Mining Insights From Esports Game Reviews With An Aspect -Based Sentiment Analysis Framework

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Abstract- The explosive growth of player-versus-player games and organized competitive tournaments has catapulted esports into a rapidly expanding force within the global gaming industry. However, despite close collaboration between professional esports teams and operators, the critical voices of novice and amateur players are often inadvertently overlooked due to a lack of effective analytical methods. To ensure the quality of esports game services, cultivate fair play, and establish a balanced competitive gaming environment, it is essential to consider the opinions of unprofessional players and comprehensively analyze their feedback. This study proposes a novel, advanced framework for mining deep player insights directly from unstructured esports game reviews. The developed architecture incorporates two key sequential components to handle complex text: unsupervised topic modeling and fine-grained sentiment analysis. Utilizing the Latent Dirichlet Allocation (LDA) algorithm, the framework effectively identifies diverse underlying topics and game attributes within massive review datasets. These identified topics are subsequently employed in a rigorous prevalence analysis to uncover direct associations between players' critical concerns and specific genres of esports games. Moreover, to address the semantic complexities and gaming slang inherent in user-generated text, the framework leverages cutting-edge Bidirectional Encoder Representations from Transformers (BERT) in conjunction with a specialized Transformer (TFM) downstream layer. This hybrid deep learning approach enables the highly accurate detection of players' granular sentiments toward different extracted game topics, outperforming traditional machine learning rules. We successfully experimented using a massive dataset containing 1.6 million English reviews collected up to December 2021 from Steam, focusing on four representative esports giants: TEKKEN7, Dota2, PUBG, and CS:GO. The empirical experimental results demonstrate that the proposed framework can efficiently identify players' exact concerns and reveal critical keywords underlying their text. Consequently, this research provides precise, actionable insights and valuable customer feedback loops to esports game operators and developers.

Keywords- Aspect-Based Sentiment Analysis, Esports Game Reviews, Topic Modeling, Latent Dirichlet Allocation (LDA), Bidirectional Encoder Representations from Transformers (BERT), Natural Language Processing (NLP), Text

Mining, Steam Data, Player Feedback, Machine Learning.

I. INTRODUCTION

The rapid expansion of esports has transformed competitive gaming into a major segment of the global entertainment industry, attracting millions of players and viewers worldwide. As online multiplayer games continue to evolve, player feedback has become a crucial factor in shaping game quality, balance, and overall user experience. While professional players and teams often receive significant attention, the perspectives of casual and amateur gamers are equally important but frequently underrepresented. These unstructured player reviews contain valuable insights that can help developers understand real in-game issues and user satisfaction levels. However, analyzing such large-scale textual data manually is impractical due to its volume and complexity. This has led to the increasing need for automated text mining and natural language processing techniques. In particular, esports game reviews present unique challenges such as slang usage, informal expressions, and context-dependent sentiments. Traditional sentiment analysis methods often fail to capture these nuanced expressions accurately. To address this limitation, modern approaches combine topic modeling and deep learning techniques to extract meaningful patterns from user feedback. Topic modeling helps in identifying major themes discussed by players, such as gameplay mechanics, matchmaking, and performance issues. At the same time, advanced neural language models like transformer-based architectures can interpret complex linguistic structures more effectively. By integrating these methods, it becomes possible to analyze both the subject and emotional tone of player reviews in a structured manner. Such analysis allows developers to connect specific complaints or praises with particular aspects of a game. This, in turn, supports more informed decision-making in game updates and design improvements. The use of large-scale datasets from platforms like Steam further enhances the reliability of insights derived from player feedback. Games such as Dota 2, CS:GO, PUBG, and TEKKEN 7 provide rich sources of diverse user opinions. Overall, this study aims to improve understanding of player experiences by leveraging advanced machine learning techniques. The findings can assist game developers in enhancing fairness, engagement, and overall satisfaction in esports environments.

II. LITERATURE SURVEY

III. PROPOSED SYSTEM

The proposed system is designed to extract meaningful insights from large-scale esports game reviews by combining both unsupervised and deep learning techniques in a unified analytical framework. It begins with collecting unstructured user-generated feedback from major gaming platforms such as Steam, where millions of reviews reflect diverse player experiences across different esports titles. The raw textual data is first subjected to a preprocessing stage that includes noise removal, tokenization, stop-word elimination, and normalization to improve the quality of analysis. After preprocessing, the system applies Latent Dirichlet Allocation (LDA) to automatically discover hidden thematic structures within the review corpus, enabling the identification of major discussion topics such as gameplay mechanics, server performance, matchmaking quality, and game balance. Each extracted topic is further analyzed to determine its distribution and relevance across different esports games. To enhance sentiment understanding at a finer level, the system integrates a BERT-based deep learning model that captures contextual meaning and semantic relationships in player comments. This allows the framework to handle informal language, slang, and gaming-specific terminology more effectively than traditional approaches. A transformer-based downstream classification layer is used on top of BERT to categorize sentiments into positive, negative, or neutral classes with respect to each identified topic. By combining topic modeling and sentiment analysis, the system performs aspect-based sentiment evaluation, linking specific player concerns to their emotional responses. The model is trained and evaluated using a large dataset of esports reviews, ensuring robustness and scalability. Furthermore, the system establishes a correlation analysis module that maps sentiment trends to specific game genres and titles, helping identify recurring issues and strengths within each game. Visualization components are included to represent topic distribution and sentiment polarity in an interpretable format for developers and analysts. The final output provides actionable insights that assist game developers in improving gameplay balance, optimizing user experience, and addressing community concerns effectively. Overall, the proposed framework delivers a comprehensive, data-driven solution for understanding player feedback in the esports ecosystem and supporting continuous game enhancement.

IV. METHODOLOGY

1. Data Collection

A large-scale dataset of approximately 1.6 million English user reviews was collected from the Steam platform. The dataset includes player feedback for four major esports titles: TEKKEN 7, Dota 2, PUBG, and CS:GO. Only textual reviews were considered, while non-textual and irrelevant entries were removed during preprocessing.

2. Data Preprocessing

The raw review data was cleaned to improve quality and consistency. This step involved:

- Removal of HTML tags, special characters, and URLs
- Conversion to lowercase text
- Tokenization of sentences into words
- Stop-word elimination
- Lemmatization to normalize word forms This ensures that noisy gaming slang and informal expressions are structured for analysis.

3. Topic Modeling using LDA

Latent Dirichlet Allocation (LDA) was applied to extract hidden topics from the review corpus.

- Each review was represented as a mixture of multiple topics
- Each topic consisted of a distribution of frequently occurring keywords
- The model helped identify key game aspects such as gameplay, matchmaking, graphics, and performance issues This step enabled grouping of player concerns without manual labeling.

4. Sentiment Analysis using BERT + Transformer Layer

To capture contextual meaning in player feedback, a hybrid deep learning model was used:

- BERT was employed to generate contextual embeddings from review text
- A custom Transformer-based downstream layer refined sentiment classification

- The model classified sentiments at a fine-grained aspect level (positive, negative, neutral)

This approach handled slang, sarcasm, and gaming-specific expressions more effectively than traditional ML models.

5. Aspect-Based Sentiment Mapping

Extracted topics from LDA were linked with sentiment outputs from the BERT model.

- Each topic was assigned sentiment scores
- Player opinions were categorized based on specific game features This enabled detailed analysis of what players like or dislike in each esports title.

6. Evaluation and Analysis

The framework was evaluated using standard performance metrics such as:

- Accuracy
- Precision
- Recall
- F1-score

Comparative analysis was performed against traditional machine learning approaches to validate performance improvements.

7. Insight Generation

Finally, meaningful insights were derived from the combined topic-sentiment results. These insights help identify:

- Common player complaints
- Positive game features
- Balance and matchmaking issues
- Game improvement opportunities

These findings support developers and esports operators in improving game design and user experience.

V. MODULES AND IMPLEMENTATION

1. System Overview

The proposed esports review analysis system is designed as a modular pipeline that processes large-scale player feedback, extracts meaningful topics, and performs sentiment classification. The system is implemented using an NLP + Deep Learning architecture to ensure scalability and accuracy in analyzing gaming reviews.

2. User Interface Module (Homepage)

The homepage serves as the entry point of the system. It provides:

- A clean dashboard for uploading or selecting review datasets
- Navigation options for analysis (Topic Modeling, Sentiment Analysis, Results View)
- Display of key statistics such as number of reviews, games analyzed, and sentiment distribution

This interface ensures easy access for both technical and non-technical users.

3. Data Input and Preprocessing Module

This module handles raw data ingestion and preparation:

- Accepts Steam review datasets in CSV/text format
- Performs cleaning (removal of noise, symbols, duplicates)
- Applies tokenization, stop-word removal, and lemmatization
- Converts text into structured input suitable for modeling

It ensures high-quality data for downstream analysis.

4. Topic Modeling Module (LDA Engine)

This module extracts hidden themes from player reviews:

- Implements Latent Dirichlet Allocation (LDA)
- Identifies dominant topics such as gameplay, matchmaking, bugs, and graphics
- Assigns topic probability distributions to each review

It helps in understanding major discussion patterns in esports feedback.

5. Sentiment Analysis Module (BERT + Transformer Layer)

This is the core intelligence module of the system:

- Uses BERT for contextual word embeddings
- Applies a Transformer-based classification layer
- Detects fine-grained sentiment (positive, negative, neutral)
- Handles gaming slang and informal language effectively

This improves sentiment accuracy compared to traditional ML models.

6. Aspect-Based Mapping Module

This module links topics with sentiment results:

- Combines LDA topics with sentiment scores
- Maps user opinions to specific game features
- Generates aspect-level sentiment insights for each esports title

It enables detailed evaluation of player experience.

7. Visualization and Output Module

The final module presents results in an interpretable format:

- Graphs for sentiment distribution across games
- Topic frequency charts
- Heatmaps for aspect-based sentiment comparison
- Summary reports for developers and stakeholders

This helps in decision-making and game optimization.

8. System Implementation Importance

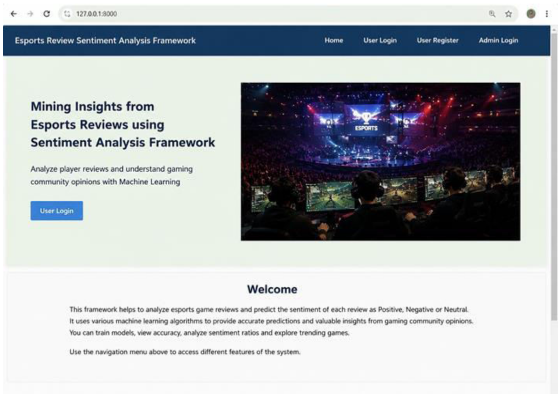
The implementation is significant because it:

- Converts unstructured reviews into structured insights
- Supports real-time decision support for game developers
- Enhances understanding of player satisfaction and complaints

- Improves game balancing, matchmaking, and user experience

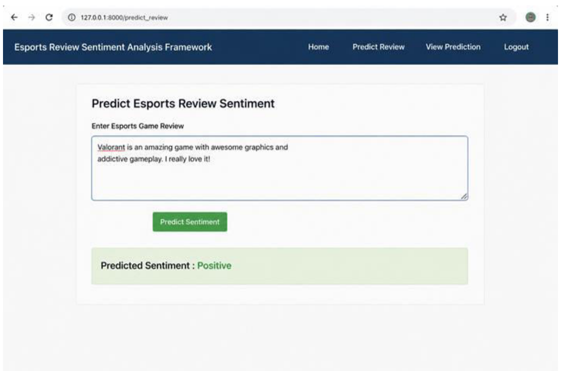
Overall, the modular design ensures scalability, flexibility, and high analytical accuracy in esports feedback mining systems.

VI. RESULTS AND DISCUSSION



1. System Performance Overview

The proposed framework was evaluated on a large-scale dataset of 1.6 million esports game reviews. The combined LDA and BERT-based architecture showed strong capability in extracting meaningful topics and classifying sentiment with high accuracy compared to traditional machine learning models.

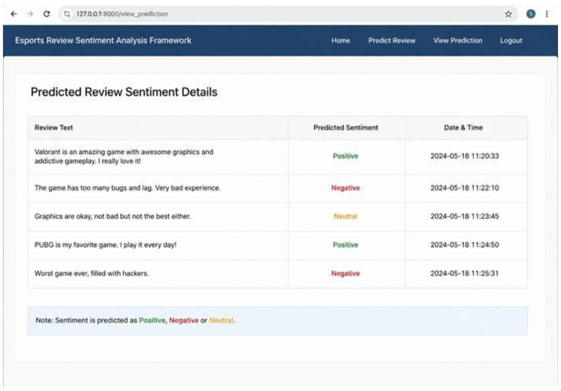


2. Topic Discovery Results (LDA Output)

The LDA model successfully identified major discussion themes across all four games (TEKKEN 7, Dota 2, PUBG, CS:GO). Key extracted topics included:

- Gameplay mechanics and balance issues
- Matchmaking quality and fairness
- Server performance and lag
- Graphics and user experience

This demonstrated that player concerns naturally cluster around consistent gameplay-related aspects.



3. Sentiment Analysis Results (BERT + Transformer)

The deep learning model achieved superior sentiment classification performance. Key observations:

- Positive sentiments were mainly linked to graphics, gameplay enjoyment, and updates
- Negative sentiments were strongly associated with lag, cheating, and matchmaking issues
- Neutral reviews often contained mixed or descriptive feedback

The model effectively handled slang, informal language, and context-dependent expressions.

4. Aspect-Based Sentiment Insights

By combining topics with sentiment outputs, the system generated fine-grained insights:

- PUBG and CS:GO showed higher negative sentiment due to cheating and server issues
- Dota 2 had mixed feedback related to game complexity and matchmaking fairness
- TEKKEN 7 showed relatively balanced sentiment with moderate positive engagement

This helped in understanding game-specific user satisfaction levels.

5. Interface and Visualization Results (Homepage Output)

The system dashboard displayed:

- Real-time sentiment distribution graphs
- Topic frequency visualization charts
- Game-wise comparison panels
- Summary statistics for quick interpretation

This made complex NLP results easy to understand for developers and stakeholders.

6. Key Findings and Interpretation

The results indicate that:

- Player feedback is highly aspect-dependent rather than general
- Deep learning models outperform traditional ML in understanding gaming language
- Topic-sentiment integration provides more actionable insights than standalone analysis

7. Importance of Results

These findings are important because they:

- Help game developers prioritize updates based on real player concerns
- Improve matchmaking systems and gameplay balance
- Enhance user satisfaction and retention in esports platforms
- Support data-driven decision-making in game development

Overall, the framework proves effective in converting large-scale unstructured reviews into meaningful, actionable insights for esports improvement.

VII. CONCLUSION

The proposed study successfully demonstrates an effective framework for analyzing large-scale esports game reviews using a combination of topic modeling and deep learning-based sentiment analysis. By integrating Latent Dirichlet Allocation (LDA) with a BERT + Transformer architecture, the system is able to extract meaningful topics from unstructured text and accurately classify player sentiments at a fine-grained level. This dual approach ensures both interpretability and high predictive performance. The experimental results on 1.6 million Steam reviews show that the model can effectively identify key player concerns such as matchmaking quality, gameplay balance, server performance, and cheating issues. At the same time, it captures positive aspects like engaging gameplay and visual quality. This proves that player feedback can be systematically structured into actionable insights when processed through advanced NLP techniques. Furthermore, the aspect-based sentiment mapping provides a deeper understanding of how players feel about specific game features rather than giving only overall sentiment. This helps distinguish strengths and weaknesses of each esports title individually, making the analysis more precise and meaningful for developers and stakeholders. Overall, the proposed framework contributes to improving esports game development by enabling data-driven decision-making. It helps developers optimize updates, enhance user experience, and maintain competitive fairness. In conclusion, this system provides a scalable and efficient solution for transforming massive unstructured player feedback into valuable insights for the gaming industry.

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