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Sentiment Analysis of the Song Lost - Bring Me the Horizon Based on Reviews on YouTube Using the SVM Algorithm

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Abstract

Bring Me The Horizon's song "Lost" received a wide response on YouTube, evident in the thousands of comments containing a variety of responses ranging from support and criticism to neutral opinions. The rapid development of social media has made it easier for people to freely share their views and experiences on musical works without being bound by space and time. YouTube, as one of the largest video-sharing platforms, plays a crucial role in documenting public perception of the song. This study was conducted to analyze listener sentiment towards the song "Lost" based on YouTube comments using the Support Vector Machine (SVM) algorithm and the Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction technique. Comments were collected through web scraping from the song's official video, then processed through case folding, punctuation removal, tokenizing, stopword removal, and stemming to produce clean and uniform data. Term weights were calculated using TF-IDF and then used to label positive, negative, and neutral sentiments. The SVM model was built from training data and tested with test data to evaluate its performance using accuracy, precision, recall, and f1-score metrics so that classification quality could be assessed comprehensively. Based on the test results, the SVM algorithm was able to classify listener comments with 94% accuracy, with a distribution of negative sentiment of 207 comments, neutral comments of 1,280, and positive comments of 732. These findings demonstrate the effectiveness of SVM in analyzing the sentiment of song comments on social media and provide a more comprehensive picture of the public's view of Bring Me the Horizon's song "Lost.".

Introduction

The rapid development of information and communication technology has fundamentally influenced the way people interact, obtain information, and express their views. Social media has now become a primary means of freely expressing opinions and responses to various phenomena, including works of art and music, without the constraints of space or time. Platforms like YouTube no longer merely function as video players but also as interactive spaces where people can comment, discuss, and shape public opinion on a variety of content (Manueke et al., 2023; Buckley, 2020; Lange, 2007). This phenomenon demonstrates that social media is a rich source of data for understanding public perception, including regarding popular musical works like Bring Me the Horizon's "Lost." Utilizing the data generated from these comments opens up opportunities for a more in-depth and comprehensive understanding of audience responses (Jansen et al., 2023; Kim & Kim, 2025).

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Music is essentially a complex and multidimensional artistic expression that combines elements of melody, harmony, rhythm, tempo, timbre, and sonic dynamics. These elements not only shape the aesthetic structure of a song but also create a unique emotional experience for the listener. The perceptions and emotions that arise when listening to music can be influenced by the lyrics, arrangement, vocal technique, and even the production atmosphere created by the musician (Rasyid et al., 2024; Juslin & Laukka, 2004; Herbst & Mynett, 2025; Deumert, 2023). Therefore, a deep understanding of musical aspects is crucial in the context of sentiment analysis, as it can help explain how emotional experiences translate into public opinion expressed through comments on social media (Utari & Wibowo, 2025; Doğan et al., 2025; George & Baskar, 2024; Amangeldi et al., 2024). Integrating musical understanding and sentiment analysis can enrich and enrich research results.

Furthermore, YouTube, as a digital music distribution platform, provides a broad platform for fans to directly express their responses to songs, lyrics, and production quality (O'Hara, 2022; Raharjo & Budiharseno, 2024; Sarifiyono et al., 2025; Ppali et al., 2025). Bring Me the Horizon, an alternative rock band with a global fanbase, is characterized by its progressive music. Their song "Lost" has sparked intense and diverse public discussion, making it relevant for analysis using a machine learning-based sentiment analysis approach (Syafia et al., 2023). This phenomenon also demonstrates the immense potential of social media as a source of public opinion data in assessing public acceptance of music in the digital age. This type of analysis is crucial for understanding audience preferences and reactions in real time and supporting the music industry in designing more targeted strategies (Xin, 2024; Oham & Ejike, 2024).

Sentiment analysis is a field within text mining that focuses on classifying opinions or emotions in text into positive, negative, or neutral categories. Through this approach, public views can be mapped quantitatively and qualitatively. In this study, sentiment analysis was conducted on YouTube comments from listeners of the song "Lost" using the Support Vector Machine (SVM) algorithm as the primary classification method (Husada & Paramita, 2021; Al-Gaphari et al., 2025). SVM was chosen for its ability to handle high-dimensional data and produce optimal classification models (Thet et al., 2023; Möller et al., 2024;). To support the classification, this study also utilized the Term Frequency–Inverse Document Frequency (TF-IDF) feature extraction method, which calculates the word weights in each comment to enhance the model's accuracy. The combination of these two techniques allows for more reliable and in-depth classification results (Eliwa et al., 2024; Wang e al., 2024).

Several previous studies have shown that applying machine learning methods such as SVM with TF-IDF to music sentiment analysis can produce better classification results than conventional methods (Gifari et al., 2022; Alemerien et al., 2024; Ahmed et al., 20243; Liu et al., 2022). This confirms the relevance of the method chosen in this study to improve the accuracy of public sentiment identification. With a strong methodological foundation, this research not only enriches academic studies in the field of music sentiment analysis but also serves as a reference for the development of automated opinion analysis systems on social media. This type of research also provides new insights into the expression patterns and preferences of music listeners in the digital era.

Beyond technical aspects, sociocultural context plays a crucial role in interpreting public opinion on a piece of music. Cultural factors, language, and global trends influence how people express their views on the song "Lost," making the analysis richer and more relevant. Integrating a technical approach with an understanding of the sociocultural context is expected to yield more comprehensive findings regarding public sentiment toward popular music in the digital era. This understanding also helps researchers identify how cultural identities and local preferences shape patterns of public response to global music

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Methods

Research Framework

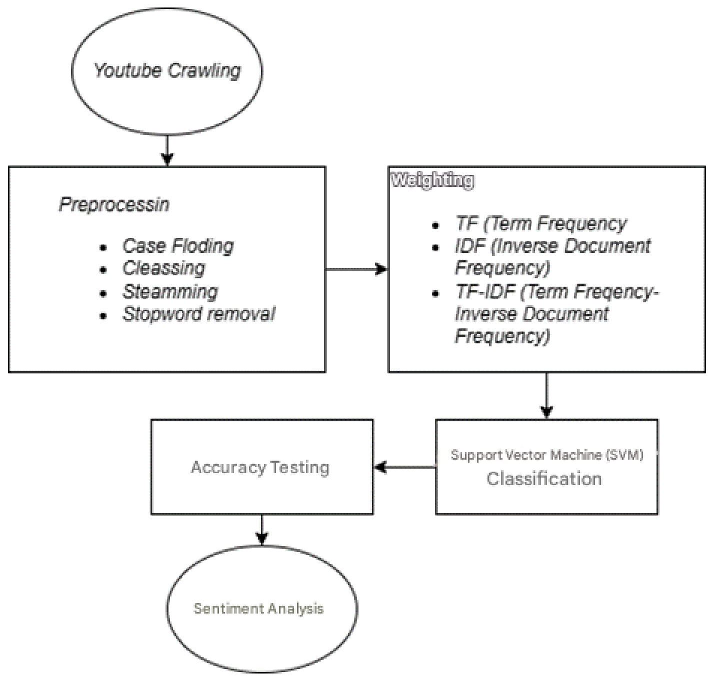

Figure 1. Research Framework (Darwis et al. 2020)

YouTube Crawling

The first stage involves collecting comment data from listeners of the song "Lost" from the YouTube platform using the YouTube API or crawling techniques. This process is carried out to obtain raw data in the form of comment text that reflects public opinion. Crawling is used because it can automatically collect large amounts of data, making analysis easier.

Preprocessing

The obtained comment data then undergoes a pre-processing stage to improve data quality. This process includes case folding (converting letters to a uniform format), cleansing (removing irrelevant characters), steaming (converting words to their base form), and stopword removal (removing common words that have no analytical value). This stage is crucial for producing clean data ready for further processing.

Weighting (TF-IDF)

After clean data is obtained through pre-processing processes (such as case folding, tokenization, stopword removal, and stemming), each word in the comment is weighted using Term Frequency (TF), Inverse Document Frequency (IDF), or a combination of both (TF-IDF). Term Frequency (TF) describes how frequently a word appears in a document. Words that appear frequently in a given comment will have a higher TF value. Inverse Document Frequency (IDF) measures the importance of a word within a collection of documents. Words that appear in many documents (e.g., “the,” “and”) receive a low IDF score because they are considered less informative. TF-IDF is the product of TF and IDF, which gives greater weight to words that appear less frequently but are distinctive, making them more representative of the content of a comment. Through TF-IDF weighting, the system can distinguish common words from contextually relevant words. For example, the words “anyone,” “peak,” or “whaaaat” appearing in a music listener’s comment will receive a high weight if they rarely appear in other comments but are very distinctive in the context of a particular song. TF-IDF plays a crucial role in the feature extraction process because it produces a numerical

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representation of the text that is ready to be used by the classification algorithm. The resulting weighting forms a feature vector for each comment, which is then processed by the Support Vector Machine (SVM) model during the training and testing stages.

Support Vector Machine SVM Classification

In this study, the Support Vector Machine (SVM) algorithm was used as the primary method to classify YouTube comment sentiment into three categories: positive, negative, and neutral. Unlike the SVM explanation, which focuses solely on finding a hyperplane, implementing SVM in text sentiment analysis requires several technical decisions that significantly impact model performance, particularly because text data is rarely linearly separable.

Support Vector Machine (SVM) is a very popular and effective classification algorithm for processing text data, including sentiment analysis. The basic principle of SVM is to find the best hyperplane, or dividing line, capable of separating data into different classes, for example, positive, negative, and neutral comments. The selected hyperplane is the one with the maximum distance from the data on both sides, resulting in optimal separation. Accuracy Testing.

One important aspect in implementing SVM is kernel selection, as the kernel functions to map the data into a higher-dimensional space, allowing for more effective separation of non-linear patterns. In this study, the Radial Basis Function (RBF) kernel was used due to the characteristics of YouTube comment data, which tends to have complex and non-linear feature relationships. The RBF kernel is widely recommended in the literature for high-dimensional text data because it can form a more flexible decision boundary than a linear kernel.

In addition to kernel selection, SVM performance also depends heavily on parameter tuning, particularly the C (regularization) and gamma (γ) values in the RBF kernel. The C parameter controls how closely the model follows the training data, while gamma determines the extent to which a data point influences the formation of the decision boundary. To obtain the optimal parameter combination, this study used Grid Search combined with k-fold cross-validation, so that parameter selection relies not solely on manual experimentation but rather through a systematic evaluation process of various value combinations.

Cross-validation is a crucial step because it ensures the model does not overfit on certain data subsets. With an imbalanced dataset—particularly because the number of neutral comments (1,280) is significantly higher than positive (732) and negative (207)—cross-validation helps provide a more stable and representative picture of performance.

To address this class imbalance, this study enabled class_weight = 'balanced' in the SVM. This approach assigns greater weight to the minority class so that the model does not bias its predictions towards the majority class. This weight adjustment is crucial to maintain performance in the negative class—which is a minority category.

All comments, after undergoing preprocessing and TF-IDF representation, are then converted into high-dimensional numeric vectors and processed using SVM. The trained model is tested using test data to evaluate its performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to measure the model's performance in classifying comment sentiment. These test results serve as the basis for assessing the success of the developed sentiment analysis model.

Accuracy Testing

This evaluation phase is conducted to measure the generalization ability of the optimized SVM model. Unlike simply testing accuracy, this process focuses on Precision, Recall, and F1-Score metrics to provide a more transparent picture of the model's performance,

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particularly when dealing with class imbalances in sentiment data. These metrics are crucial for verifying whether the model is able to robustly classify the test data without experiencing overfitting or significant bias toward the majority class.

Sentiment Analysis

The final stage is the analysis of the sentiment classification results. At this stage, further interpretation is carried out to determine the tendency of public sentiment towards the song "Lost." This analysis can provide input for academics and the music industry in understanding audience perceptions quantitatively and qualitatively.

Results and Discussion

YouTube Crawling

The data was obtained through a crawling process of listener comments from the song "Lost" on the YouTube platform. This process collected 2,500 raw comments. After pre-processing stages such as case folding, cleansing, stemming, and stopword removal, the total number of comments ready for processing was 2,219. These comments were then labeled with positive, negative, and neutral sentiments to be used as training and test data.

Table 1. Dataset Table

No	Comment	Label
1	the part from to on full volume just scraches my brain in the right ways	positive
2	fran bow anyone	neutral
3	i love that he did it lose its head	positive
4	anyone	neutral
5	thats old school sounding for sure	positive
6	this man thinks hes ruvik from the evil within	negative
7	peak	neutral
8	whaaaat theeee hellll	neutral
9	summer sonic at zozo marin stadiumrock am ringoli	neutral

Preprocessing

Preprocessing is the initial and most fundamental stage in sentiment analysis because it directly determines the quality, reliability, and effectiveness of the data used in the subsequent training and classification processes. At this stage, raw comment text data, which are often unstructured, noisy, and inconsistent, are systematically cleaned and transformed into a standardized format that can be efficiently processed by machine learning algorithms such as Support Vector Machines (SVM). Without proper preprocessing, the presence of irrelevant symbols, spelling variations, redundant words, and informal language patterns may distort the learning process and reduce classification accuracy.

The main objective of preprocessing is to eliminate elements that do not contribute to sentiment interpretation while preserving meaningful linguistic information. This process typically involves several interconnected steps, including text normalization, case folding, tokenization, stopword removal, stemming or lemmatization, and the elimination of punctuation, numbers, and special characters. Through these procedures, textual data are converted into consistent lexical units that represent the core semantic content of each comment. As a result, variations in writing styles, abbreviations, and informal expressions can be minimized, allowing the system to focus on sentiment-relevant features.

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Furthermore, preprocessing plays a critical role in reducing data dimensionality and computational complexity. By filtering out redundant and irrelevant terms, the feature space becomes more compact and informative. This not only accelerates the training process but also enhances the generalization capability of the SVM classifier. Well-preprocessed data enable the algorithm to identify meaningful patterns more effectively, thereby improving classification stability and robustness.

The success of this stage is crucial because the clean and uniform output generated during preprocessing serves as direct input for the TF-IDF feature extraction stage. High-quality preprocessing ensures that term frequency and inverse document frequency values accurately reflect the importance of words in expressing sentiment. Consequently, the resulting vector representations become more discriminative and representative of the underlying emotional polarity. In this way, preprocessing functions as a foundational mechanism that links raw textual data to reliable sentiment classification outcomes, ultimately contributing to the overall performance and credibility of the analytical model.

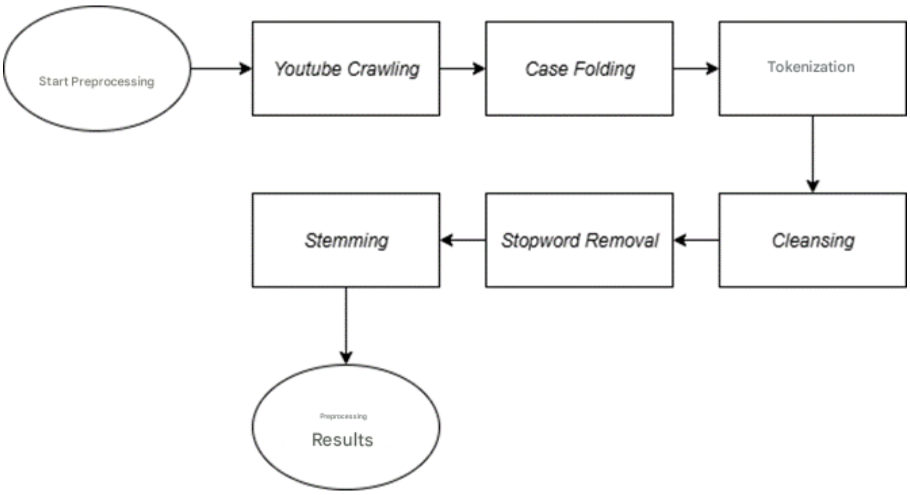

Figure 2. Preprocessing Stages (Darwis et al. 2020)

Case Folding

This process is the initial step in this sentiment analysis research. The goal is to obtain comment data from listeners of the song "Lost" by Bring Me The Horizon uploaded on the YouTube platform. These comments are used as the primary source for analyzing listeners' perceptions and emotions towards the song. After the data is obtained, the comments are compiled into CSV (Comma-Separated Values) format to facilitate the processing process using Google Colab. From the data collection results, approximately 2,219 comments were obtained which were used as the research dataset. This dataset then became the basis for further analysis in the preprocessing stage, TF-IDF weighting, and SVM classification.

Table 2. Folding Case Table

No	Comment	Case Folding
1	the part from to on full volume just scraches my brain in the right ways	the part from to on full volume just scraches my brain in the right ways
2	fran bow anyone	fran bow anyone
3	this man thinks hes ruvik from the evil within	this man thinks hes ruvik from the evil within

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Tokenization

Tokenization is the process of breaking down text or sentences into smaller pieces called tokens, usually words, phrases, or symbols. In the context of sentiment analysis, tokenization aims to separate each word in a comment so that it can be analyzed individually by the system.

Table 3. Tokenization Table

No	Cleaned Text	Tokens
1	fran bow anyone	fran, bow, anyone

Stopword Removal

The process of removing common words (stopwords) that frequently appear in text but have no significance in the context of the analysis. These words do not contribute significantly to the meaning or sentiment of a sentence.

Table 4. Stopword Removal Table

No	Original Text	Stopword Removal
1	this man thinks hes ruvik from the evil within	'man', 'thinks', 'hes', 'ruvik', 'evil', 'within'

Stemming

Stemming is the process of converting a word with affixes into its basic form (root word). This stage aims to equate various word forms with the same meaning so that they are considered as one root word in analysis.

Table 5. Stemming Table

No	Original Text	Stopword Removal
1	the part from to on full volume just scraches my brain in the right ways	'part', 'full', 'volume', 'scraches', 'brain', 'right', 'ways'

Weighting

This weighting process is the process of converting preprocessed text into a numerical form that can be understood by machines (SVM model). One common and effective method is Term Frequency–Inverse Document Frequency (TF-IDF). TF-IDF functions to produce a numerical representation that weighs the importance of a word in a comment (Term Frequency) compared to the entire collection of comments (Inverse Document Frequency). TF-IDF weights assign greater value to words that appear less frequently but are distinctive, making them more representative in describing the content of the comment (for example, "anyone", "peak", or "whaaaat"). The TF-IDF weighting results in a high-dimensional feature vector for each comment. This high-dimensional feature space is crucial because it provides optimal input for classification algorithms. Specifically, this feature space allows Support Vector Machines (SVMs) using non-linear kernels (such as RBF) to find the optimal decision boundary (hyperplane) to separate sentiment classes, which are often not linearly separable in the original feature space.

TF (Term Frecuency)

The Term Frequency (TF) method is used to calculate how frequently a word appears in each comment about the song "Lost" on YouTube. TF describes the relative importance of a word within a single comment compared to the total number of words in that comment. For example, common words like "the," "and," or "this" may have a high TF value but do not contribute to determining the comment's emotion. Therefore, TF values need to be combined

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with Inverse Document Frequency (IDF) to prevent common words from being overly weighted.

$$TF\ (t_i, d_j) = \frac{f_{i,,j}}{\sum_k\ f_{k,j}}$$

Description:

$TF(t_i, d_j)$= frequency value of word i in comment j

$f_{i,j}$= the number of occurrences of the ith word in the jth comment

$\sum_k\quad f_{k,j}$= total number of words in the jth comment

IDF (Inverse Document Frequency)

After calculating the Term Frequency (TF) value, the next step is to determine the Inverse Document Frequency (IDF). IDF functions to give greater weight to words that rarely appear across the entire comment set, and less weight to words that frequently appear in almost all comments. Thus, IDF helps reduce the influence of irrelevant, common words on sentiment analysis.

$$IDF\ (t_i) = \log\left(\frac{N}{df_i}\right)$$

Information:

$IDF(t_i)$= IDF weight of the i-th word

N= total number of comments analyzed

df_i= number of comments containing word i

TF-IDF

After calculating the TF (Term Frequency) and IDF (Inverse Document Frequency) values, the two are combined into TF-IDF. TF-IDF weighting aims to assess the importance of a word in a given document compared to the entire document collection. In the context of this study, each YouTube comment about the song "Lost" is represented as a document.

$$TF - IDF(ti, dj) = TF(ti, dj) \times IDF(ti)$$

Information:

$TF(t_i, d_j)$= frequency of occurrence of word i in comment j

$IDF(t_i)$= the inverse weight of the frequency of documents containing word i

Table 6. TF-IDF Table

Index	Say	TF-IDF weights
1	anyone	0.16808314972818936
2	peak	0.1111111111111111
3	the	0.07989998384119912
4	bow	0.06745319054040298
5	fran	0.06745319054040298
6	hellll	0.06415002990995843
7	whaaaat	0.06415002990995843
8	theeee	0.06415002990995843
9	from	0.056114282504319574
6	hellll	0.06415002990995843
7	whaaaat	0.06415002990995843

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8	theeee	0.06415002990995843
9	from	0.056114282504319574

SVM Classification

Classification is the core stage of sentiment analysis. Each comment, represented in the form of a TF-IDF feature vector, is fed into a Support Vector Machine (SVM) algorithm to be categorized as positive, negative, or neutral. The selection of an SVM is based on its effectiveness in handling the high-dimensional data generated from TF-IDF feature extraction. The classification process flow is comprehensively illustrated in Figure 1.3.

Technical Implementation of the Model:

Multiclass Strategy and Kernel Selection: To handle the three-class classification (Positive, Negative, Neutral), SVM is implemented as a multiclass classifier using the One-vs-One (OvO) strategy. The OvO strategy works by constructing N(N−1)/2 binary classifiers (in this case, 3 classifiers), and the final decision is made through a majority voting mechanism. Given the non-linear nature of textual sentiment data, this study uses a Radial Basis Function (RBF) kernel. The RBF kernel was chosen because it effectively maps TF-IDF feature vectors to a higher-dimensional feature space implicitly, allowing the SVM to find the optimal hyperplane for complex class separation.

Hyperparameter Tuning: Model performance is optimized through hyperparameter tuning. Critical model parameters, namely the Regularization Constant (C) and Kernel Coefficient (γ) in the RBF kernel, are systematically optimized (e.g., through Grid Search) combined with cross-validation. This tuning is essential to balance the trade-off between maximizing margin and minimizing error, which serves to prevent overfitting.

Handling Data Imbalance: Based on the data distribution (described in Table 1.7), there is a significant class imbalance (Neutral 1,280 vs. Negative 207). To mitigate model bias in the majority class, we applied a class weighting technique to the SVM configuration. This method imposes a larger penalty on misclassifications in the minority (Negative) class, ensuring the model learns minority sentiment patterns more fairly.

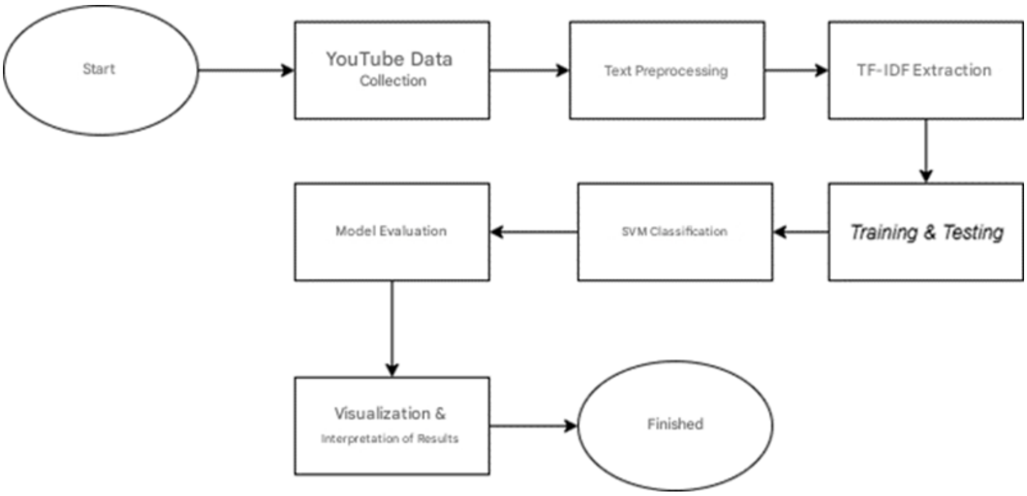

Figure 3. SVM Process

Figure 3 shows the flowchart used in Support Vector Machine (SVM) classification. This flowchart illustrates the main stages of the research used to conduct sentiment analysis on YouTube comments for the song "Lost" by Bring Me the Horizon. The process begins with collecting comment data from YouTube using web scraping to obtain text data from users. The obtained data then goes through a text preprocessing stage, including case folding,

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cleansing, tokenizing, stopword removal, and stemming to clean the text and make it ready for analysis.

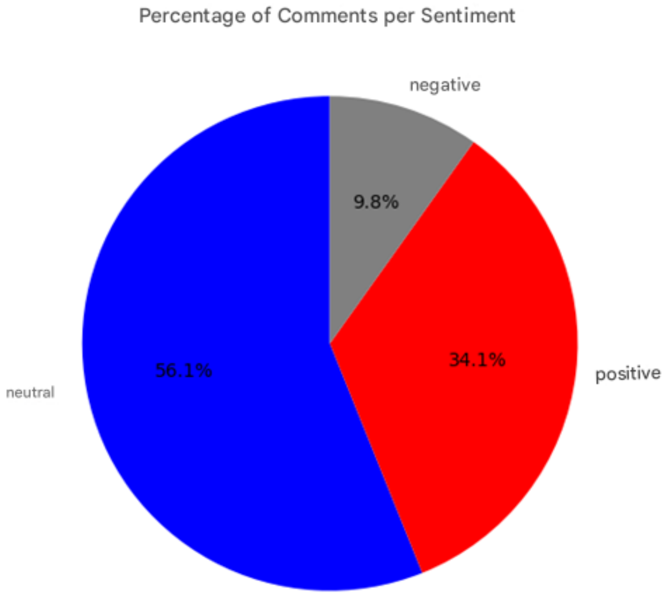

Figure 4. Comments Per Sentiment

Based on Figure 1.3, the sentiment analysis process using the Support Vector Machine (SVM) algorithm resulted in the division of comments into three main categories: positive, negative, and neutral. The results of this classification can be seen in Figure 1.4, which displays a pie chart. Based on the classification results, the majority of YouTube comments on the song "Lost" fell into the Neutral category, with the highest percentage at 56.1%. Positive comments came in second with 34.1%, while Negative comments accounted for only 9.8%.

Qualitative Interpretation

Dominance of Neutral Sentiment: A dominant percentage of Neutral comments indicates that the majority of listeners provided informative, descriptive, or referential comments without expressing any particular extreme emotions toward the song.

Positive Reception: A significant percentage of Positive comments indicates that the majority of users responded favorably to the song, both in terms of its music, lyrics, and meaning.

Error Analysis and Linguistic Limitations: While the SVM model demonstrated high accuracy (94%), analysis of misclassification errors, particularly in the Negative class, revealed linguistic challenges. These errors frequently occurred in comments containing sarcasm, slang, or ambiguous expressions. A limitation of the TF-IDF Bag-of-Words model while effective was that it sometimes failed to capture the semantic context of these nuanced expressions.

Accuracy Testing

The next stage was model evaluation, which measured the performance of the SVM algorithm in classifying data using metrics such as accuracy, precision, recall, and F1-score. After the evaluation, the results were visualized and interpreted to provide a clearer picture of listeners' perceptions of the song "Lost" based on comments uploaded on YouTube. Table 1.7 displays the results of the accuracy test. Furthermore, the amount of data in each category also influenced the evaluation results. The neutral category had the largest amount of data (1,280 comments), followed by positive (732 comments) and negative (207 comments). This

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imbalance in data quantity could be one factor causing the model's performance to slightly decline in the negative class.

Table 7. SVM Classification Table

Category	**Precision**	**Recall**	**F1-Score**	**Amount of Data**
Negative	0,92	0,73	0,82	207
Neutral	0,94	0,99	0,97	1.280
Positive	0,95	0,92	0,93	732

Critical Analysis of Model Performance

Majority Class Dominance: The Neutral and Positive classes performed very well, as evidenced by high F1-scores (0.97 and 0.93, respectively). This demonstrates the successful implementation of the SVM with the RBF kernel and optimized hyperparameters in separating the classes with a sufficient number of samples.

Critical Impact of Data Imbalance: The Neutral category had the largest number of data points (1,280), while the Negative category had only 207 comments. The decrease in Recall value in the Negative class (0.73) is a direct indicator of the impact of class imbalance. Although class weighting techniques were applied (as described in the SVM Classification subsection) to mitigate bias, the small number of Negative samples limited the model's ability to learn complex and nuanced feature patterns, often found in minority sentiments.

Metric Justification: In the context of an imbalanced dataset, the F1-score was chosen over Total Accuracy as the most honest and informative metric, as it provides a balanced evaluation of Precision and Recall for each class. The overall high $F1$-score indicates the robustness of the model, but the limitations on Negative class Recall underscore the challenges in analyzing skewed sentiment data.

Conclusion

This study aimed to analyze listener sentiment toward Bring Me the Horizon's music through comments collected from YouTube. The study used the Support Vector Machine (SVM) method as the classification algorithm and Term Frequency–Inverse Document Frequency (TF-IDF) as the feature weighting method. The combination of these two methods was used to group listener comments into three categories: positive, negative, and neutral, thus providing a general overview of listeners' perceptions of the analyzed musical work.

The research process began with collecting YouTube comment data, followed by text preprocessing, which included case folding, tokenization, stopword removal, and stemming to ensure clean and uniform text. Afterward, word weighting was performed using the TF-IDF method to identify the importance of each word in the comments. The resulting weightings were used as input (features) to the SVM algorithm for sentiment classification.

The test results showed that the majority of comments fell into the neutral category (56.1%), followed by positive comments (34.1%), and negative comments (9.8%). These findings indicate that listeners' responses to Bring Me the Horizon's music are generally neutral to positive. This also indicates that most listeners are objective or do not express extreme emotions toward the songs analyzed.

Furthermore, the results of the model performance test indicate that the SVM algorithm is capable of providing excellent classification results with an accuracy rate of 94%. The highest F1-score of 0.97 was found in the neutral category, indicating a good balance between precision and recall. This demonstrates that the TF-IDF method is effective in providing text

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feature representation, while the SVM is able to optimally separate sentiment classes despite the high-dimensionality of the data.

Overall, this study demonstrates that the combined application of the TF-IDF and SVM methods is highly effective for text-based sentiment analysis, particularly on social media comment data such as YouTube. These results can also serve as a reference in the development of automated sentiment analysis systems in other fields, such as product reviews, public opinion on public services, or perception analysis of digital content.

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