Harnessing Sentiment Analysis with VADER for Gaming Insights: Analyzing User Reviews of Call of Duty Mobile through Data Mining

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ABSTRACT

This study investigates the application of sentiment analysis to understand user feedback for Call of Duty Mobile, a highly popular mobile game, by analyzing 50,000 reviews sourced from the Google Play Store. The research aimed to extract actionable insights from user sentiments, which could guide future game development and improvement. To achieve this, the sentiment of each review was analyzed using VADER (Valence Aware Dictionary and sEntiment Reasoner), a robust tool for classifying sentiment in textual data. The study categorizes reviews into three sentiment groups—positive, negative, and neutral—to identify and analyze prevailing user emotions. The findings revealed that the majority of reviews were positive, with users primarily praising the gameplay, graphics, and overall mobile experience. These aspects were considered crucial in driving user satisfaction and contributed to a majority of the positive feedback. Conversely, negative reviews were often focused on issues such as network connectivity problems, long loading times, and performance errors, indicating areas where users experienced frustration. These results highlight the importance of technical performance and network stability as key factors influencing player satisfaction. The study also delved deeper into keyword analysis to uncover common themes in the reviews, such as in-app purchases and concerns related to technical performance, which were frequently mentioned by users in both positive and negative feedback. These insights provide developers with a clearer understanding of what players value most in the game and where improvements are necessary. The study concludes that sentiment analysis can serve as a powerful tool for understanding user feedback, offering developers a data-driven approach to enhance game features and address user concerns. Moving forward, future research could benefit from the application of additional machine learning models to refine sentiment classification accuracy, as well as the integration of cross-platform reviews to gain a more comprehensive understanding of player sentiment across different user groups and devices. Such approaches would provide a richer, more nuanced view of user experiences, enabling game developers to create even more engaging and satisfying gaming experiences.

Keywords Sentiment Analysis, VADER, Call of Duty Mobile, Game Development, User Feedback, Data Mining, Sentiment Trends, Gameplay Features, Network Issues, In-App Purchases

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Additional Information and Declarations can be found on page 136

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INTRODUCTION

The mobile gaming industry has experienced remarkable growth over the past decade, with titles like Call of Duty Mobile exemplifying this trend. This expansion can be attributed to several interrelated factors, including

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technological advancements, changing consumer behaviors, and effective marketing strategies.

Technological advancements have played a crucial role in the proliferation of mobile gaming. The introduction of smartphones equipped with high-performance processors and advanced graphics capabilities has enabled developers to create more sophisticated and engaging games. Mobile games now leverage the unique features of smartphones, such as touch screens and sensors, to enhance user interaction and engagement [1]. The increasing accessibility of mobile devices has led to a broader audience for mobile games, with an estimated 2.5 billion smartphone users globally [2]. This accessibility has fostered an environment where mobile games can thrive, catering to diverse demographics and gaming preferences.

However, it is not just technological prowess that drives this industry forward. Consumer behavior has shifted significantly, with mobile games becoming a preferred form of entertainment. The convenience and portability of mobile gaming allow users to engage with games anytime and anywhere, which has contributed to their popularity [3]. Equally compelling is the rise of social gaming, which has transformed how players interact with games and each other, creating a community-driven gaming experience that enhances user retention and engagement research [4]. The social aspect of mobile gaming, particularly in multiplayer formats, has been a significant factor in the success of titles like Call of Duty Mobile, which incorporates competitive and cooperative elements that appeal to a wide range of players [4].

Effective marketing strategies have further propelled the growth of mobile gaming. Entrepreneurs in the mobile game sector have adopted innovative marketing approaches to capture the attention of potential players. Leveraging new technologies and understanding consumer psychology are essential for mobile game entrepreneurs to succeed in a competitive market [5]. Additionally, the use of in-game purchases and advertisements has become a prevalent revenue model, allowing developers to monetize their games effectively while providing free access to players [6]. This model has been particularly successful in the context of free-to-play games, where players can enjoy the core experience without upfront costs, thus attracting a larger user base [7].

Despite this bright horizon, the rapid growth of mobile gaming is not without its shadows. Issues related to gaming addiction and mental health have emerged as significant concerns. Research indicates a correlation between excessive mobile gaming and negative psychological outcomes, such as depression and social anxiety [8]. This engagement-addiction dilemma highlights the fine line between meaningful engagement and obsessive gaming behavior, suggesting that developers must implement measures to mitigate these risks [9]. As the industry continues to evolve, addressing these challenges will be crucial for sustaining growth and ensuring a positive gaming experience for users.

Understanding user feedback is paramount in the game development process, as it directly influences user satisfaction and the overall success of a game. The integration of user feedback mechanisms allows developers not just to glean insights, but to refine gameplay and enhance user experience, ultimately fostering a loyal player base that breathes life into the virtual world created.

User feedback serves as a critical barometer for assessing game usability and player engagement. Barnett et al. underscore the importance of First Time User Experiences (FTUEs) in mobile games, suggesting that adherence to usability heuristics can significantly enhance player understanding of game mechanics and interface interactions [10]. By collecting and analyzing user feedback during the onboarding phase, developers can identify usability issues and make necessary adjustments to improve the overall gaming experience research [11]. This iterative process of feedback incorporation is essential for creating games that not only resonate with players but exceed the evolving expectations of a dynamic audience.

Moreover, the sphere of user feedback is not limited to mere usability; it encompasses the emotional and social fabric of gaming. Fox et al. reveal that player experiences in multiplayer environments are profoundly shaped by social interactions and the feedback received from peers, which can either amplify or diminish the enjoyment of the game [12]. The specter of negative feedback in these social contexts can lead to frustration and disengagement, underscoring a pivotal challenge: developers must craft supportive environments that encourage positive interactions among players. Understanding these social dynamics can guide developers in designing features that promote constructive feedback and foster a vibrant gaming community.

Additionally, the impact of user feedback stretches across the spectrum of game design and functionality. Jian et al. highlight that factors such as functional experience and social interaction wield substantial influence over user satisfaction in mobile educational games [13]. This insight compels developers to prioritize user feedback as a cornerstone of enhancing these elements, ensuring that games transcend mere entertainment and enter the realm of meaningful experience. The iterative development process, vividly demonstrated by Bressler, further illustrates how incorporating user feedback can revolutionize game functionality and boost user engagement [14]. By continuously refining gameplay based on player input, developers craft not just a game, but an experience that reverberates with the audience.

Furthermore, the evolution of standardized tools for measuring user satisfaction, such as the Game User Experience Satisfaction Scale (GUESS), provides a structured methodology for gathering and analyzing feedback [15]. These tools enable developers to evaluate various facets of user satisfaction, such as enjoyment, usability, and engagement, paving the way for informed decisions about game design and features. Systematic evaluation of user feedback through these lenses can lead to more pinpointed improvements and ensure a harmonious alignment of the game with player aspirations.

This study embarks on a journey to unveil player sentiments, wielding the power of the Valence Aware Dictionary and sEntiment Reasoner (VADER) to distill actionable insights for gaming development. Sentiment analysis stands as an indispensable tool in the digital age, particularly within the arena of games, where player feedback not only echoes through the design chambers but reverberates in the functionality of the final product.

VADER, a tool uniquely attuned to the nuances of social media sentiment, thrives on deciphering emotions in short textual bursts—tweets and reviews—ubiquitous in gaming discourse [16]. This capability transforms bland data into a rich tapestry of user sentiment, equipping developers with the perception to steer design and marketing strategies with precision. The work of Abimanyu et al. on Apex Legends exemplifies this utility; by dissecting sentiments, they unveil the undercurrents of player perceptions, guiding developers to bolster strengths and rectify weaknesses [17]. Such insights act as a compass, pointing towards enhancements that resonate with the gaming ethos.

Yet, the efficacy of sentiment analysis seldom dwells in isolation. When entwined with machine learning techniques—as explored by Arief—it transcends mere prediction accuracy, diving into the depths of large datasets with renewed vigor [18]. This hybrid methodology crafts a more intricate understanding of user sentiments, allowing developers to sculpt games that are a closer reflection of player desires and anticipations.

User feedback in game development finds further validation in Schwarz et al.'s findings, which emphasize that intrinsic elements such as rewards and feedback are pivotal to user engagement [19]. By scrutinizing sentiments tied to these elements, developers glean invaluable insights into feature resonance and areas demanding recalibration. This dynamic feedback loop underpins the creation of vibrant and fulfilling gaming experiences.

The iterative cadence of game development, underpinned by the rigor of sentiment analysis, harmonizes with user-centered design paradigms. Yardley et al. underscore the necessity of this approach—melding user-centric strategies with iterative refinement based on feedback—to achieve successful digital interventions [20]. This methodology not only amplifies user satisfaction but also cultivates a camaraderie and loyalty among players, ensuring they feel integral to the development narrative.

In the dynamic realm of the gaming industry, a conspicuous research gap emerges concerning the systematic application of sentiment analysis through data mining techniques. Despite the deluge of data from user reviews and social media exchanges, the formulation and deployment of advanced sentiment analysis methodologies remain mysteriously underexplored. This lacuna presents an untapped opportunity for researchers: to leverage sentiment analysis in unearthing profound insights into player experiences and preferences, catalytic in informing game development and strategic marketing endeavors.

One of the foremost challenges in sentiment analysis within the gaming milieu is the requirement for robust methodologies capable of accurately capturing the intricacies and subtleties of player sentiments. Existing studies have embarked on journeys utilizing various machine learning techniques for sentiment classification. Tan and Chow, for instance, ventured into this terrain and offered a comparative study of algorithms tailored specifically for gaming reviews [21]. Yet, the quest for comprehensive frameworks that systematically apply these techniques across diverse gaming platforms and genres remains largely unfulfilled. This void signals a clarion call for more exhaustive research endeavors that not only embrace machine learning but also weave in natural language processing (NLP) techniques, enhancing the precision and profundity of sentiment analysis in this context.

Moreover, the promise of advanced models like SKEP (Sentiment Knowledge Enhanced Pre-training) in sentiment analysis tasks shines brightly. Wang's endeavors showcase superior performance in sentiment classification tasks utilizing this model on game reviews [22]. However, the exploration of such models within the gaming domain is embryonic, beckoning further research to adapt and validate these sophisticated techniques specifically for gaming data. Venturing into this uncharted territory could unlock a trove of actionable insights tailored for developers.

The intricacies of user context and preferences in sentiment analysis demand further illumination. Strååt et al. accentuate the necessity of analyzing user opinions indirectly to encapsulate the broader gaming experience [23]. This methodology underscores the latent potential of sentiment analysis to inform game design by synchronizing features with user expectations and experiential realities. Yet, the focused application of these methodologies within the gaming universe is scant, highlighting a fertile ground for targeted investigative pursuits.

Furthermore, marrying sentiment analysis with user engagement metrics could unveil a holistic vista of player experiences. Danda elucidates the potential of scrutinizing sentiment in relation to subscriber growth rates on digital platforms like YouTube to extract insights on how player sentiments sway community engagement and, subsequently, game popularity [24]. The intersection of sentiment analysis and user engagement metrics presents an arena ripe for exploration, promising valuable revelations for developers keen on enhancing player retention and satisfaction.

The significance of this study unfurls through its capacity to enlighten game developers about user preferences and delineate areas ripe for enhancement in both design and functionality. By harnessing the systematic analysis of user sentiments through advanced data mining techniques—particularly utilizing the VADER tool—developers stand to gain insights that tangibly shape the user experience, imbuing it with increased satisfaction and engagement.

Within the fiercely competitive gaming industry, understanding user preferences serves as the bedrock of a game’s triumph or downfall. As Xu et al. elucidate, capturing and analyzing player feedback is pivotal in forming a symbiotic bond between game companies and their user base, enabling developers to tailor game content based on user evaluations [25]. This dynamic feedback loop not only amplifies the gaming experience but also cultivates player loyalty, as users perceive a tangible investment in their feedback being valued within the development process.

Furthermore, the iterative progression of game development, as articulated by Wang et al., underscores the necessity of integrating both user and expert feedback throughout the design lifecycle [26]. This cyclical approach permits developers to continually refine their creations, ensuring alignment with the dynamic needs and preferences of players. By leveraging user insights, developers can craft informed decisions concerning game mechanics, narrative structures, and holistic design, ultimately culminating in a more engaging and satisfying gaming journey.

In addition to immediate practical implications, this study's findings expand the broader understanding of how user-centered design axioms are applied within the gaming industry. Yardley et al. emphasize that successful digital intervention design necessitates a user-centered and iterative approach, indispensably resonating with users research [20]. By transposing these principles onto game development, developers are equipped to create products that transcend mere entertainment, catering specifically to the nuanced needs and expectations of their audience.

Moreover, the study holds profound implications for enhancing educational and serious games. Nicolaidou et al.'s research underscores the criticality of user feedback in evaluating the efficacy of gamified interventions, especially within educational contexts [27]. By deciphering user preferences and identifying avenues for improvement, developers can concoct more effective serious games that stimulate both learning and engagement in meaningful ways.

Literature Review

Sentiment Analysis in Game Research

The tapestry of existing research consistently underscores the pivotal role of sentiment analysis in decoding user experiences within the vast and variegated landscape of gaming. Through diligent inquiry and analysis of player sentiments, expressed across reviews, social media platforms, and other digital avenues, developers attain a vantage point from which invaluable insights into user preferences and opportunities for advancement in game design are discernible.

A landmark study by Britto and Pacífico elucidates the efficacy of sentiment analysis in gauging user acceptance of games. They propose that sentiment analysis, particularly when synergistically paired with machine learning techniques, provides a formidable toolkit for assessing acceptance rates culled from game reviews, thus equipping developers with pertinent information to steer forthcoming game design decisions [28]. This postulation suggests that by harnessing sentiment data, developers can refine their products to resonate more profoundly with player expectations, thereby fostering an enriched user satisfaction landscape.

Venturing into the realm of advanced methodologies, the work of Wang showcases the potency of the SKEP model within the ambit of game review sentiment analysis. This pioneering study reveals that SKEP surpasses traditional methods in sentiment classification and opinion target extraction tasks, illuminating the path to extracting deeper, more nuanced insights into player experiences [22]. By employing such sophisticated analytical techniques, developers can decipher the subtleties of player feedback, making judicious decisions regarding game features and enhancements.

Parallelly, the research spearheaded by Tan and Chow provides a comparative lens through which the effectiveness of various machine learning algorithms in sentiment analysis for gaming can be examined. Their study elucidates that distinct algorithms yield diverse results in the classification of sentiments from reviews, emphasizing the criticality of selecting contextually appropriate methods for sentiment analysis in gaming research [21]. This insight reinforces the necessity for developers to adopt efficacious sentiment analysis strategies to faithfully capture player sentiments, thus refining and elevating the overall gaming experience.

Moreover, the aspect-based sentiment analysis framework introduced by Yu offers a deftly structured methodology for mining insights from esports game reviews. This framework facilitates a granular examination of user preferences and extant issues within games, empowering operators to enhance game quality predicated on player feedback [29]. As such, these frameworks are instrumental in pinpointing specific areas necessitating improvement, thereby enabling precise, targeted advancements in game design.

VADER for Sentiment Classification

VADER emerges as a luminary in the realm of text sentiment classification, showcasing particular prowess in the analysis of social media exchanges and online reviews. Its lexicon and rule-based approach render it especially adept at parsing sentiments in short texts—an environment replete with tweets and online reviews that characterize the modern gaming landscape.

A salient advantage of VADER lies in its capacity for precision in sentiment classification across diverse contexts, not least within the gaming sphere. The research conducted by Arief illustrates the formidable synergy achieved by coupling VADER with Multinomial Logistic Regression to amplify sentiment classification accuracy in online customer reviews [18]. This hybrid approach excels in detecting neutral sentiments, a frequently encountered hurdle in sentiment analysis. By capitalizing on VADER's comprehensive lexicon, the study elucidates a path to more nuanced and dependable sentiment classification, equipping developers with reliable insights into user dispositions.

Moreover, Shah's contributions underline VADER's application in social intelligence analysis, employing its capabilities to dissect sentiments from tweets research [16]. This utility is acutely pertinent for game developers keen on deciphering player sentiments articulated on social media platforms. Such analyses grant developers a window into the lived experiences and preferences of players, influencing not only game design but also strategic marketing initiatives.

In a separate vein, the comparative study orchestrated by Bonta et al. scrutinized a suite of sentiment analysis tools, including VADER, within the framework of movie reviews. Their findings underscore VADER's superiority over alternatives like TextBlob, particularly in terms of accuracy and reliability for sentiment classification [30]. This reinforces the rationale for selecting VADER as a robust tool in gaming, where comprehending player feedback is imperative for enhancing game quality and user satisfaction.

Within the gaming context, Abimanyu et al. harnessed VADER to scrutinize player sentiments expressed on Twitter concerning Apex Legends. Their analysis revealed that VADER's classifications were in close concordance with expert evaluations, underscoring its efficacy in capturing player sentiments with fidelity [17]. Such validation highlights VADER's reliability for developers aiming to gauge player reactions and sentiments in real-time, thus aligning game adjustments with user expectations.

Furtherakmre, research by Tan and Chow emphasizes the criticality of sentiment analysis in apprehending user needs and preferences within the gaming domain. Their comparative examination of machine learning approaches for sentiment classification demonstrates VADER's efficacy in parsing game reviews into positive, negative, and neutral sentiments [21]. segmentation serves as an essential tool for developers striving to elevate user engagement and satisfaction.

Data Mining Techniques

Data mining techniques have found pervasive utility in the extraction of illuminating patterns from sprawling datasets, particularly within the ambit of sentiment analysis. This methodological approach empowers researchers and developers to derive insightful inferences from extensive volumes of unstructured data, such as social media posts and user reviews, thereby significantly informing decision-making processes with rigor and precision.

Among the pantheon of sentiment analysis tools, VADER stands out for its effectiveness in classifying sentiments within textual data. Arifka et al. adeptly employed VADER to decode Twitter sentiments concerning health protocols during the tumultuous COVID-19 pandemic, illustrating its adeptness in converting sentiments woven into tweets into actionable insights [31]. This application not only underscores VADER's capacity to process voluminous datasets but also highlights its utility in unveiling public sentiment trends over time—a crucial facet for grasping user attitudes within ever-changing socio-cultural milieus.

In a similar vein, the sentiment analysis model proposed by Chiny et al. adeptly marries VADER with Long Short-Term Memory (LSTM) networks and Term Frequency-Inverse Document Frequency (TF-IDF) to bolster sentiment classification accuracy [32]. This synthesis of distinct techniques exemplifies the versatility of VADER when integrated with other data mining methodologies, permitting a more nuanced detection of sentiments within intricate datasets.

Interestingly, the realms of finance have not remained untouched by the reach of sentiment analysis. Long et al. illuminated this versatility by employing VADER to understand stock market dynamics, particularly using the GameStop share rally as a case study [33]. This exploration eloquently illustrates the expansive applicability of sentiment analysis beyond customary domains, affirming its relevance in financially driven decision-making processes galvanized by social media sentiments.

Sukmana's investigations further reaffirm VADER's prowess in social media sentiment analysis, particularly focusing on nuanced subjects like waqf and education [34]. By leveraging VADER for tweet sentiment classification, her study elucidates its applicability across a spectrum of fields, yielding valuable insights into public perceptions and apprehensions.

The significance of sentiment analysis extends into the legislative arena as demonstrated by Cruz and Balahadia, who ingeniously employed VADER to parse public responses to pertinent legislative issues [35]. Their findings accentuate the pivotal role of sentiment analysis in informing policy decisions, enabling lawmakers to discern public sentiment and adapt their strategies acutely in response to prevailing winds of public opinion.

Moreover, a comparative study by Tan and Chow elucidates VADER’s efficacy in dissecting game reviews, adeptly categorizing sentiments into positive, negative, and neutral hues [21]. This capacity is particularly instrumental for game developers keen on deciphering player feedback to refine game design that resonates with user preferences.

Formula for Sentiment Scoring

The analytical prowess of VADER lies in its adept application of a lexical approach, meticulously computing sentiment scores through a specific weighted formula. This methodology emerges as particularly efficacious when faced with the idiosyncrasies of social media and user reviews, domains where brevity and informal expression often defy traditional sentiment analysis techniques.

VADER's operation hinges on assigning sentiment scores to individual words based on a pre-defined lexicon that classifies words as positive, negative, or neutral. Each lexical entry carries a sentiment intensity score, spanning from -4 for the most dour expressions to +4 for the most jubilant. The overall sentiment score for a text emerges from the summation of these word scores, augmented by rules that finesse the interpretation based on contextual nuances. For instance, negations, such as "not good," modulate the positive score of "good," while intensifiers, such as "very good," amplify its positive sentiment [36], [37].

The VADER algorithm's final output presents an array of sentiment scores: discrete positive, negative, and neutral scores, synthesized into a compound score. This compound score, a normalized metric ranging from -1 (indicative of robust negativity) to +1 (indicative of robust positivity), lends itself to intuitive interpretation of the text's overarching sentiment [38], [39]. The calculation of this compound score follows the formula:

$$\text{Compound Score} = \frac{\sum \text{sentiment scores}}{\sqrt{(\sum \text{sentiment scores})^2 + \text{constant}}}$$

The constant serves as a stabilizing factor, particularly crucial when managing texts of diverse lengths. This compound score is then categorized into sentiment classes—positive, negative, or neutral—based on predefined thresholds, streamlining the assessment of user sentiment [30], [40].

The efficacy of VADER within sentiment analysis has been robustly validated through various empirical studies. Ranganathan et al. utilized VADER to dissect public sentiments concerning COVID-19 vaccination expressed through Twitter, illustrating its adeptness in capturing the real-time nuances of user sentiment [41]. In parallel scope, Singh et al. confirmed VADER's reliability in decoding sentiments across varied contexts through its application to COVID-19-related tweets [39].

Method

Dataset Description

The dataset consists of 50,000 anonymized user reviews from the Google Play Store for the game Call of Duty Mobile. It includes three key columns: userName, content, and score. The userName column represents the reviewer's identifier, though it is anonymized for privacy reasons. The content column contains the textual review of the user, which is the main data used for sentiment analysis. The score column contains ratings given by users, ranging from 1 to 5, with 5 being the highest rating. The dataset offers a substantial amount of feedback, allowing for a broad analysis of user sentiment across a variety of opinions and experiences.

Exploratory Data Analysis (EDA)

To gain a better understanding of the dataset, an initial exploratory data analysis (EDA) was performed. This included checking for missing values in the dataset, which showed no missing entries, ensuring the data was complete. The basic statistical properties of the score column were examined, revealing a mean score of 3.77, indicating that the reviews were generally positive, but with noticeable variation. The score distribution showed that most reviews were rated either 5 or 3 stars, with fewer reviews rated 1 or 2 stars. These basic statistics helped identify that while the majority of reviews were favorable, there was a significant presence of critical feedback as well.

Data Preprocessing

Data preprocessing was a critical step to ensure that the textual content in the content column could be effectively analyzed for sentiment. The preprocessing steps included cleaning the text by removing non-essential elements such as special characters, numbers, and stopwords (common words such as "the," "is," etc., that do not contribute meaningfully to sentiment analysis). The content column was tokenized into individual words using NLTK's `word_tokenize` function. These tokens were then filtered to remove any non-alphabetic characters and stopwords, ensuring that the remaining text was clean and suitable for sentiment analysis.

Sentiment Analysis with VADER

The primary tool used for sentiment analysis in this study was VADER, a lexicon and rule-based sentiment analysis tool specifically designed for social media text. VADER assigns sentiment scores to text based on a combination of lexicon (positive, negative, and neutral words) and grammatical rules. For each review, the SentimentIntensityAnalyzer from the VADER library was used to calculate a compound score that represents the overall sentiment. Reviews with a positive compound score (>= 0.05) were classified as positive, those with a negative compound score (<= -0.05) were classified as negative, and those with a compound score between -0.05 and 0.05 were classified as neutral. This classification enabled the study to quantify user sentiments effectively and categorize them into three distinct groups.

Visualization Techniques

To visualize the sentiment distribution, a pie chart was created to show the proportion of positive, negative, and neutral reviews in the dataset. This chart visually highlighted the predominance of positive sentiment among users, with a significant portion of the reviews categorized as neutral, and a smaller portion being negative. Additionally, a correlation table was generated to explore the relationship between sentiment and ratings. This table revealed a clear pattern: positive sentiments were strongly correlated with higher ratings (5 stars), while negative sentiments were linked to lower ratings (1 or 2 stars).

Furthermore, keyword analysis was conducted to identify common themes in the reviews. This was done using word clouds to visualize the most frequently mentioned terms in positive and negative reviews. Positive reviews often mentioned terms related to gameplay and graphics, while negative reviews frequently highlighted issues such as in-app purchases and performance problems. This keyword analysis provided insights into the features that users valued and the areas that needed improvement.

Finally, a keyword frequency analysis was performed across the entire dataset to identify the most common terms in all reviews. This analysis revealed the recurring topics discussed by users, such as gameplay, graphics, and in-app purchases, giving a clear picture of the issues and features most important to users.

Result and Discussion

Sentiment Distribution Visualization

The Sentiment Distribution of the user reviews was visualized using a pie chart, shown in figure 1, which clearly highlighted the predominance of positive sentiments among users. Based on the analysis, the majority of reviews were classified as positive (68.99%), followed by neutral (14.51%) and negative (16.49%). This distribution suggests that the overall reception of Call of Duty Mobile was favorable, with a substantial portion of players expressing satisfaction with the game. The high percentage of positive sentiment aligns with the general perception of mobile gaming titles, where players often enjoy the experience but may voice dissatisfaction over specific issues, which is reflected in the smaller proportion of negative reviews.

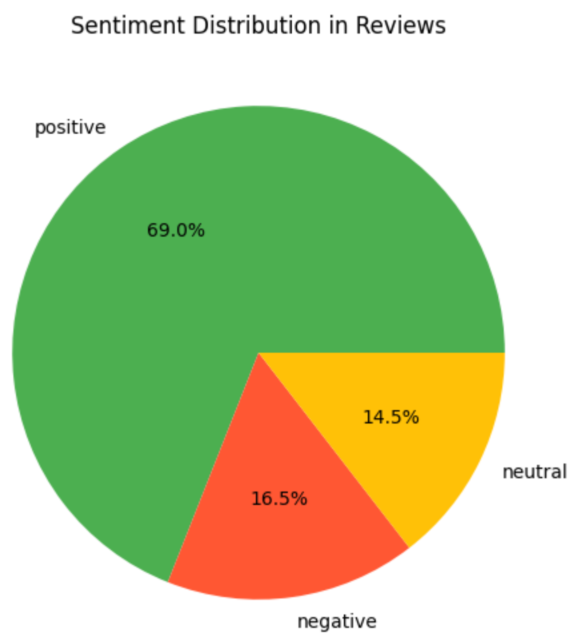

Figure 1 Sentiment Distribution in Reviews

Figure 1 illustrates the Sentiment Distribution in the user reviews for Call of Duty Mobile. The chart clearly highlights the predominance of positive sentiments among users. 69% of the reviews were classified as positive, indicating that the majority of users expressed satisfaction with the game.16.5% of the reviews were categorized as negative, pointing to areas of dissatisfaction among a smaller group of users. 14.5% of the reviews were labeled as neutral, reflecting that a portion of users had neither strongly positive nor negative feedback.

This distribution suggests that while most users are happy with the game, there are still concerns that need to be addressed, particularly in the areas that garnered negative sentiment. The neutral sentiment shows that some users had mixed feelings or felt indifferent about certain aspects of the game.

Correlation Between Sentiment and Ratings

A contingency table was created to analyze the correlation between sentiment and ratings. The table 1 showed that positive sentiments were strongly correlated with higher ratings (4 and 5 stars). In fact, 72.5% of the reviews with a 5-star rating were classified as positive, further confirming the strong relationship between positive user sentiment and higher ratings. Conversely, negative sentiments were mainly associated with lower ratings, particularly 1-star ratings, where 63.6% of 1-star reviews were classified as negative. The correlation table also revealed that neutral sentiment was most common for 3-star ratings, accounting for 38.4% of the total 3-star reviews. This suggests that players who had an average experience, neither strongly positive nor negative, were more likely to leave a neutral review. These insights can guide developers in identifying areas where user satisfaction could be improved by addressing negative feedback or building on aspects that contribute to positive experiences.

Table 1. Sentiment and Rating Correlation

	1	2	3	4	5	Total
negative	5249	500	1500	0	1000	8249
neutral	1805	500	500	500	3949	7254
positive	4565	0	2500	2446	24986	34497

Identification of Common Themes

To identify the common themes in the user feedback, keyword analysis was performed. Word clouds were generated for positive and negative reviews to highlight frequently mentioned terms. In the positive reviews, common words included "game", "best", "good", "like", and "play", reflecting general satisfaction with the game's quality and playability. This suggests that players appreciated the overall gameplay experience and the game's position as one of the best mobile games.

On the other hand, the negative reviews commonly mentioned terms such as "account", "network", and "please", which could indicate issues related to account management or network performance. These common themes in negative reviews point to potential pain points that developers may need to address, such as improving server stability or account recovery processes.

Additionally, an overall analysis of all the reviews identified common terms such as "game", "best", "good", "like", and "mobile", with "game" being the most frequent term, appearing in 39,968 reviews. This further reinforces that the core subject of most reviews is the gameplay experience itself, underlining the importance of maintaining and enhancing the quality of the game to sustain user satisfaction.

These keyword findings suggest that while most users are satisfied with the gameplay and overall experience, there are still critical areas such as network issues and account management that need attention. Addressing these concerns could improve the overall user experience and help reduce the number of negative reviews. By focusing on the themes identified, developers can prioritize updates and features that directly impact user satisfaction.

The word clouds created for both positive and negative reviews provide clear insights into the common themes discussed by users in their feedback. The word cloud for positive reviews (figure 2) reveals several recurring themes related to user satisfaction, such as "good" and "game" dominate the word cloud, with both terms appearing frequently, indicating that users appreciate the overall gameplay experience. Then "best" and "mobile" also appear prominently, suggesting that users consider Call of Duty Mobile as one of the top mobile games. Terms like "free", "cp" (which likely refers to in-game currency), "graphics", and "love" highlight areas where users have expressed positive opinions, with "graphics" pointing to the visual quality of the game and "love" indicating a strong attachment to the game. Additionally, "Call", "Duty", and "mobile" are common, underscoring the branding of the game and its appeal to fans of the Call of Duty franchise on mobile platforms. These positive themes suggest that the gameplay, graphics, and overall experience are highly valued by users. Players appreciate the game's quality, including the fun of playing, and many express excitement about the game's mobile version. It also highlights that players are enjoying the in-game challenges and free content.

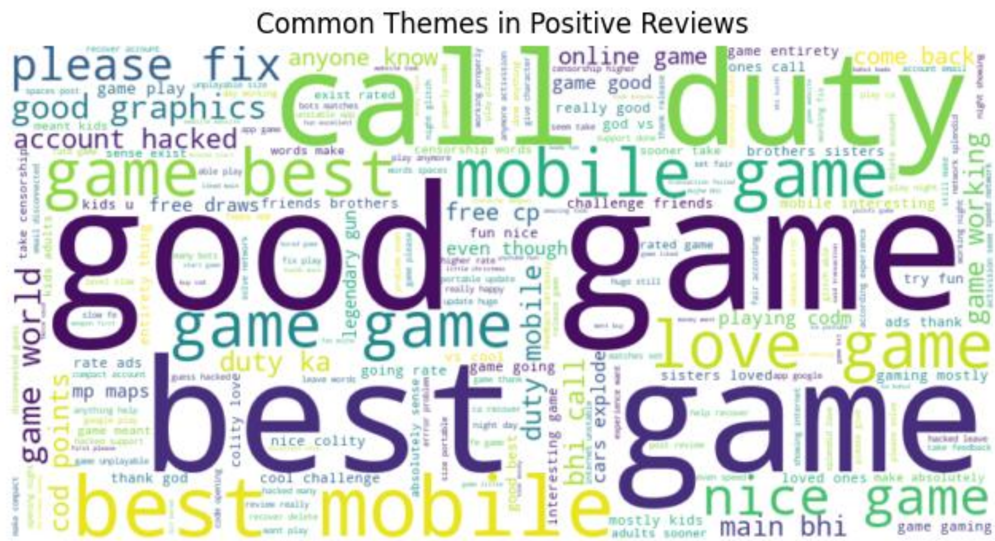

Figure 2 **Word Cloud for Positive Reviews**

The word cloud for negative reviews (figure 3) indicates recurring issues or dissatisfaction, such as "network" and "error" appear as the most prominent terms, suggesting that network issues are a major concern for users, with frequent complaints about "network errors" and "loading" problems. This aligns with users reporting that the game frequently "shows network errors" or "takes too long to load". Words like "experience", "bad", "take", and "minutes" indicate that players are frustrated with the game's performance, particularly with the time it takes to load the game or start matches. Keyword like "everytime", "issue", and "account" highlight complaints regarding recurring technical problems, such as account management issues and persistent loading delays. Terms such as "stuck", "irritating", "error", and "log" point to frustrations with bugs, errors, and performance issues, affecting the overall gaming experience. The common negative themes suggest that network instability and technical issues (like loading times and account errors) are significant pain points for users. These problems negatively impact the overall experience, leading to user frustration and dissatisfaction.

Figure 3 **Word Cloud for Negative Reviews**

The keyword analysis clearly indicates that while users generally enjoy the gameplay and graphics of Call of Duty Mobile, many face challenges with the network performance and technical stability of the game. The presence of in-app purchases is also a common topic in both positive and negative reviews, suggesting that this aspect of the game may influence user sentiment in both directions. Developers can take this feedback into account by focusing on improving network stability and addressing performance bugs while continuing to enhance gameplay features that users are clearly enjoying.

Insights for Game Developer

The results from sentiment analysis and keyword identification offer invaluable insights for game developers seeking to understand user preferences and enhance the Call of Duty Mobile experience. The positive reviews revealed a strong appreciation for features like gameplay, graphics, and the overall mobile experience, with users frequently mentioning words like "best", "good", and "game". These themes reflect the satisfaction users feel toward the gameplay quality, the visual appeal of the game, and its success as a mobile adaptation of the popular franchise. As highlighted by Britto and Pacífico, sentiment analysis plays a crucial role in understanding user acceptance and guiding future game design [28]. By leveraging these insights, developers can continue to refine gameplay elements and graphical features, aligning with player expectations to foster deeper engagement.

However, negative reviews brought attention to recurring issues with network connectivity, performance errors, and account management. Words like "network", "error", and "experience" were prominently mentioned, indicating a significant concern regarding technical aspects of the game. This aligns with findings from Yu's framework on aspect-based sentiment analysis, which emphasizes the importance of identifying specific issues within games to prioritize improvements [29]. Developers should focus on addressing these technical challenges, such as optimizing network stability and enhancing account functionalities, to prevent frustration and reduce the volume of negative feedback.

These findings underscore the importance of both enhancing features that are appreciated by players and addressing technical concerns that detract from the overall experience. In this context, sentiment analysis serves as a powerful tool to drive decisions that make the game more enjoyable and user-friendly.

The sentiment analysis results from this study were compared with findings from other studies to validate and contextualize the insights obtained. In particular, the research by Arief and colleagues, which applied VADER for sentiment analysis in online reviews, demonstrated similar patterns in user sentiment and confirmed the tool's accuracy in classifying sentiments within reviews [18]. By employing VADER, this study achieved comparable results, showing a strong alignment between positive sentiments and higher ratings (5 stars), and negative sentiments with lower ratings (1 star), which mirrors the findings from Arief's work in sentiment classification.

Moreover, the study conducted by Tan and Chow, which examined various machine learning algorithms for sentiment analysis, emphasized the versatility and reliability of VADER in the gaming domain. This reinforces the decision to use VADER for this research, as it consistently provided high precision in detecting player sentiments in reviews [21]. The identification of key themes such as gameplay, graphics, and network issues in both positive and negative reviews further corroborates the findings from Yu's aspect-based sentiment analysis framework, which highlights the significance of such features in determining user satisfaction and areas for improvement in gaming [29].

Additionally, studies by Bonta et al. and Abimanyu et al. highlighted the effectiveness of VADER in analyzing player sentiments on platforms like Twitter, further validating its use in classifying sentiments from diverse sources and contexts [30], [17]. These studies also emphasized the importance of contextually relevant sentiment analysis, aligning with the approach taken in this study to enhance game development by addressing specific areas of user feedback.

Conclusion

In this study, sentiment analysis using VADER was successfully employed to analyze user reviews of Call of Duty Mobile, enabling the identification of significant trends in user sentiment. The analysis revealed that a substantial portion of user feedback was positive, particularly highlighting aspects such as gameplay and graphics, which were key drivers of satisfaction. On the other hand, network issues, performance errors, and account management concerns were identified as major pain points in the negative reviews, suggesting areas for improvement. These findings align with previous studies that emphasize the value of sentiment analysis in understanding user experiences and making data-driven decisions for game development.

The insights derived from this sentiment analysis provide valuable guidance for game developers, particularly in terms of enhancing user experiences. By improving technical aspects such as network stability and optimizing performance, developers can address the negative feedback while continuing to refine features that contribute to the positive sentiment. The study highlights the utility of sentiment analysis as a powerful tool for identifying specific areas that influence player satisfaction and dissatisfaction, offering actionable recommendations to improve overall user engagement.

Future research could explore the application of additional machine learning algorithms for a broader and more nuanced analysis of user sentiment, possibly enhancing the precision and scope of sentiment classification. Furthermore, incorporating cross-platform reviews (e.g., reviews from iOS users, social media feedback) would provide a more comprehensive view of player sentiments, enabling a deeper understanding of the user experience across different platforms and devices. Expanding the scope of sentiment analysis would further refine the insights gained from user feedback and provide developers with a more holistic approach to improving game design.

Declarations

Author Contributions

Conceptualization: M.B., P.S., and V.K.; Methodology: P.S.; Software: M.B.; Validation: M.B., P.S., and V.K.; Formal Analysis: M.B., P.S., and V.K.; Investigation: M.B.; Resources: P.S.; Data Curation: P.S.; Writing—Original Draft Preparation: M.B., P.S., and V.K.; Writing—Review and Editing: P.S., M.B., and V.K.; Visualization: M.B. All authors have read and agreed to the published version of the manuscript.

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