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Sentiment Analysis and Topic Modelling on Twitter Related to Mobile Legends: Bang Bang Game Using Lexicon-Based, LDA, and SVM

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Abstract - Mobile Legends: Bang Bang (MLBB) has become a significant phenomenon within the global e-sports landscape, attracting millions of active players and fans. This study presents a comprehensive sentiment analysis and topic modelling of MLBB-related discussions on Platform Twitter, combining a lexicon-based approach, Latent Dirichlet Allocation (LDA), and Support Vector Machine (SVM) classification within a unified analytical pipeline. A dataset of 4,313 tweets was analysed, revealing that 70.8% expressed neutral sentiment, suggesting that much of the community's communication is informational rather than emotionally charged. Positive sentiments were associated with game content updates and rewards, while negative sentiments focused on technical and competitive issues. The SVM model achieved a sentiment classification accuracy of 90.57%, and cluster classification reached 85.13%. These findings offer valuable insights into how players engage with the game and reflect the underlying sentiments that influence the perception of gameplay and system updates. Furthermore, the predominance of neutral sentiment suggests opportunities for developers and content creators to enhance emotional resonance and community interaction through more engaging content and responsive design. The effectiveness of the combined methodology demonstrates the potential of integrating lexicon-based techniques with machine learning and topic modelling in analysing social media discourse within gaming communities. Future research is recommended to adopt advanced deep learning techniques, develop domain-specific sentiment lexicons, conduct multilingual sentiment analysis, and perform temporal tracking of community sentiment over time, enabling more dynamic and inclusive assessments of user experience and satisfaction.

Keywords—Mobile Legends: Bang Bang, Sentiment Analysis, Support Vector Machine, Lexicon-based, Latent Dirichlet Allocation.

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1. INTRODUCTION

Mobile Legends: Bang Bang (MLBB), one of the foremost well-known versatile diversions all inclusive, empowers players to lock in in day by day 5-on-5 competitions, cultivating an energetic and competitive gaming environment. Online recreations, a frame of digital entertainment, permit people to associate and take part through the web, giving different viewpoints for assessment, counting gameplay, execution, visuals, and by and large player encounter. Understanding player reactions to such recreations offers profitable bits of knowledge from different viewpoints. For this think about, Twitter (X) was chosen as the essential social media stage due to its broad selection by e-sports communities, known for their dynamic engagement and assorted perspectives. X is especially suited for opinion examination and point modelling, as its organised and brief tweet arrange encourages information extraction and investigation. Additionally, its dynamic community habitually talks about e-sports-related themes, such as competitions, techniques, and amusement discharges, making it a wealthy source of real-time information through its open Application Programming Interface (API) [1].

Both basic techniques used for analysing predictions and issues related to Mobile MLBB on X are the estimation assessment and theme modelling. By categorising them based on positive, negative, or neutral, estimation research looks for the users' states of thoughts or conclusions about a particular subject [2]. This approach becomes especially relevant to distraction creators and competition developers since it offers pieces of information on the way individuals respond to execution results, methods, or entertainment announcements. On the other hand, theme modelling determines significant problems or themes that X users frequently study. Latent Dirichlet Allocation (LDA), a well-known point modelling method, classifies tweets into particular topics based on basic designs [3]. This ponder classifies opinion naturally using a lexicon-based approach for the presumption studies, which uses referred to positive and negative phrases. This approach was chosen for its proven viability in particularly capturing opinions expressed through composed writings, which includes tweets. By giving machines the capacity to get it, comprehend, and analyse human dialect, Artificial Intelligence has changed many fields, particularly that of natural language processing (NLP). Machine learning methods and subject modelling are vital in social media and online environments for choosing valuable bits of knowledge from huge quantities of unstructured data. While subject modelling reveals hidden subjects in huge quantities of subject matter, feeling examination identifies the emotional tone of feedback from users or posts. In the field of mobile gaming, particularly in Mobile Legends.

2. LITERATURE REVIEW

2.1 Sentiment Analysis in E-Sports and NLP

Sentiment analysis is increasingly used to interpret user-generated content in e-sports, such as chat logs, reviews, and social media posts. The [4]'s works outlines the standard pipeline for sentiment analysis, i.e.; data collection, preprocessing, feature extraction, classification, and evaluation which underpins its use in gaming contexts. BLIP-NLP model was introduced which integrates contextual NLP features to enhance sentiment classification accuracy, relevant for tracking real-time gamer feedback [5]. Sentiment analysis models (VADER and TextBlob) was applied to analyse Steam reviews of GTAV and Cyberpunk 2077, showing that VADER better captures emotional shifts in player sentiment [6]. Their method involved assigning sentiment scores across gameplay, storyline, community, sound, and graphics. The [7]'s work explored sentiment in voice communications during *Overwatch*, linking emotional tone to game difficulty and team dynamics through LDA and sentiment scoring. This work highlights how sentiment analysis can reveal player psychology during cooperative play. In e-commerce, NLP enhances user interactions through sentiment-aware virtual assistants, a model that can be translated to e-sports platforms [8]. The parallels show that real-time sentiment monitoring is useful for user experience enhancement in digital environments. Overall, lexicon-based models like VADER are useful for short reviews, while hybrid NLP systems better handle complex contextual sentiment. Topic modelling and sentiment fusion also allow analysis of emotional trends over time and context. These insights enable developers to tailor gameplay, improve moderation, and enhance community engagement. Collectively, these studies illustrate the growing value of sentiment analysis in understanding and shaping e-sports experiences.

2.2 Lexicon-Based Approach

Lexicon-based sentiment analysis relies on predefined dictionaries of positive and negative terms. The study addresses the subjectivity and labour-intensive nature of manual lexicon labelling by employing Particle Swarm Optimization (PSO) to automatically assign sentiment polarity scores to words, optimising these scores to improve classification accuracy [9]. Recognising that traditional lexicon-based methods struggle with texts lacking known sentiment words, the authors integrate a machine learning component to classify such texts, resulting in a hybrid model capable of analysing over 99% of inputs effectively. The research includes the creation of two Slovak-language lexicons, i.e.; 'Small' and 'Big', and a new dataset of short texts, all made publicly available for further research. Experimental results demonstrate that the PSO-labelled lexicons outperform those labelled manually, and the hybrid model surpasses the standalone lexicon-based approach in classification performance. This methodology is particularly applicable in domains like human–robot interaction, where understanding human emotions is crucial for effective communication. By combining optimization techniques with traditional sentiment analysis, the study offers a scalable and less subjective framework for emotion detection in textual data. We employed lexicon-based techniques consisting of TextBlob, VADER, and SentiWordNet, alongside machine learning classifiers consisting of Naive Bayes, Support Vector Machines, and Decision Trees, to organise tweets into positive, negative, or neutral sentiments [10]. Their results indicate that lexicon-based techniques are simple and work well over general sentiment identification, but machine learning algorithms are more accurate, particularly when it comes to picking into subtle emotions in casual social media language. This comparison investigation gives researchers and policy makers who intend to find out what people believe during emergencies in health useful data. It also shows how useful it can be to incorporate various approaches for a full sentiment analysis.

2.3 Support Vector Machine (SVM) in Text Classification

Sentiment analysis of public data was carried out using a comparative analysis of four machine learning methods. Using Term Frequency-Inverse Document Frequency (TF-IDF), the researchers processed a dataset including complaints from the public by text cleaning, tokenising, and vectorising methods. Trained and tested each algorithm—SVM, Naive Bayes, Random Forest, as well as Extreme Gradient Boosting (XGBoost)—to classify attitudes into positive, negative, or neutral. With regards to both accuracy and F1-score, the study discovered that XGBoost surpassed the other models, so demonstrating its better capacity in managing complex structures in the complaint texts. These results indicate that sentiment analysis assignments including complex and varied textual data benefit especially from ensemble methods such as XGBoost [11]. For better sentiment classification of short documents, the [12] work presents a hybrid machine learning models combining Enhanced Vector Space Models (EVSM) with Hybrid Support Vector Machines (HSVM). Whereas the HSVM classifier, augmented alongside decision tree methods, classifies sentiments into positive, negative, and neutral classes, the EVSM component corresponds textual data into high-dimensional vector spaces, capturing contextual interactions among words. The work introduces weight-enhancing methodologies for processing text features and stretches sentiment lexicons using Stanford's GloVe tool in order to improve accuracy. With positive and negative sentiment identification rates of 91.33% and respectively 97.32%, the proposed model attained an overall accuracy of 92.78%. Particularly in social media applications, these results show how effectively the model manages the complexity of short-text analysis of sentiment.

2.4 Topic Modelling in E-Sports

Topic modelling helps reveal trends in the player comments about e-sports communities [13]. Based on four well-known games available on the Steam platform, the researchers collected and analysed over 1.2 million English-language comments. To find latent thematically structures in the review materials, they employed LDA—an unsupervised machine learning technique. Following the moment preliminary processing and dataset enhancement, the researchers discovered 19 distinct themes out of which three more general topical groups were created. The study demonstrated among players recurrent interests and concerns which include gameplay mechanics, game updates, and community interactions. These findings help developers who would like to improve game design and community involvement by gaining greater understanding of players attitude and priorities. The study shows the importance of LDA for obtaining useful insights from big-scale content created by users on online gaming systems. Aiming to reflect the viewpoints of novice and amateur players occasionally ignored in conventional analyses, the study suggests an innovative method to evaluate player reviews from esports games [14]. The approach employs Bidirectional Encoder Representations from Transformers (BERT) incorporated with a Transformer downstream layer for precise sentiment analysis as well as integrates topic modelling using LDA to find prevalent patterns inside the reviews. Using an extensive data set consisting of 1.6 million English-language reviews from four popular esports games available on Steam: TEKKEN7, Dota2, PUBG, and CS: GO, the paper This method allows the framework effectively expose players' worries and opinions about many facets of the games. The results provide insightful information for operators and game creators for enhancing game quality and player experience by attending to the specific needs and comments of the larger gaming community.

2.5 Research Gaps and Contributions

Previous research in the domain of e-sports sentiment analysis has predominantly focused on generic sentiment classification or single-game case studies, often overlooking comparative and multilingual perspectives across gaming contexts. This study addresses these limitations by introducing a multifaceted analytical framework that advances both methodological rigor and domain relevance through the following key contributions:

1. Hybrid Sentiment Classification Approach: The study integrates a lexicon-based method with a SVM classifier to enhance sentiment detection accuracy for tweets related to MLBB. The lexicon provides semantic grounding, while the SVM model enables contextual adaptability to the dynamic and informal nature of social media discourse.
2. Multilingual Topic Modelling with LDA: To capture thematic diversity across a wider audience, this study extends LDA topic modelling to handle both Indonesian and English tweets. This multilingual strategy uncovers cross-cultural perspectives and linguistic nuances in player discussions, which are often ignored in prior mono-language models.
3. Cross-Game Benchmarking and Validation: The proposed methods are benchmarked against findings from prior e-sports sentiment studies (e.g., [15]), enabling a comparative assessment that highlights the model's superior classification performance, topic coherence, and real-world applicability. The cross-validation ensures robustness and positions this study as a scalable framework for other competitive gaming titles.

By combining advanced machine learning techniques with multilingual data handling and comparative evaluation, this research contributes a more comprehensive understanding of community sentiment within the evolving digital ecosystem of competitive gaming.

3. RESEARCH METHODOLOGY

3.1 Support Vector Machine

Within the context of MLBB, AI-driven research offers helpful analysis of the player experience, feedback from players, and the dynamics of multiplayer gaming communities. Researchers can carefully investigate player-generated evidence across platforms like X or in-game chats employing methods which includes lexicon-based sentiment analysis, LDA for modelling topics, and SVM for sentiment categorization. From a large quantity of unstructured text, these techniques allow the extraction of subtle sentimental trends and thematic structures. The insights that comply with are extremely actionable and enable game developers to improve gameplay elements, improve user retention plans, and develop a more involved player base. Furthermore, such AI-supported systems assist players by showing the larger community sentiment, developing meta-strategies, as well as reputational dynamics, so enhancing the general experience of playing and collaborative atmosphere within competitive e-sports settings [16].

To complement our sentiment analysis framework, we employ SVM algorithm to model and classify emotional polarities based on features extracted from tweets. Given the inherently high dimensionality of textual data, SVM is particularly well-suited for this task due to its robustness and proven effectiveness in handling sparse and complex feature spaces. SVM maximises the margin between classes to enhance generalization by identifying the best hyperplane that most effectively separates points of data into sentiment categories, positive, neutral, and negative [17]. The kernel functions, which map data elements into higher-dimensional regions in which they turn linearly separable, assist to further improve the classification process. Frequently used kernels are linear, polynomial, radial basis function (RBF), and sigmoid, each of having the flexibility for capturing various data distributions. SVM's ability to represent non-linear boundaries for decisions in sentiment classification tasks helps to achieve a better accuracy and computational efficiency even in intricate, real-world datasets [18]. Considering the above background, the primary concerns of this study are: The way users of Platform X's posts represent their opinions with regard to the e-sports sport MLBB. The way lexicon-based phrases be employed for automatically categorising these emotions. Furthermore, what are the common trends in tweets about MLBB and how can the SVM algorithm be used to properly model these emotions? The goals of this article are three-fold: first, recognise and evaluate audience emotions toward e-sports MLBB on Platform X using lexicon-based labelling; secondly, to develop models for these emotions with the use of the SVM algorithm; and thirdly, to identify the main themes discussed in MLBB tweets using LDA.

MLBB has grown into one of the most favoured mobile games in the e-sports sector, thereby supporting a dynamic and enthusiastic gaming community [19]. MLBB, an online multiplayer battle arena game, offers an environment for strategic cooperation and worldwide competitions as well as a form of entertainment. Game developers, the competition organisers, and marketers have to enhance the user experience and handle community issues by recognising player feelings and conversations within MLBB. Because of their real-time, unorganised, and highly engaging character, social media platforms, especially Platform X (Twitter), are crucial to capturing these discussions [2]. Widespread use by e-sports communities and its appropriateness for sentiment analysis as well as topic modelling led to Platform X being selected for the study [20]. While its active user base confirms a rich source of different viewpoints on MLBB-related subjects which includes tournaments, updates, and gameplay experiences, the platform's brief tweet format enables quick data extraction. Platform X's open API additionally supports systematic data gathering, thereby making it perfect for examining community responses [21].

This study aims to address the following research questions:

1. What are the predominant sentiments (positive, neutral, or negative) expressed by users on Platform X regarding MLBB?
2. How can lexicon-based methods effectively categorise these sentiments?
3. What are the common themes discussed in MLBB-related tweets, as identified through LDA?

To answer these questions, the study employs a lexicon-based approach for sentiment classification and LDA for topic modelling. The SVM algorithm is utilised to enhance sentiment classification accuracy. The findings aim to provide actionable insights for stakeholders in the e-sports industry, enabling them to tailor strategies based on community feedback. This study utilises a real-time dataset of tweets in the Indonesian language collected during major MLBB tournaments in 2023, ensuring an up-to-date and culturally relevant analysis. Specific preprocessing techniques, including slang normalization, spam filtering, and data balancing, were applied to improve data quality. Moreover, the SVM model was optimised through grid search to fine-tune the c and gamma parameters, achieving superior classification accuracy for Indonesian social media texts.

3.2 Data Collection

The dataset comprises 8,363 tweets collected from Platform X (Twitter) between November 16, 2023, and January 16, 2024, using web scraping techniques. This two-month period captures discussions during major MLBB tournaments and updates, ensuring data representativeness. Keywords such as "MLBB," "Mobile Legends," "MPL," "ONIC Esports," and "RRQ Hoshi" were selected because they: Reflect official game terms, team names, and league abbreviations widely used by the MLBB community and cover both gameplay discussions ("MLBB") and competitive e-sports events ("MPL"), capturing diverse sentiments.

3.3 Data Preprocessing

The preprocessing phase was designed to improve the accuracy and reliability of sentiment analysis by reducing noise and normalising textual content commonly found in social media data. Each step was systematically aligned with the requirements of SVM and LDA to ensure compatibility with downstream modelling tasks:

1. Data Cleaning: URLs, user mentions, hashtags, and special characters were removed to isolate pure textual content, as these non-text elements offer little semantic value and may distort feature extraction in SVM models [22].
2. Case Folding: All text was converted to lowercase (e.g., “Mobile Legends” → “mobile legends”) to ensure consistency during lexicon-based sentiment labelling and prevent redundancy in token representation.
3. Slang Normalization: Informal terms and abbreviations, such as “GG” (Good Game), were normalised using an Indonesian slang lexicon to better match sentiment lexicon entries, given the domain-specific language often present in MLBB-related tweets [23].
4. Tokenization & Stopword Removal: Text was tokenised into individual words and filtered through stopword removal using the Natural Language Toolkit (NLTK) library. Common function words like “dan” (and) or “di” (in) were excluded, as they contribute minimal semantic value and introduce noise into both LDA topic modelling and SVM-based classification [24].
5. Stemming: The Nazief–Adriani algorithm was applied to reduce words to their root forms (e.g., “bermain” → “main”), enhancing consistency across word variants and improving topic coherence in LDA and sparsity

reduction in vectorised features [25].

6. Feature Selection: For vectorization, TF-IDF using unigram and bigram models was adopted to capture both individual word importance and adjacent word pairings that reflect context in sentiment expression.
7. Evaluation Metrics: Model performance was assessed using accuracy, precision, recall, and F1-score to ensure robust evaluation across both balanced and imbalanced sentiment distributions.
8. Duplicate Removal: Identical tweets were removed from the dataset to mitigate sentiment bias caused by spam or retweets, ensuring a more representative and unbiased sentiment distribution.

Figure 1 illustrates the research workflow including data preprocessing. It outlines the sequential stages from raw data acquisition to sentiment classification.

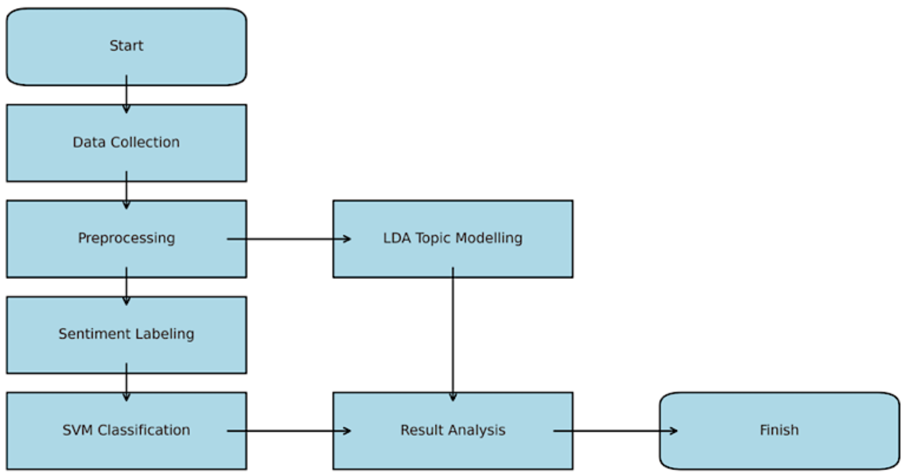

Figure 1. Research Workflow

3.4 Ethical Considerations

Tweets were anonymised to protect user privacy, ensuring that no personally identifiable information (PII) such as usernames, profile photos, or location metadata was retained. This anonymization process involved removing or masking any direct or indirect identifiers prior to data analysis. The data collection process strictly adhered to Platform X's API usage policies and terms of service, ensuring full compliance with technical and legal requirements. In addition, all data handling procedures were conducted in alignment with institutional ethical guidelines for research involving publicly available social media content. This approach maintains both ethical research standards and compliance with platform-specific data governance regulations, safeguarding the rights and privacy of all users involved [26].

4. RESULTS AND DISCUSSIONS

4.1 Dataset

The data extraction procedure was executed via Harvest tweets. A add up to of 8,363 tweets were assembled from November 16, 2023, to January 16, 2024 presented in Table 1. The obtained information envelops assorted data sorts, counting client suppositions on gameplay, appraisals of player execution, discoursed with respect to occasions and competitions, and reactions to overhauls or adjustments within the diversion. Earlier to extra handling, this crude information comprises a few components, counting created_at, username, tweet substance, retweet number, like number, and once in a while images or recordings inserted within the tweet. Consequently, the column will be eliminated, displaying only created_at, username, and tweet text.

Table 1. Raw Data of Tweets

Created_at	Username	Tweet
Mon Dec 18 05:25:56 +0000 2023	kampung_esport	Reaction Oura Kairi Blunder di Match Terakhir #MLBB #MobileLegends #updatemlbb https://t.co/j9yBHRpbg3
Fri Dec 01 15:38:11 +0000 2023	ibnu_bonsai	Capaian baru manager Tim Esport wkwkwkk Thank you Tim MLBB Florisen kalian keren asli.
Sun Dec 17 16:58:54 +0000 2023	Hayu_kamu	Nice try Onic Esport udah keren kalian walaupun tahun ndak dapet tahun depan bakal dapet lets Clean Sweep again all MLBB Tournament kayak tahun ini lagi sama M6 @onic_esports https://t.co/lw9HnK3Pac
Mon May 27 02:51:37 +0000 2024	naayaanika	Tanpa banyak perlawanan Tim @echophilippines mengalahkan juara M5 dengan skor yang mengejutkan 4-0 tanpa balas dan langsung menjadi juara MPL PH Season 13. Apakah ini pertanda eranya AP.Bren berakhir? #liquid #liquidecho #echo #echophiliphines #mlbb #mobilelegends https://t.co/FgkbwJgZ1b

The data distribution throughout the collection period was relatively uniform; however, there was a notable surge in tweet volume during and following significant tournaments or major updates from the game developer. This indicates that the MLBB community is very engaged in conversations concerning significant occurrences. Furthermore, the data indicates discrepancies in the language employed in tweets, predominantly featuring Indonesian, with a few in English. The utilization of many languages indicates that MLBB possesses a broad and diverse user demographic.

4.2 Preprocessing

The preprocessing phase is a crucial step in text data analysis to guarantee that the data utilised in model training is clean and well-organised. This study employed multiple preprocessing strategies to convert raw data into an analysable format. The preprocessing phases executed encompass several primary procedures, example of detailed preprocessing presented in Table 2.

4.3 Data Labelling

After the data preprocessing stage is complete, the next step is to label the data. In this stage, an assumption investigation strategy based on supposition vocabulary is connected to bunch tweets into positive, negative, or unbiased assumptions. This strategy utilises a predetermined list of certifiable and negative terms, accessible within the lexicon_positive.txt and lexicon_negative.txt records. Each word in the tweet is compared to the lexicon. In the event that the term is within the positive lexicon, at that point it is recognised as a positive word. On the other hand, in the event that the term is recorded within the negative vocabulary, at that point it is distinguished as a negative word. The result of data labelling depicted in Figure 2.

Table 2. Example Preprocessing

Stages	Before	After
Case folding	Pertandingan di hari ketiga #Snapdragon Mobile Open Finals MLBB Season 5 sudah dimainkan dengan maksimal oleh semua team yang bertanding buat hari ini! ï¸ #SnapdragonProSeries #Snapdragon#MLBB https://t.co/08Fl2zQM0S	pertandingan di hari ketiga mobile open finals mlbb season sudah dimainkan dengan maksimal oleh semua team yang bertanding buat hari ini.
Slang word	pertandingan di hari ketiga mobile open finals mlbb season sudah dimainkan dengan maksimal oleh semua team yang bertanding buat hari ini.	pertandingan di hari ketiga mobile open finals mlbb season sudah dimainkanm dengan maksimal oleh semua team yang bertanding buat hari ini
tokenising	pertandingan di hari ketiga versatile open finals mlbb season sudah dimainkan dengan maksimal oleh semua group yang bertanding buat hari ini	['pertandingan', 'di', 'hari', 'ketiga','mobile', 'open', 'finals', 'mlbb', 'season', 'sudah', 'dimainkan','dengan', 'maksimal', 'oleh', 'semua', 'team', 'yang', 'bertanding', 'buat', 'hari', 'ini']
Filtering stopword	pertandingan di hari ketiga mobile open finals mlbb season sudah dimainkan dengan maksimal oleh semua team yang bertanding buat hari ini	pertandingan ketiga open finals mlbb season dimainkan maksimal team bertanding.
Stemming	pertandingan ketiga open finals mlbb season dimainkan maksimal team bertanding.	tanding di hari tiga mobile open finals mlbb season sudah main dengan maksimal oleh semua team yang tanding buat hari ini

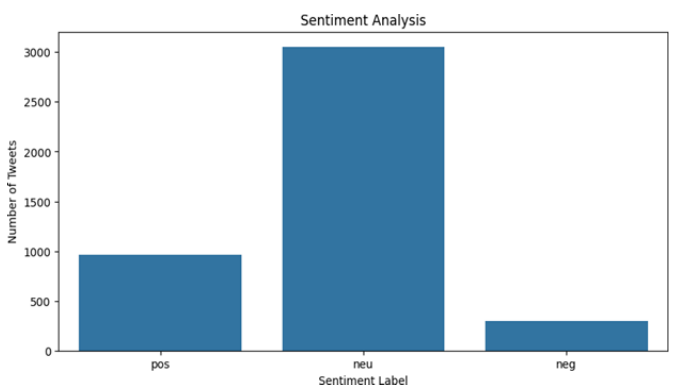

Figure 2. Result Data Labelling

After the information labelling handle was carried out, assumption dissemination investigation appeared that out of a add up to of 4313 tweets, 3052 tweets, comparable to around 70.8%, were categorised as impartial. Meanwhile, 965 tweets, or around 22.4%, were classified as positive, and 296 tweets, speaking to roughly 6.9%, were categorised as negative. Blast Blast were impartial, with the extent of steady tweets surpassing the extent of negative ones. This data provides an initial insight into how X users viewed MLBB during the study period. A word cloud is a technique for visualising text data that depicts words with sizes according to how frequently they appear, depicted in Figure 3 for positive and Figure 4 for negative. The larger the size of a word in a word cloud, the more frequently the word appears in the data set studied.

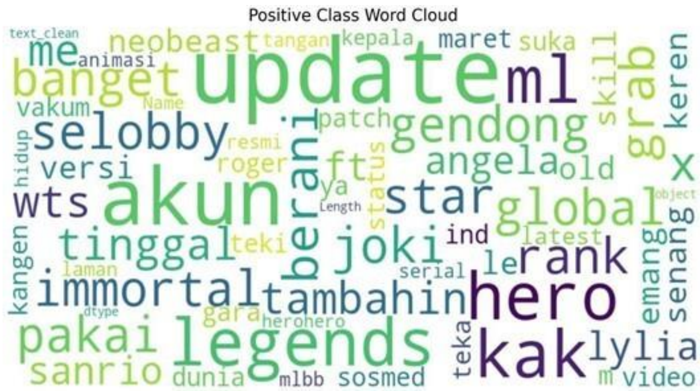

Figure 3. Wordcloud Positive

This word cloud illustrates terms frequently encountered in unfavourable classroom discussions. Terms such as "update", "mlbb", "afk", dan "lag" Specify grievances or issues pertaining to gaming and internet connectivity. Profanity such as "asu" dan "anjir" juga muncul, Additionally, it signifies the use of foul words.

Figure 4. Wordcloud Neutral

This Wordcloud illustrates terms frequently encountered in neutral classroom discussions. Terms such as "update", "teman", "langsung", dan "akun" shows common and everyday conversation topics. Some technical words likespecify grievances or issues pertaining to gaming and internet connectivity. Profanity such as "object", "dtype", dan "text_clean" may indicate a discussion regarding a lesson or assignment. Other words such as. Kata-kata lain seperti "grab", "goreng", dan "matang" may indicate casual conversation about food or daily activities.

The dominance of neutral sentiment, accounting for approximately 70.8% of the tweets, can be interpreted in several ways. First, it may indicate a general tendency of users to share factual updates, information, or non-emotional content about MLBB rather than expressing strong personal feelings. This could be influenced by the characteristic of tweets in the gaming community, where users often focus on reporting match results, sharing game updates, or discussing strategies without emotional bias. Another possibility is user apathy or detachment, where players interact with the game as casual consumers without deep emotional investment, especially during non-major tournament periods. For the MLBB development team and community managers, this phenomenon suggests an opportunity to enhance user engagement by fostering more emotional connections through content strategies such as interactive campaigns, storytelling, personalised updates, or community-building activities. Encouraging players to express opinions and emotional feedback could help strengthen the brand-community relationship.

4.4 Topic Modelling

This study applies the LDA approach to analyse topics, aiming to explore the main themes contained in tweets related to Mobile Legends: Bang Bang. This subject modelling method contributes to understanding the focus and main debates that emerged among the MLBB community during the analysis period. Documents are divided into categories by examining each tweet and determining key themes based on the topic probability distribution generated by the LDA model.

Before the topic modelling process, a vectorization step is performed first. Vectorization is the method of changing over content into a numeric arrange that can be prepared by a machine learning calculation. In opinion investigation, this for the most part requires converting each word within the content into a vector in a high-dimensional space, where each measurement speaks to a diverse property of the word. The significance of this step is pivotal, because machine learning calculations work with data in the shape of numbers, not information within the shape of content. Subsequently, sometime recently applying this strategy, the content must be converted into a numeric representation. This code utilises the "TfidfVectorizer" from the "sklearn" library to run the vectorization prepare. "TfidfVectorizer" changes over content into a TF-IDF include lattice, which could be a metric to demonstrate the significance of words in a record compared to a broader set of content.

Term Frequency (TF): Determination of the frequency of each word. Topic modelling utilising LDA effectively discerned four primary subjects within the dialogue. Figure 5 is the visualization results of the number of sentiments based on clusters:

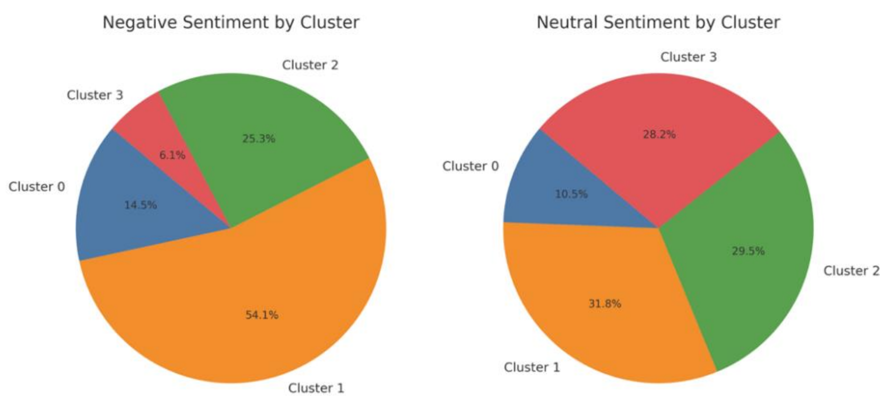

Figure 5. Result of Sentiment by Cluster

Left Pie Chart (Negative):

- Topic 0: 14.5% Topic 1: 54.1%
- Subject 2: 25.3%
- Topic 3: 6.1%

The pie graphic indicates that Category 1 comprises the majority of negative sentiment data at 54.1%, followed by Category 2 at 25.3%. Category 0 comprises 14.5%, whereas Category 3 represents the smallest share at 6.1%.
Right Pie Chart (Affirmative):

- Subject 0: 10.5%
- Subject 1: 31.8%
- Subject 2: 29.5%
- Subject 3: 28.2%

This pie chart illustrates that the distribution of positive sentiment data is more uniform than that of negative sentiment data. Category 1 comprises the biggest proportion at 31.8%, followed by Category 2 at 29.5%, and Category 3 at 28.2%. Category 0 comprises the smallest proportion, specifically 10.5%.

Through LDA, several dominant topics were identified within the tweet corpus. Notably, topics associated with positive sentiments often revolved around themes like game rewards, new skins or updates, and successful tournaments — indicating user excitement and satisfaction with fresh content and achievements. Conversely, topics linked to negative sentiments mainly pertained to technical issues (e.g., lag, bugs), team performance disappointments, or match controversies. Interestingly, a significant portion of neutral tweets was aligned with discussions on general match outcomes, event schedules, and basic game commentary. This reflects that much of the community's communication is oriented toward informative or event-driven discourse rather than emotional reaction, reinforcing the earlier analysis of sentiment neutrality. From a strategic perspective, understanding these patterns enables developers to identify which game aspects trigger strong emotional responses and which are perceived more passively. By leveraging this insight, developers can design targeted interventions to amplify positive engagement and address the sources of user dissatisfaction more effectively.

4.5 Classification

Sentiment categorization is executed via a SVM with a linear kernel. Pre-processed and labelled data is utilised to train the SVM model. The dataset is partitioned into training data and testing data in an 80:20 ratio.

4.5.1 Sentiment Classification

The obtained sentiment data showed an imbalance: there were 3052 examples of neutral sentiment, 965 examples of positive sentiment, and 296 examples of negative sentiment. To balance this data, a hybrid technique was applied, where oversampling was performed on the minority data and undersampling on the majority data, resulting in 2438 neutral data points, 764 positive data points, and 764 negative data points. To find the best parameters for the SVM algorithm, the process began with the SVM model (SVC()), and GridSearchCV was used to optimise the Support Vector Machine parameters. The best configuration was found with a value of C: 1, Gamma: 0.1, and kernel: linear, which achieved an accuracy score of 0.9057. Table 3 presents the results of the classification report.

Table 3. Classification Report

Label	Precision	Recall	F1-Score	Support
Negative	0.58	0.54	0.56	48
Neutral	0.91	0.96	0.94	614
Positive	0.96	0.80	0.87	201
Accuracy			0.90	863
Macro Avg	0.82	0.77	0.79	863
Weighted Avg	0.90	0.90	0.90	863

4.5.2 Cluster Classification

Subsequently, classification is performed on the cluster by modifying y = df['cluster'], resulting in the following distribution of tweet clusters: Cluster 1 contains the highest volume of data, totalling 1,664 entries; Cluster 2 comprises 1,032 entries; Cluster 3 includes 844 entries; and Cluster 0 has the least, with 773 entries as depicted in Figure 6.

The optimal parameters for the SVM classification model for the cluster were C: 10, Gamma: 1, and kernel: rbf, achieving an accuracy score of 0.8513. The subsequent outcomes of the classification report presented in Table 4.

4.5.3 Model Evaluation

Model evaluation is an essential phase in model creation to guarantee optimal performance. A frequently employed technique is the confusion matrix. The confusion matrix for sentiment classification depicted in Figure 7 and Figure 8.

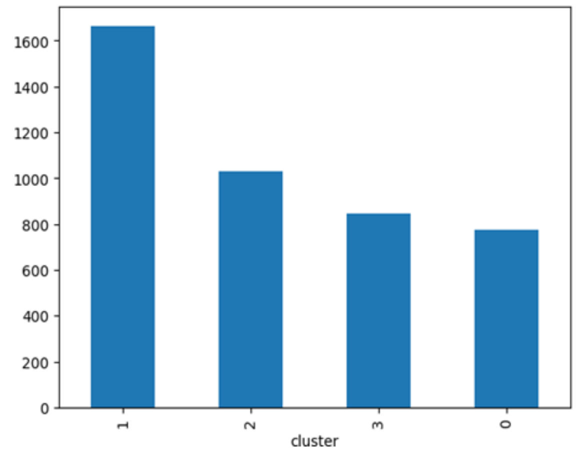

Figure 6. All Cluster in Tweet

Table 4. Classification Report Cluster

Cluster	Precision	Recall	F1-Score	Support
0	0.87	0.85	0.86	159
1	0.85	0.93	0.89	315
2	0.86	0.85	0.85	181
3	0.94	0.84	0.89	208
Accuracy			0.87	863
Macro Avg	0.88	0.87	0.87	863
Weighted Avg	0.88	0.87	0.87	863

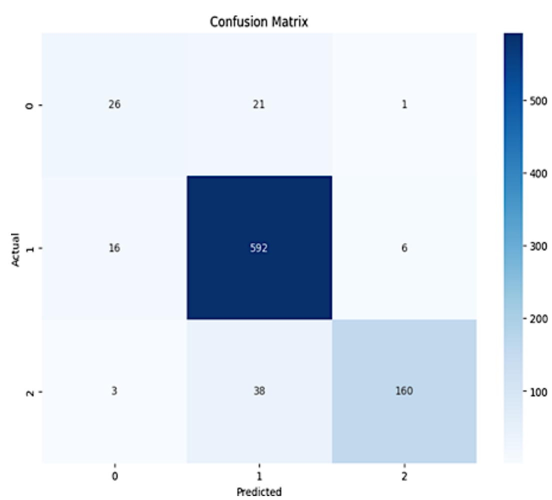

Figure 7. Confusion Matrix Sentiment

The confusion matrix presented earlier reflects the effectiveness of the classification model in predicting the three categories (0, 1, and 2). The model performed very well in predicting category 1, with 592 correct predictions out of a total of 614 actual examples of category 1. However, the model was less successful in predicting category 2, with only 38 correct predictions out of 203 examples of category 2. In addition, there were several misclassifications where the model incorrectly predicted category 0 as category 1 in 21 examples and category 2 as category 1 in 6 examples.

The confusion matrix provides an in-depth evaluation of the model's classification accuracy for each category and the types of errors that occurred.

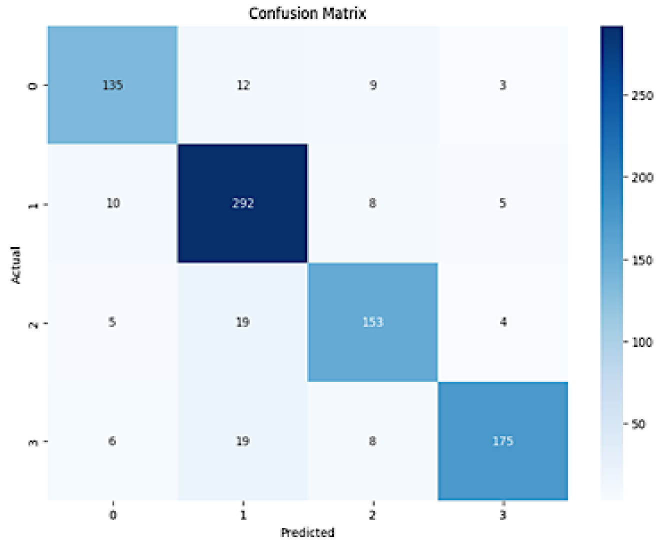

Figure 8. Confusion Matrix Cluster

The confusion matrix mentioned earlier explains the effectiveness of the classification model in predicting the four categories (0, 1, 2, and 3). The model performed best when predicting class 1, with 292 correct predictions out of a total of 324 class 1 examples. In addition, the model also performed well in predicting classes 2 and 3, with 153 and 175 accurate results, respectively. However, the model performed poorly in predicting class 0, with only 135 correct predictions out of 168 class 0 examples. There were many misclassifications, especially between classes 0 and 1, and between classes 2 and 3. The confusion matrix provides a complete assessment of the model's classification accuracy for each category and the nature of the errors.

5. CONCLUSION

The analysis of 4,313 tweets related to MLBB revealed that 70.8% were neutral, 22.4% positive, and 6.9% negative. This indicates that most community conversations on Platform X tended to be informational rather than emotional. Sentiment classification using the SVM algorithm achieved a high accuracy of 90.57%, and cluster classification based on topics achieved 85.13%. For game developers and community managers, the predominance of neutral sentiment highlights the need for more engaging content strategies to foster emotional attachment among users. Interactive content, personalised updates, and enhanced community-driven events could increase user engagement and brand loyalty.

This study has several limitations. First, the lexicon-based sentiment analysis approach may overlook contextual nuances such as sarcasm, idioms, or multi-layered sentiments, leading to potential bias. Furthermore, the keyword-based data scraping process might introduce selection bias, capturing tweets heavily centered around specific terms while ignoring broader community discussions. Future studies should explore the use of more advanced deep learning models, such as Bidirectional Encoder Representations from Transformers (BERT) or RoBERTa, to capture more nuanced sentiments. Expanding the dataset to include multilingual tweets would provide a more comprehensive view of the global MLBB community. Additionally, conducting temporal analysis could reveal how sentiments evolve during major events like tournaments or game updates.

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AUTHOR CONTRIBUTIONS

Hikmal Muhammad: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation;
Fauzi Adi Rafrastara: Project Supervision, Writing – Review & Editing;
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Arley Japardi: Project Administration, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflict of interests were disclosed.

ETHICS STATEMENTS

All tweet data utilised were publicly available and collected in compliance with Platform X's API policies. Sensitive information such as user identifiers and personal data was anonymised to ensure user privacy. Our publication ethics follow The Committee of Publication Ethics (COPE) guideline [26].

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