Sentiment Analysis of Genshin Impact on X: Mental Health Implications Using TF-IDF and Support Vector Machine

Sava Irhab Atma Jaya[1]), Junta Zeniarja[2)*]
[1,2)] Department of Informatics Engineering, Faculty of Computer Science, Universitas Dian Nuswantoro, Semarang, Indonesia
[1)]sava.atmajaya@gmail.com, [2)]junta@dsn.dinus.ac.id

Abstract: Genshin Impact are now an integral part of daily life for many, potentially influencing mental well-being. Sentiment analysis window into these emotional effects, especially given the varied findings on gaming's impact on mental health. Analyzing X responses Genshin Impact using Support Vector Machine crucial, given its effectiveness in sentiment analysis. This study aims to deepen our understanding game's psychological impact and support development mental health interventions for gamers. The SVM classification report shows promising precision: 0.68 for Negative, 0.63 for Neutral, and 0.72 for Positive sentiment. However, recall rates favor Positive reviews (0.87) over Negative (0.56) and Neutral (0.51), reflected in the F1 score, highest for Positive sentiment at 0.79. With 174 Negative, 216 Neutral, and 333 Positive support counts, model achieved an overall accuracy of 0.69, effectively classifying Genshin Impact reviews based on sentiment. Analysis findings suggest a prevalence of positive opinions, indicating widespread player satisfaction with the game.

Keywords: Sentiment Analysis; Support Vector Machine; TF-IDF; Genshin Impact; Mental Health;

INTRODUCTION

In the contemporary digital era, online games such as Genshin Impact have become an indispensable component of numerous individuals' daily routines. Apart from providing entertainment, these games also exert a profound influence on the mental well-being of their users. Sentiment analysis is a methodology that can be employed to discern the emotional impact of the game on players (Arias et al., 2022; Iram & Aggarwal, 2020). The TF-IDF clustering technique is employed to analyze the sentiment of X social media users towards Genshin Impact, with the objective of elucidating the sentiment of players on social media regarding the topic (Olajuwon et al., 2024). Previous research has demonstrated that the impact of online games on mental health can be both positive and negative, contingent upon variables such as content, social interaction, and the frequency of gameplay (Mathematics, 2022; Oyebode et al., 2020). It is therefore crucial to analyse the sentiments of players towards Genshin Impact using the Support Vector Machine (SVM) algorithm, which has been proven effective in various sentiment analysis studies. By understanding the sentiments of players, it is possible to evaluate the implications of the game on their mental health and provide recommendations for the development of a more psychologically healthy game (Jeong et al., 2022; Patel & Passi, 2020).

The Support Vector Machine (SVM) is an effective machine learning technique for classification and regression. In this context, it is used to predict sentiment from X social media data (Kaur et al., 2021; Shofiya & Abidi, 2021). The mental health of individuals who engage in gaming, such as those who play Genshin Impact, can be influenced by a multitude of factors, including the potential for
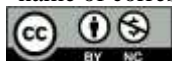
addiction to online games and the social interactions that occur within these games (Primandani Arsi et al., 2023; Shu et al., 2022). It is well documented that online gaming addiction can have a detrimental effect on teenagers' social adaptability, as well as on their personal monthly expenses through microtransactions (Prawida & Wahyuningsih, 2023). The objective of this study is to provide insight into the psychological impact of gaming and to facilitate the development of effective mental health intervention strategies for the gaming community.

Given the considerable popularity of Genshin Impact and its impact on mental health, this study employs a Support Vector Machine algorithm to ascertain user sentiment towards the game and its implications on mental health. The results are anticipated to furnish valuable insights for game developers, mental health practitioners, and players, thereby encouraging a more positive and healthy gaming environment.

LITERATURE REVIEW

The study, entitled "Association of Social Gaming with Well-Being (Escape COVID-19): A Sentiment Analysis," revealed that social gaming and social media, particularly through the game Animal Crossing: New Horizons, can be a tool to cope with stress during the COVID-19 pandemic. Sentiment analysis of Twitter posts revealed that 16% of tweets indicated that the game helped with anxiety, although 4.6% reported worse anxiety due to game-related stress. In addition, 72% of tweets stated that playing the game helped with relaxation. However, while 2.2% of tweets mentioned that the game helped with depression, there were also reports of the game causing depression in some players. The analysis of the tweets revealed that 80% of the tweets reported positive experiences related to playing Animal Crossing: New Horizons. This indicates a general positive impact on mental health and well-being during the pandemic (Krittanawong et al., 2022).

Furthermore, the study "Sentiment Analysis of Dota 2 Videogame Chat in Context of Cyber-bullying" has been conducted. The updated lexicon dictionary has demonstrated enhanced performance, with an 82% accuracy rate, 0.73 precision, and 0.72 recall. Negative chats can be subjected to further review by human supervisors. This research underscores the significance of grasping player interactions and their emotions in games to foster a more constructive playing environment and diminish cyber-bullying (Singh, 2022).

The following study, entitled "Sentiment Analysis on COVID-19-Related Social Distancing in Canada Using Twitter Data," presents the results of an investigation into the sentiments expressed in Canadian tweets pertaining to social distancing during the COVID-19 pandemic. The analysis revealed that 40% of tweets exhibited a neutral sentiment, 35% expressed a negative sentiment, and 25% conveyed a positive sentiment. This research employed a hybrid approach, integrating the sentiment analysis tool SentiStrength for sentiment polarity extraction and the SVM (Support Vector Machine) algorithm for sentiment classification. The SVM algorithm achieved an accuracy of 71%, which increased to 81% when considering only positive and negative sentiment polarity. By reducing the test data by 10%, the accuracy increased to 87%. This research underscores the significance of comprehending public sentiment regarding social distancing during the pandemic for the formulation of public health decisions and policies that are informed by public sentiment analysis on Twitter (Shofiya & Abidi, 2021).

Furthermore, "An Exploratory Content and Sentiment Analysis of The Guardian Metaverse Articles Using Leximancer and Natural Language Processing". The Leximancer Concept Map (LCM) identified key findings about the metaverse, including "platform" and concept relationships such as "platform-harmful-content" and "user-security." Additionally, sentiment analysis of the Guardian.com dataset demonstrated a prevalence of positive sentiment (61%) towards the metaverse. The application of Monkeylearn enabled a more profound comprehension of the impact of the metaverse across diverse sectors and events. The utilisation of AI and NLP tools, including Orange 3, Leximancer, NLTK, and Monkeylearn, facilitated the effective processing of voluminous textual data. The findings are constrained to the perspectives and narratives of specific sources, yet they offer insights into the

metaverse discourse in Western media. The study offers an overview of the metaverse discourse, emphasizing both positive sentiments and concerns regarding harmful content and user safety (Tunca et al., 2023).

Finally, the study "The Analysis of Gacha Game Addiction on The Players' Personal Monthly Expenses" yielded the following results: gacha game addiction and microtransactions have a significant impact on players' monthly expenses. Players who were loyal to the game in 2016 and 2018 recognized that the unique gacha game kept them playing and making microtransactions to enhance the gaming experience, even though this affected their budget. Players emphasized the importance of maintaining a balance between in-game spending and personal budgets, as well as good budget management and self-control to avoid financial loss. Despite being aware of the financial risks, players still find value and satisfaction in the gacha system. This research reveals that despite the awareness of financial risk, loyalty and addiction to gacha games remains strong, with players understanding the importance of budget management and self-control while still enjoying the entertainment on offer (Prawida & Wahyuningsih, 2023).

METHOD

The research employs a quantitative approach, with sentiment analysis serving as the principal methodology. The research stages include Data Collection, Data Pre-Processing, Sentiment Analysis using Support Vector Machine, and Results.

Data Collection

Data was collected from X using Tweet Harvest with the following steps, Use of Genshin Impact-related keywords, such as "Genshin", and "HoYoverse". Amount of Data: Collecting a large number of tweets to ensure statistically significant analysis results.

Pre-Processing Data

The data collected from X will go through a preprocessing stage to prepare the raw data to be analysis-ready,
Cleaning, a step in which the data is cleaned of elements that are not needed or could interfere with further analysis. Case Folding, converts text into a consistent form, such as converting all letters to lowercase. Word Normalization:, the process of converting nonstandard words or abbreviated forms into their more common or formal standardized forms. Tokenization, breaks the text into smaller word units. Stop Words Removal, removes common words that have no effect on sentiment (e.g., "yang", "ini", "di"). Data Stemming, converts words in text to their basic form which can help in text analysis such as information retrieval, text classification, or text mining.

Sentiment Analysis

Sentiment analysis is performed using the Support Vector Machine (SVM) algorithm. Data Labeling, data is manually or semi-manually labeled to determine sentiment polarity (positive, negative, or neutral). Training and Testing, the data is divided into training set and testing set to train TF-IDF and Support Vector Machine models. Model Evaluation, using metrics such as accuracy, precision, recall, and F1-score to evaluate the performance of Support Vector Machine models.

Results

The results of the sentiment analysis were interpreted to understand the mental health implications of the users. Positive, Negative, and Neutral Sentiment. identifies the proportion of positive, negative, and neutral sentiments of the analyzed tweets. Correlation with Mental Health, assess how sentiments expressed in tweets relate to mental health issues, such as stress, anxiety, or happiness. Pattern Identification, finding common patterns in user sentiment, for example, in-game factors that are often associated with negative or positive sentiment.
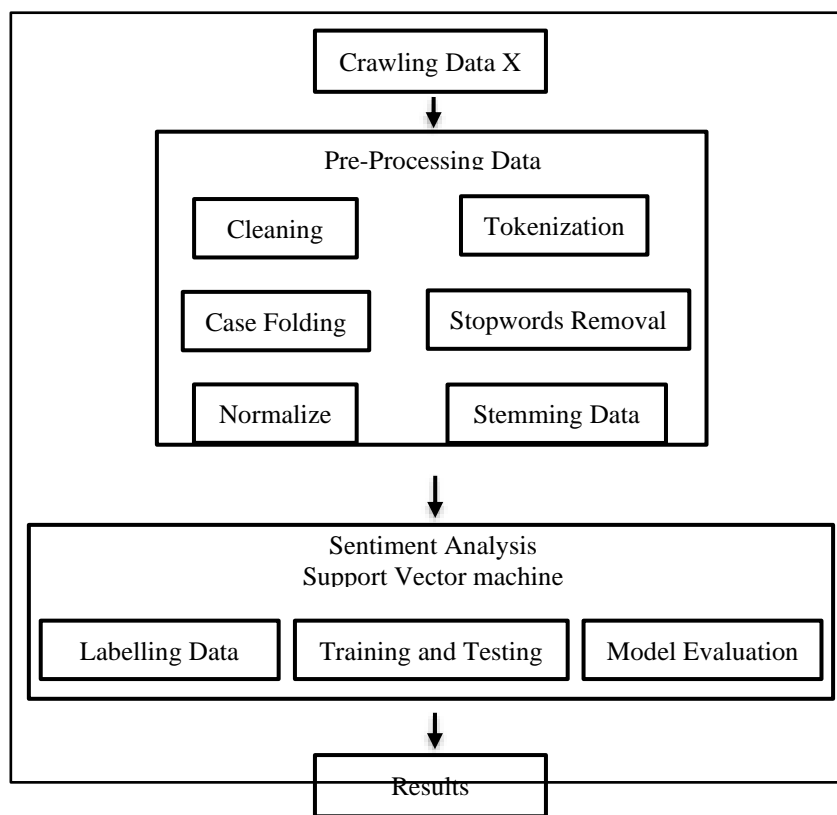
RESULT

Research Stages

Fig. 1 Research Stages

This research will be divided into several stages as follows:
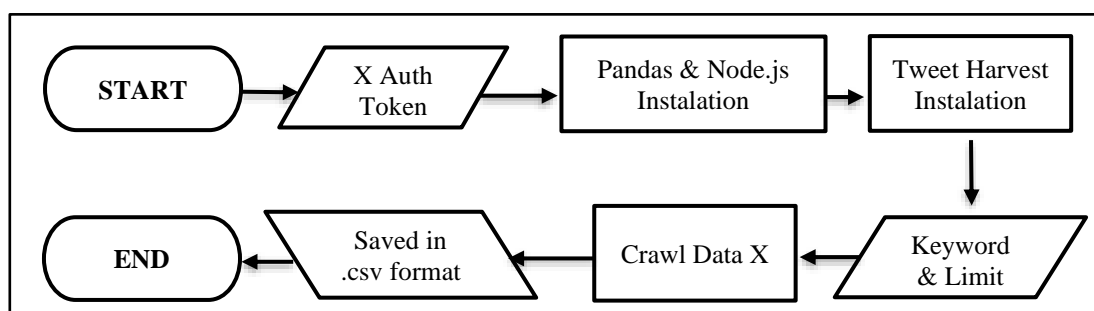**Data Collecting**

Fig. 2 X Tweet Harvest Flow Chart

The flow chart above illustrates the utilization of TweetHarvest to retrieve the most recent tweets, a tool provided by third-party provider HelmiSatria that is accessible via the Github repository. The initial step is to obtain the auth token from the X account cookies. Subsequently, the pandas library is employed to present the data in the form of a DataFrame. The installation of node.js is necessary because TweetHarvest is constructed using node.js. The data crawling process is conducted using the keywords "genshin" and "hoyoverse," with a maximum limit of 2500. The data is then automatically saved in the .csv format.

*name of corresponding author
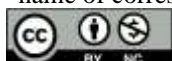
conversat	created_a	favorite	full_text	id_str	image_url	in_reply_t	lang	location	quote_c	reply_c	retwee	tweet_url	user_id_s	username
1.8E+18	Tue May 2	1	[MMD/Ge	1.8E+18	https://pbs.twimg.c		in		0	0	0	https://x.	1.77E+18	Tenshimaru_san
1.8E+18	Tue May 2	1	WTS AKUN	1.8E+18	https://pbs.twimg.c		in		1	0	0	https://x.	1.78E+18	jrmyse
1.8E+18	Tue May 2	1	HoYoVers	1.8E+18		JustOrdina	in		0	1	0	https://x.	1.61E+18	JustOrdinaryid
1.8E+18	Mon May	0	@haitanir	1.8E+18		haitanirin	in	aro/ace |	0	0	0	https://x.	1.29E+18	meropidepok
1.79E+18	Mon May	0	@CmsnAr	1.79E+18		CmsnArtis	in	ðŸ‡®ðŸ‡©	0	0	0	https://x.	1.52E+18	NIWVNVN
1.79E+18	Mon May	0	@paimon	1.79E+18		paimonfe	in	Tasikmala	0	0	0	https://x.	1.21E+18	mufti_sunan
1.79E+18	Mon May	0	Semua ya	1.79E+18			in	DKI Jakart	0	0	0	https://x.	1.6E+18	GamerwkID
1.79E+18	Mon May	0	Meskipun	1.79E+18			in	he/him â€	0	1	0	https://x.	1.29E+18	konbuoui_
1.79E+18	Sun May 2	0	@olioleo	1.79E+18		olioleoo	in		0	1	0	https://x.	1.68E+18	matchaiscream_
1.79E+18	Sun May 2	4	EH LUPA JI	1.79E+18		anachrone	in	they/ther	0	0	0	https://x.	1.65E+18	anachronen
1.79E+18	Sun May 2	1	My belove	1.79E+18			in		0	0	0	https://x.	1.56E+18	tapiocatamarind
1.79E+18	Sun May 2	0	Up up up.	1.79E+18			in	Indonesia	0	0	1	https://x.	1.13E+18	feitadunkelheit
1.79E+18	Sun May 2	3	RT &	1.79E+18	https://pbs.twimg.c		in		1	1	4	https://x.	2.28E+09	Ashy_rein
1.79E+18	Sat May 25	0	@babyfire	1.79E+18		babyfireli	in	Snezhnay	0	2	0	https://x.	7.39E+17	einsteinweebs
1.79E+18	Sat May 25	0	Update ba	1.79E+18	https://pbs.twimg.c		in	Fatmawat	0	1	0	https://x.	9.93E+17	NawalaKarsa
1.79E+18	Sat May 25	0	@wandca	1.79E+18		wandcaim	in	Luofu.	0	1	0	https://x.	1.26E+18	jingyouan
1.79E+18	Sat May 25	64	Anime pe	1.79E+18	https://pbs.twimg.c		in		1	4	2	https://x.	1.21E+18	Otaku_Anime_Ind
1.79E+18	Fri May 24	0	cowo gw h	1.79E+18			in		0	2	0	https://x.	1.57E+18	kowloonshi
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Fig. 3 Genshin Dataset

The dataset from X above contains the following information for each conversation: the conversation ID, the time at which it was created, the number of times it has been marked as a favorite, the full text, the ID, the URL of the image, the reply, the language, the location, the number of quotes, the number of retweets, the URL of the tweet, the ID, and the username. The total number of data points obtained is 2431.
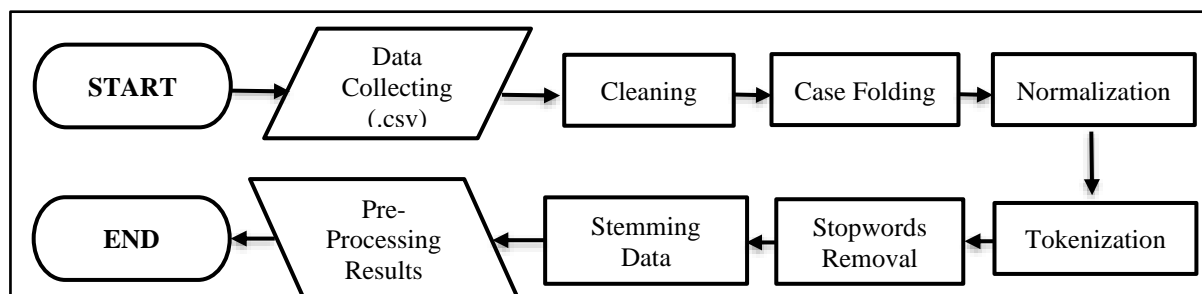
Data Pre-Processing

Fig. 4 Data Pre-Processing Flow Chart

The preceding flow chart depicts the pre-processing phase, which commences with the collection of data in the CSV format. This is followed by the cleansing of the data, which entails the removal of noise and irrelevant data. The next step is the case folding, which involves transforming all text into lowercase for standardization purposes. Normalization is then applied to standardize word variants to their base forms. Tokenization is the subsequent step, which breaks the text into smaller units such as words or phrases. Stopword removal is the next stage, which involves the removal of common words that have no significant meaning. Finally, data stemming is applied to derive the base form of words. This process involves the removal of affixes from words in order to obtain the base word. Tokenization, on the other hand, entails the division of text into smaller units, such as words or phrases.

The use of two libraries, namely NLTK and Sastrawi, serves as tools for text stemming. However, it should be noted that these two libraries focus on different languages. NLTK is used to process text in English, while Sastrawi is specifically designed to process text in Indonesian. In the code shown, Sastrawi is installed first, then the stemmer object of Sastrawi is created using StemmerFactory. The

NLTK library offers two distinct types of stemmers: PorterStemmer and SnowballStemmer. These can be employed for the purpose of stemming English text.

| reply_co	retweet_c	favorite_c	full_text	cleaning	case_folding	normalisasi	tokenize	StopwordRemoval	stemming_data
0	0	1	[MMD/Genshin Impact] Ayaka Gomi Gomi MMD ani	MMDGenshin Impact Ayaka Gomi Gomi MMD animati	mmdgenshin impact ayaka gomi gomi	mmdgenshin impact ayaka gomi gomi mmd animatio	[mmdgenshin, impact, ayaka, gomi, mmd, a	[mmdgenshin, impact, ayaka, gomi, gomi, mmd, a..	mmdgenshin impact ayaka gom gom mmd animation
0	0	1	WTS AKUN GENSHIN IMPACT HARGA	WTS AKUN GENSHIN IMPACT HARGA k	wts akun genshin impact harga	beli akun genshin impact harga ke login	[beli, akun, genshin, impact, harga,	[beli, akun, genshin, impact, harga, login, ho.	beli akun genshin impact harga login
1	0	1	HoYoVerse membuktikan diri sebagai developer g	HoYoVerse membuktikan diri sebagai developer g	hoyoverse membuktikan diri sebagai	hoyoverse membuktikan diri sebagai	[hoyoverse, membuktika n, diri, sebagai,	[hoyoverse, membuktikan, developer, game, gach	hoyoverse bukti developer game gacha
0	0	0	@haitanirind game barunya hoyoverse (developer...	game barunya hoyoverse developer genshin amp	game barunya hoyoverse developer genshin	game barunya hoyoverse developer genshin amp	[game, barunya, hoyoverse, developer, genshin	[game, barunya, hoyoverse, developer, genshin	game baru hoyoverse developer genshin amp
0	0	0	@CmsnArtist_Id aku familiar sama art hoyoverse...	aku familiar sama art hoyoverse kayak	aku familiar sama art hoyoverse kayak	aku familiar sama art hoyoverse kayak	[aku, familiar, sama, art, hoyoverse,	[familiar, art, hoyoverse, kayak, genshin, nde	familiar art hoyoverse kayak genshin

Fig. 5 Clean Data Pre-Processing Results
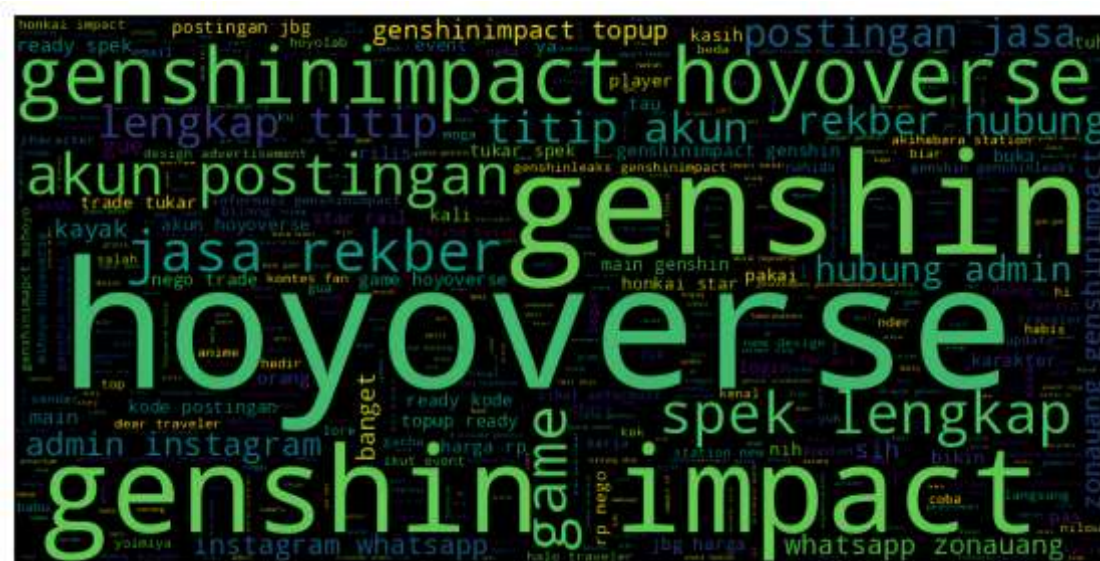
Fig. 6 Wordcloud

The word cloud above displays the most frequently occurring words from the processed text data. The words "genshin," "hoyoverse," and "impact" are the most prominent, indicating that these are the most frequently occurring or important terms in the analyzed text. Other words such as "post," "account," "service," as well as the names of social media platforms such as "Instagram" and "WhatsApp" also appear at a smaller size. This indicates the topics or keywords that are often associated with discussions around Genshin Impact. The use of colors such as green, blue, yellow, and red adds to the clarity of this visualization.
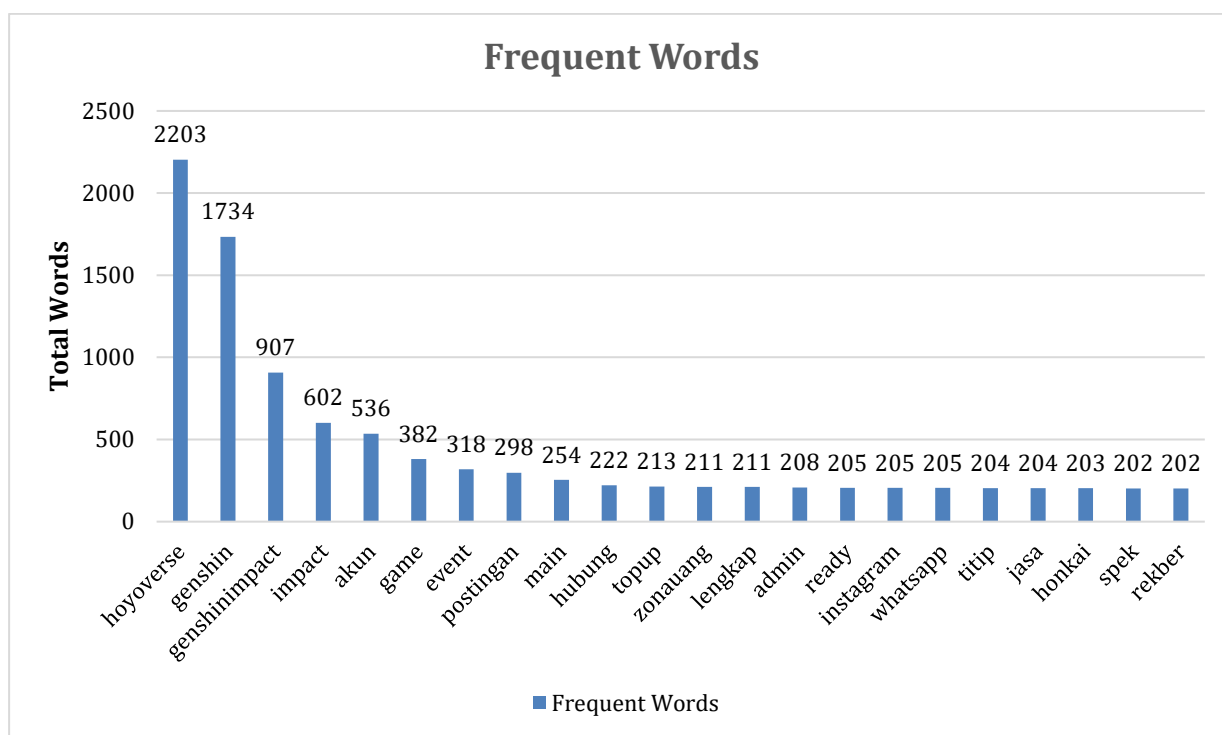
Fig. 7 Word Frequency

The diagram above displays an x-axis labeled "Frequent Words" and a y-axis labeled "Number of Words." The numerical values on the y-axis range from 200 to 2200, with increments of 500. Each bar represents a word with a corresponding number of frequencies. The first bar represents the word "hoyoverse," which has the highest number of frequencies at 2203, followed by "genshin," which has 1734, and so on. This diagram is important because it visually summarizes the most common words in the dataset, showing which terms are the most dominant or significant after removing irrelevant or redundant information during pre-processing.
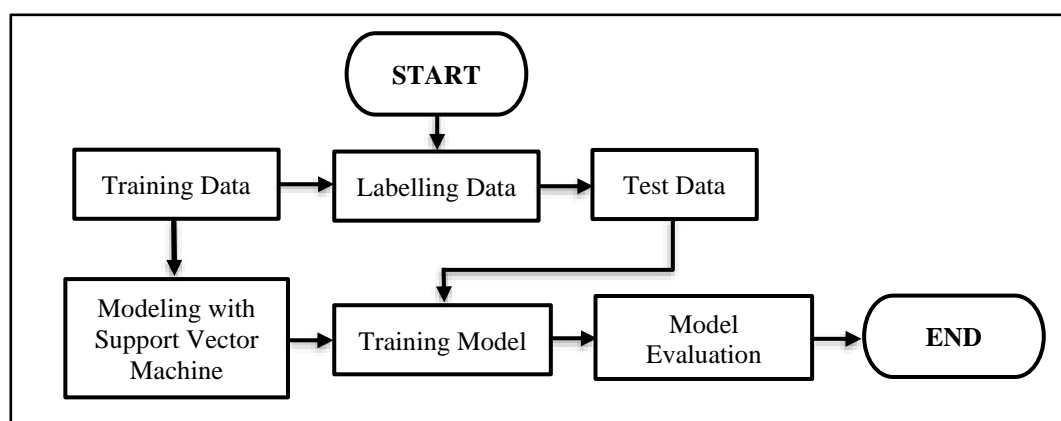
Sentiment Analysis

Fig. 8 Support Vector Machine Flow Chart

The flow chart above depicts the analysis process using Support Vector Machine (SVM), which commences with data labeling. This entails marking the data with the appropriate label. The subsequent stages include test and training, where a portion of the data is separated for model testing. The SVM

*name of corresponding author

algorithm is then applied to the data in the modeling stage. Model training follows, during which the model is trained with training data. Finally, model evaluation is conducted to assess the model's performance with test data.

A labeling script for the lexicon dictionary with three classes was employed in this process. This approach facilitated the classification of data as positive, negative, or neutral based on the overall weight generated. Consequently, sentiment analysis can provide a more detailed understanding of the sentiment contained in the dataset, with the lexicon dictionary and weighting serving as the foundation for this analysis.
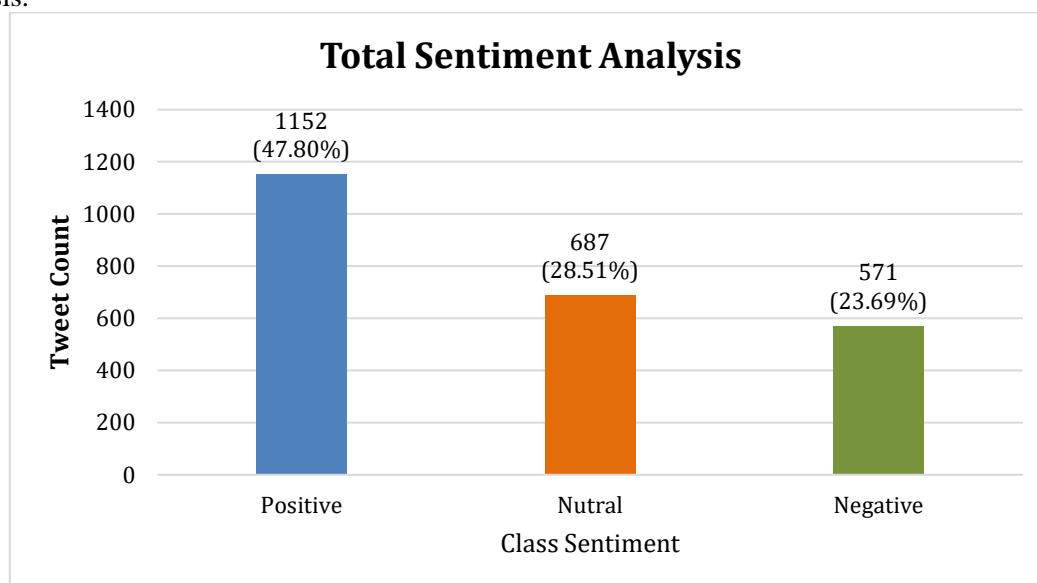

Fig. 9 Visualization of Data Labeling Result Diagram

The bar chart above illustrates the distribution of data in the dataset related to opinions about Genshin Impact. Based on the graph, data labeled as "positive" dominates approximately 47.80% of the entire dataset. In contrast, data labeled as "negative" reached approximately 28.51%, while data labeled as "neutral" accounted for approximately 23.69%. These results indicate that the majority of opinions in the dataset are positive in regard to the controversy surrounding Genshin Impact.

	precision	recall	f1-score	support
Negative	0.68	0.56	0.61	174
Neutral	0.63	0.51	0.57	216
Positive	0.72	0.87	0.79	333
accuracy			0.69	723
macro avg	0.68	0.65	0.66	723
weighted avg	0.68	0.69	0.68	723

Fig. 10 Output of Classification Report

The classification report for the Support Vector Machine (SVM) model indicates that it exhibits satisfactory precision, with values of 0.68 for the Negative class, 0.63 for the Neutral class, and 0.72 for the Positive class. However, the recall rate indicates that the model is more adept at identifying Positive reviews (0.87) than Negative (0.56) and Neutral (0.51) reviews. The F1 score, which is the harmonic mean of precision and recall, also reflects this, with the highest score for positive reviews (0.79) compared to negative reviews (0.61) and neutral reviews (0.57). The model achieved an overall accuracy of 0.69, indicating that it is quite effective in classifying reviews of the game "Genshin Impact" based on user sentiment. This was achieved with a support count of 174 for Negative, 216 for Neutral, and 333 for Positive.
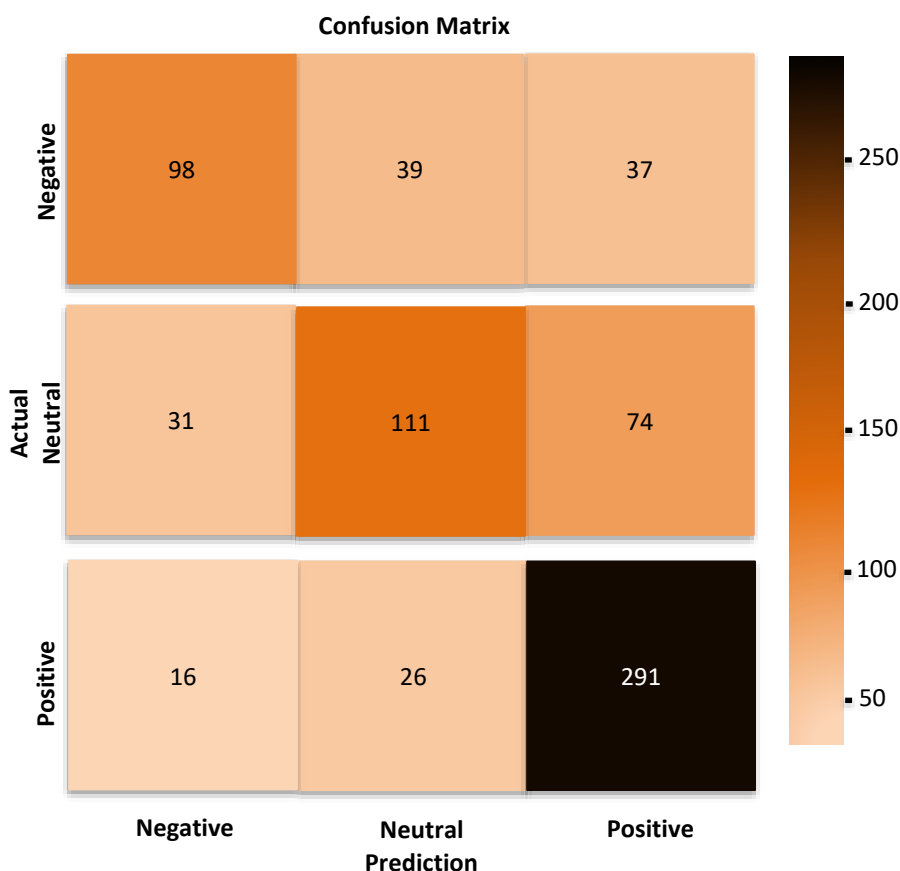
*name of corresponding author

Fig. 11 Confusion Matrix

The confusion matrix above illustrates the performance of the classification model for the three classes. In the negative class, the model correctly predicted 98 cases as negative, but 39 actual negative cases were predicted as neutral and 37 cases were predicted as positive. In the neutral class, 111 cases were correctly predicted as neutral, but 31 cases were actually neutral predicted as negative and 74 cases were predicted as positive. The model demonstrated a high degree of accuracy in predicting positive cases, with 291 correct predictions. However, it also exhibited a tendency to misclassify positive cases as negative or neutral, with 16 positive cases incorrectly classified as negative and 26 as neutral. Overall, the model exhibited the highest accuracy in predicting positive cases and the lowest accuracy in predicting negative cases.

The analysis revealed that the majority of opinions in the dataset were positive. While this study did not explicitly address mental health, these findings may provide insight into how users' sentiments towards the game may reflect or affect their mental well-being. For instance, significant negative reviews could indicate a level of frustration or dissatisfaction that may have a negative impact on users' mental health. Conversely, X positive reviews may reflect an enjoyable and satisfying experience, potentially contributing to their psychological well-being. Consequently, the sentiment analysis of reviews of games such as Genshin Impact not only facilitates the comprehension of users' perceptions of the game but also represents a valuable instrument for the monitoring and comprehension of the mental health of its user community. By identifying these patterns and X trends in sentiment, game developers and researchers are better positioned to assess the emotional impact that games have and to implement the necessary measures to enhance the overall user experience.

The majority of positive sentiments indicate player satisfaction, which can contribute to their psychological well-being. This satisfaction could be an indicator that the game provides an enjoyable experience and supports good mental health. Conversely, although fewer in number, negative sentiments

*name of corresponding author

reflect frustration or dissatisfaction, which can have an adverse impact on a player's mental health. The lower recall rate for negative sentiments (0.56) suggests that the model may be less sensitive to negative reviews, which could mask serious mental health issues. The SVM model demonstrated satisfactory precision with 0.68 for negative sentiment, 0.63 for neutral, and 0.72 for positive. However, the overall accuracy of the model was 0.69, indicating that there is still room for improvement in sentiment classification. One of the principal limitations of this model is the potential for bias towards positive sentiment, as evidenced by the elevated recall rate for positive reviews (0.87). This may result in an overly optimistic assessment of the general sentiment of players and the overlooking of potential mental health issues that may not be detected by the model.

DISCUSSIONS

In this case, sentiment analysis of the game Genshin Impact on social media X revealed that the majority of opinions in the dataset were positive, indicating that users generally had a positive experience. While this study did not explicitly investigate the impact on mental health, these findings provide important insights into the relationship between users' sentiments and their mental well-being. Significant negative reviews reflect high frustration or dissatisfaction, which may negatively impact users' mental health. In contrast, predominantly positive reviews reflect satisfaction and excitement, which may enhance psychological well-being. These findings are consistent with previous research, suggesting that games with positive reviews tend to have a more favorable impact on mental well-being. The use of TF-IDF and Support Vector Machine methods in this analysis proved effective in classifying sentiments with high accuracy. The observation of these patterns and trends in sentiment allows developers and researchers to better assess the emotional impact of games, take steps to improve user experience, and opens up further research opportunities on using sentiment as an early indicator to monitor the mental health of user communities. The classification report for the Support Vector Machine (SVM) model demonstrated good precision with values of 0.68 for the Negative class, 0.63 for the Neutral class, and 0.72 for the Positive class. However, the recall rate demonstrated superior performance in identifying positive reviews (0.87) in comparison to negative (0.56) and neutral (0.51) reviews. The F1 score also reflected this, with the highest score for positive reviews (0.79). The model achieved an overall accuracy of 0.69, with a support count of 174 for negative, 216 for neutral, and 333 for positive reviews, respectively. This demonstrates the effectiveness of the model in classifying Genshin Impact reviews based on user sentiment.

CONCLUSION

The majority of opinions in the dataset are positive, indicating a satisfying experience with the Genshin Impact game. While this study does not specifically address mental health, the findings provide insight into the impact of user sentiment on their mental well-being. Negative reviews indicate frustration, which can have a negative impact, whereas positive reviews improve psychological well-being. This study confirms the importance of sentiment analysis to understand users' perceptions and mental well-being. However, it should be noted that this study has certain limitations, including the inability to explore the direct impact on mental health and the data collection methodology. The Support Vector Machine (SVM) model classification report demonstrated good accuracy, with higher recall values for positive reviews (0.87) than negative (0.56) and neutral (0.51) reviews. The highest F1 value for positive reviews (0.79) and overall accuracy of 0.69 demonstrate the effectiveness of the model in classifying Genshin Impact reviews based on user sentiment. However, one of the main drawbacks of the model is the possible bias towards positive sentiment, which could lead to overly optimistic assessments of general player sentiment and overlook potential mental health issues that may not be detected by the model. This study reaffirms the significance of sentiment analysis as a tool for comprehending and monitoring the perceptions and mental health of the user community. It also provides a robust foundation for further research. Future research is recommended to be more comprehensive, linking user sentiment with mental health indicators, as well as employing more diverse data collection methods and longitudinal analysis.

*name of corresponding author

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