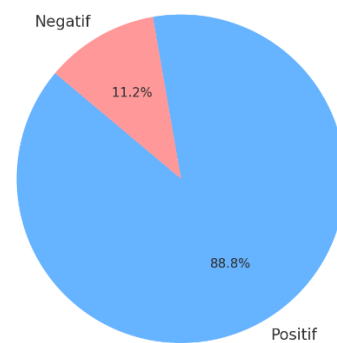
Figure 4. Distribution of sentiment proportions in user reviews of GTA V
Source: Author's visualization using Google Colab.

Figure 4 illustrates a pie chart depicting the sentiment distribution within user reviews for *Grand Theft Auto V (GTA V)*. A thorough analysis of the dataset indicates that approximately 88.8% of the reviews express positive sentiment, while the remaining 11.2% fall under the negative sentiment category.

The overwhelming proportion of positive reviews underscores the game's favorable reception among its player base, suggesting a high degree of user satisfaction with the overall gaming experience. Nevertheless, although smaller in number, negative reviews are of critical importance, as they provide constructive criticism that can inform developers about potential areas requiring improvement.

This sentiment distribution offers a valuable preliminary insight into public perception of the game's quality. It serves as a strategic guide for developers to strengthen features that are well-received and to address the concerns highlighted by dissatisfied users.

Following the data preprocessing stage—including normalization, stopword removal, and TF-IDF-based transformation of textual content into numerical feature vectors—the dataset was subjected to sentiment classification.

This phase utilized the Support Vector Machine (SVM) algorithm, selected for its robust performance in high-dimensional spaces and its compatibility with the sparse matrices generated by TF-IDF.

To ensure a rigorous and unbiased evaluation, the dataset was split into training and testing subsets using an 80:20 ratio via the standard train-test split method. This strategy was adopted to mitigate overfitting and to evaluate the model's generalizability to unseen data.

The classification model's effectiveness was quantified using four widely adopted metrics: accuracy, precision, recall, and F1-score. These metrics offer a multidimensional perspective on the model's predictive capabilities, encompassing both overall correctness and performance in handling each sentiment class. A summary of the evaluation results is presented in Table I.

TABLE I. PERFORMANCE EVALUATION RESULTS OF SENTIMENT CLASSIFICATION MODEL USING SVM
Source: Author's analysis using Google Colab.

Metric	Value (%)
Accuracy	94.2%
Precision	92.8%
Recall	95.6%
F1-score	94.2%

Following the preprocessing phase and the transformation of textual data into numerical features using the Term Frequency–Inverse Document Frequency (TF-IDF) method, the Support Vector Machine (SVM) classification model was trained and evaluated. The dataset was proportionally divided using an 80:20 split between the training and testing sets to ensure objective evaluation and reduce the likelihood of overfitting.

The model's performance was assessed using four widely recognized evaluation metrics: accuracy, precision, recall, and F1-score. The results demonstrated that the SVM model was highly effective in discerning sentiment polarity within user reviews.

The model achieved an accuracy of 94.2%, indicating a strong capability to correctly classify the majority of reviews into their respective sentiment categories. The F1-score, also reported at 94.2%, highlights a well-balanced performance between precision and recall. This balance suggests that the model successfully minimizes misclassification while consistently identifying both positive and negative sentiments in a representative manner.

This high level of performance can be attributed to the complementary strengths of the methods employed. The TF-IDF technique proved instrumental in emphasizing the most informative terms by assigning weight based on their importance in differentiating sentiment classes. Concurrently, the SVM algorithm effectively handled the high-dimensional and sparse nature of the feature space, constructing an optimal hyperplane that distinctly separates the two sentiment categories.

In summary, the combination of TF-IDF feature extraction and SVM classification yielded a reliable and robust model for sentiment analysis. These findings provide actionable insights for game developers, enabling a deeper understanding of user perceptions. The ability to mine sentiment patterns from large-scale user-generated reviews empowers developers to adopt data-driven strategies aimed at enhancing product quality and addressing user concerns based on authentic feedback from the gaming community.
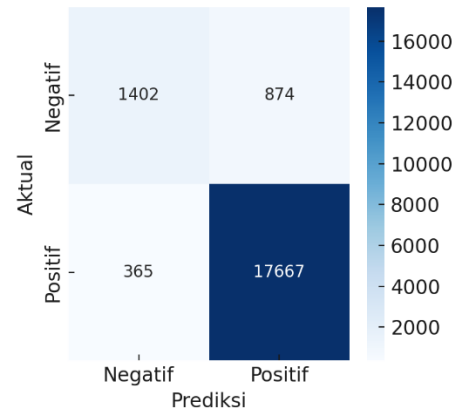

Figure 5. Visualization of the confusion matrix resulting from sentiment classification using the SVM algorithm
Source: Author, generated using Google Colab.

Figure 5 presents the confusion matrix derived from the evaluation of the Support Vector Machine (SVM) model applied to the sentiment classification of user reviews for *Grand Theft Auto V*. In this matrix, the diagonal elements correspond to correct classifications for both positive and negative sentiment classes, whereas the off-diagonal elements represent misclassified instances—cases where the model assigned an incorrect sentiment label.

The evaluation results based on this confusion matrix confirm that the SVM model achieved a high degree of accuracy across both sentiment categories, with a minimal number of misclassifications. This indicates that the model generalizes well to previously unseen data and does not exhibit symptoms of overfitting or underfitting.

When benchmarked against related studies, the model's performance is notably superior. For example, Arinal and Purnomo (2023) utilized a hybrid model combining Decision Tree and Particle Swarm Optimization (PSO), achieving an accuracy of 89%. Similarly, Iriananda et al. (2023) implemented SVM with Grid Search and reported an accuracy of 93%. In contrast, the present study attained an accuracy of 94.2%, thereby establishing a new performance benchmark within this domain.

This enhanced classification performance is attributed to several key factors:
- **Rigorous data preprocessing**, involving

comprehensive steps such as **text normalization, stopword removal, tokenization**, and **stemming**, which collectively improve the uniformity and quality of the input data;

- Utilization of a **larger and more heterogeneous dataset**, offering greater contextual diversity and sentiment variation, thereby enabling the model to better generalize across complex review patterns;
- **Optimal model parameterization**, achieved through deliberate and systematic tuning of SVM hyperparameters, which significantly contributes to improved classification outcomes.

These findings underscore the effectiveness of integrating TF-IDF for feature extraction with SVM as the classification algorithm in sentiment analysis tasks. In addition to delivering high accuracy, this method is computationally efficient and relatively straightforward to implement, making it well-suited for large-scale opinion mining applications.

Moreover, the implications of this research extend beyond conventional business use cases. The demonstrated capability of sentiment analysis in this context highlights its value in the entertainment and gaming industries, where it can serve as a strategic tool for assessing and understanding user perceptions. By leveraging insights from user-generated content, developers and stakeholders can make informed decisions to enhance game quality, user satisfaction, and market responsiveness.

IV. CONCLUSION

The results of this study affirm the effectiveness of integrating Term Frequency–Inverse Document Frequency (TF-IDF) with the Support Vector Machine (SVM) algorithm for conducting sentiment analysis on user reviews of the video game *Grand Theft Auto V (GTA V)*. Analyzing a substantial dataset of 101,540 user reviews, the sentiment distribution revealed that 88.8% expressed positive sentiment, while 11.2% conveyed negative sentiment.

Word cloud visualizations further supported these findings. Positive reviews frequently contained terms such as *"fun," "graphics," "amazing,"* and *"story,"* indicating high levels of user satisfaction with the game's entertainment value and narrative quality. In contrast, negative sentiment was often associated with words like *"bug," "lag,"* and *"crash,"* highlighting the continued relevance of technical issues that may impact user experience and should be prioritized in future updates or optimizations.

The sentiment classification model exhibited excellent performance, achieving an accuracy and F1-score of 94.2%. These metrics demonstrate not only the model's precision in correctly identifying sentiment polarity but also its balance in handling both classes, despite class imbalance in the dataset. Compared to previous studies, the model outperformed benchmarks, validating the strength of the data preprocessing pipeline and the suitability of the TF-IDF–SVM approach for this task.

The main contribution of this research lies in empirically validating a scalable and replicable sentiment analysis framework that can process large volumes of user-generated text data with high accuracy. This framework provides game developers with objective, data-driven insights into user perceptions, enabling better-informed decisions in product improvement and customer engagement strategies.

Beyond the context of video games, the proposed methodology exhibits strong potential for cross-domain application in areas such as e-commerce, tourism, public services, and digital marketing. As a lightweight yet powerful approach, it contributes meaningfully to the growing field of intelligent opinion mining systems, showcasing the practical utility of artificial intelligence in capturing and responding to consumer sentiment in real time.

In conclusion, this study advances the methodology for automated text classification and reinforces the value of sentiment analysis as a strategic tool for understanding and enhancing user experience in the digital age.

The proposed framework offers actionable insights by enabling developers to identify key issues, such as bugs and lag, directly from user reviews. This supports targeted improvements and enhances overall user satisfaction. The combination of TF-IDF and SVM has proven effective in accurately capturing user sentiment and can be implemented as a data-driven tool to aid game development strategies.

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