A Hybrid Approach to Measure Students' Satisfaction on YouTube Educational Videos

https://doi.org/10.3991/ijet.v18i09.38473

Samia Naz(✉), Saman Hina, Ubaida Fatima, Huma Tabassum
NED University of Engineering & Technology, Karachi, Pakistan
samianaz505@gmail.com

Abstract—Every aspect of life has undergone innovation in recent years. Information Technology has revolutionized the concept of teaching and learning. Both educators and students are now utilizing contemporary resources for learning and teaching. One of the primary sources of contemporary educational resources is educational videos posted on various channels on YouTube. This study intends to investigate the opinions voiced in YouTube comments for educational videos with the help of Sentiment Analysis. In this research, three techniques namely SentiStrength, TextBlob, and Naive Bayes Classifier were utilized to analyze the sentiments. According to the results, the majority of the remarks made about the videos have positive sentiments that concluded that students are satisfied with YouTube educational videos and consider YouTube as a beneficial learning tool.

Keywords—learning, YouTube educational videos, satisfaction, students

1 Introduction

Since the early days, man has been continuously striving to improve the quality of living. This continuous struggle has brought several revolutions that changed the world completely. Information Technology is one of those revolutions. With all the other opportunities which the Internet is providing to people, it has now become a goldmine for those who want to learn. One of the biggest reasons for people to visit online platforms is to seek information [1]. Teaching and learning have vastly shifted to the online paradigm. People are no longer bound to go to a particular place or have to study at a specific time [2]. Literature provides evidence that online educational videos are being used as an effective tool for learning. With over 2 billion active users, YouTube is the most popular video hosting website [3]. It is commonly used to watch educational content [4]. A review of the existing literature revealed that educational videos on YouTube help students improve their learning [5]. Hundreds of universities and colleges have created their own educational YouTube channels. YouTube contains a lot of information on a vast variety of topics which is available for public use without any cost [6]. YouTube users can provide feedback in the form of likes, dislikes, and comments. Comments can be used to examine how viewers feel about the content.

Thus, the emotions expressed in comments might be utilized as indicators [7]. Natural language processing is a collection of techniques used to analyze and represent the textual forms of languages that humans naturally use for communication purposes. These techniques train machines to process language like humans to perform various tasks more efficiently [8]. Sentiment analysis is the process of assessing a written text and extracting opinions or other information from it [2]. Sentiment analysis can be performed on customers' reviews, feedback, blogs, news articles, etc. It helps businesses to make effective policies for their growth, content creators to make their content better, and researchers and analysts to understand the data. Sentiment analysis can be performed with the help of machine learning and lexicon-based methods. A hybrid approach can also opt which employs both lexicon-based and machine learning techniques [9]. Machine Learning approaches require labeled data to train the classifiers then the classifiers are applied to new data. Conversely, lexical-based techniques use a predetermined collection of words, where each word is connected to a particular emotion [10].

Satisfaction is an important feature that is often used to define the success and reliability of a system. It reflects whether the system is pleasurable or capable of fulfilling the consumers' requirements or not. Consumer satisfaction has become a high priority for service providers as it predicts long-term success [11]. Students' attitude toward their educational services, experience, and institute defines their satisfaction [12]. Students' satisfaction and the sentiment scores of their feedback have a direct relation. High sentiment scores predict high satisfaction [13]. Students have high satisfaction while learning from the internet as the process is different from conventional learning. It is fun to learn from websites because they are more engaging and interactive [14].

In this research, machine learning techniques were employed for the sentiment analysis of comments under YouTube educational videos to measure the satisfaction level of students. During the literature, it was found that various researchers have measured the satisfaction level of consumers through Sentiment Analysis [15] [16] [17]. For this work, positive and negative sentiments expressed by viewers in the comments will be compared. The results will be used to conclude if the students are satisfied with the educational content available on YouTube.

2 Related work

The literature review disclosed that analyzing the educational content on YouTube has received substantial attention in the recent past and persists remaining the focus of research and discussion. Several studies investigated the students' feedback on YouTube educational videos.

Alhujaili and Yafooz proposed the model for sentiment analysis of Arabic educational videos on YouTube using different machine learning classifiers and a deep learning model. SVC and RF classifiers gave an accuracy of 96% while 74% was the worst accuracy given by the KNN classifier using the under-sampling technique. DL model for oversampling and SOMTE technique gave 96% and 89% accuracy was obtained for manually balanced data set [18].

Al-Maroof et al investigated if people use YouTube and TikTok to gain knowledge and to keep themselves updated about the advancement in the field of medicine. The researchers collected the data from UAE health care service providers through an online questionnaire and analyzed it through the software Smart PLS 3.2.7 using partial least squares-structural equation modeling (PLS-SEM). Results indicated that both social media platforms were helpful and had up-to-date information; however, in comparison, YouTube was found to be more effective and had more information [19].

Wang et al. focused on informal learning models through YouTube. The questionnaires were distributed to the people who use YouTube for learning about handmade leather goods. The responses were analyzed for validity and reliability. SEM verifies the research model. The results concluded that 1) YouTube self-efficacy and learning interest, YouTube self-efficacy and learning attitude, learning attitude and learning satisfaction, and Learning interest and learning satisfaction are positively related. Moreover, YouTube enhances learning skills and can be a good source of learning if provided with appropriate learning material [20].

Tahat et al explored the impact of YouTube utilization as an instructive device on the growing experience of debilitated individuals during the COVID-19 pandemic. 60 people functioning as handicapped subject experts were chosen. The study model was examined through structural equation modeling. According to the results, YouTube features are developing handicapped individuals' growth opportunities [21].

Giray analyzed the e-learning experiences of Computer and Software Engineering students. Student perspective was received using a questionnaire then the data were analyzed using qualitative and quantitative statistical techniques. It was found that students find video recording helpful but they preferred face-to-face lectures over videos. They observed that students also take help from online resources when they are stuck somewhere and want to make their concepts clear [22].

Almobarraz researched to know the opinion of undergraduate university students and their experience of YouTube as learning support. The data was obtained from the College of Computer and Information through a questionnaire and then it was analyzed statistically using frequency and simple percentages. The findings were that YouTube has a substantial impact on students learning. Students understand the importance of YouTube as an educational tool however professors are still reluctant to use YouTube videos as an educational aid in the classrooms [23].

Amarasekara et al analyzed STEM (Science, Technology, Engineering, and Mathematics) videos available on YouTube to examine the gender gap using sentiment analysis, they randomly selected YouTube STEM channels with the help of an Excel random number generator. From the selected channels they collected up to 100 comments from any five videos on each channel. Then the comments were coded for sentiments. SPSS software was used to analyze the results. The study reveals that gender has a noticeable effect on STEM channels on YouTube [24].

Lee et al investigated the capability of YouTube to spread educational instructions as well as its helpfulness for self-directed learners. Using sentiment and qualitative sentiment analysis they concluded that YouTube has great potential to empower the concept of self-directed learning but the learners have to be careful about the quality and credibility of the content available on YouTube [2].

Muhammad et al. used Naïve Bays and Support Vector Machine (SVM) for the classification of comments under Indonesian YouTube channels having educational content. Results show the model got 91% precision 83% recall and 87% for F1 score [25].

Tisdell conducted a study to analyze how Australian students engaged with YouTube and use it to learn the concepts of engineering. The researchers concluded that a large number of students take aid from online videos. This usage increased largely at the time of exams. Students found YouTube a significant source to learn [26].

The literature review about YouTube learning videos mentioned above shows that students find learning videos on YouTube helpful. Most of the literature discussed above was domain-specific or region specific. For this study, any particular subject or any particular region was not specified. Moreover, it was found that most of the work that has been done on YouTube educational videos uses statistical techniques to conclude. Very few articles were found to have machine-learning approaches. Lexicon-based and Machine learning techniques will be used for this study to measure the satisfaction of the students with YouTube educational content to bring diversity to the existing literature.

3 Research methodology

This section discusses the methodology adopted for this research. Figure 1 illustrates the overview of our proposed model. The essential actions performed to complete this study are thoroughly discussed.

3.1 YouTube comments collection

The data collection comprised three steps. First, the appropriate channels were selected then from selected channels few videos were chosen after that from each video comments were extracted.

Channel selection. YouTube contains some educational channels both for "school, university" learning and "lifelong" learning [3]. During the channel selection, we preferred the channels which have a good number of subscribers and have high school/university lectures like "Khan academy", "Academic lessons", "The organic chemistry tutor" etc.

Video selection. While selecting videos, different educational domains were chosen. To bring variety, videos on the topics of medicine, physics, chemistry, mathematics, finance, statistics, etc. were selected. The purpose was to take opinions from a variety of audiences.

Comments extraction. A total of twenty videos were selected and a hundred comments were extracted from each video. The comments were extracted using the website "exportcomments.com". The first hundred comments from each video were collected. This website allows its users to save the extracted comments in either .xls or .csv files for data analysis.

Comments annotation. For this paper SentiStrength, TextBlob, and Naïve Bayes were used. SentiStrength and TextBlob are lexicon-based methods. However, Naïve bays requires data annotation for processing it further. Two educationists from NED

University of Engineering and Technology annotate the data to avoid bias ness. For data annotation, positive comments such as "Thank you", "great video", "you are the best teacher" etc were labeled as 1, and negative comments such as "bad audio", "I couldn't get anything" etc. were labeled as −1, while the comments which have no positive or negative sentiment such as queries related to the content were labeled as 0.

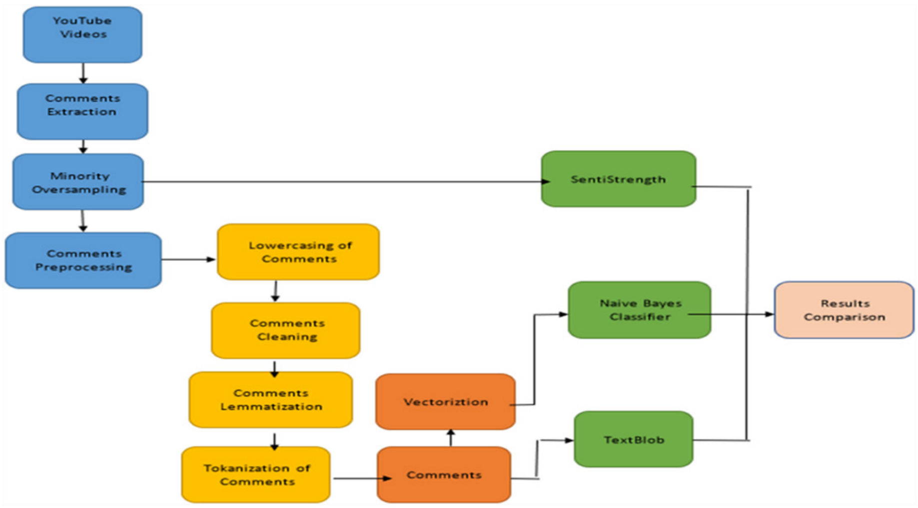

Fig. 1. Proposed framework

Figure 2 depicts the distribution of manually annotated comments. The negative and neutral comments had formed the minority class as shown in Figure. There were 1175 positive comments in the original data, 660 neutral comments, and only 165 negative comments. So, before processing further, the data first needed to be balanced.

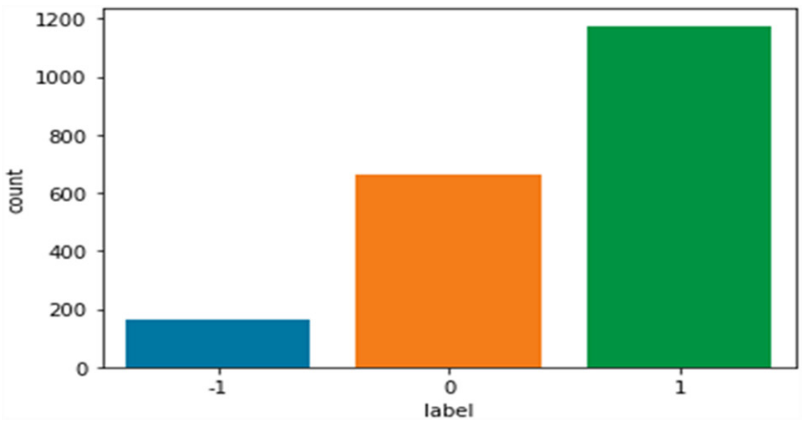

Fig. 2. Manually annotated comments

3.2 Minority oversampling

As the data is highly imbalanced, we first have to balance the data. Several methods have been proposed to address the issue of class imbalance. Literature shows that under-sampling and oversampling techniques are the most widely used. Oversampling is preferred over under-sampling because under-sampling results in the loss of a large amount of data. The strategy is to oversample the minority group by introducing different synthetic sample ratios. Oversampling by SMOTE is quite famous in literature but SMOTE technique can be applied after the vectorization of the data. As this research required the same data for all three techniques, oversampling was done with repetition as [18] suggests that both SMOTE and oversampling techniques evaluated similar results. The annotated data had 1175 positive comments 165 negative and 660 neutral comments. Figure 3 shows, by employing oversampling, the number of comments for the three categories became equal. The oversampled data had 1175 positive comments 1175 negative comments, and 1175 neutral comments.

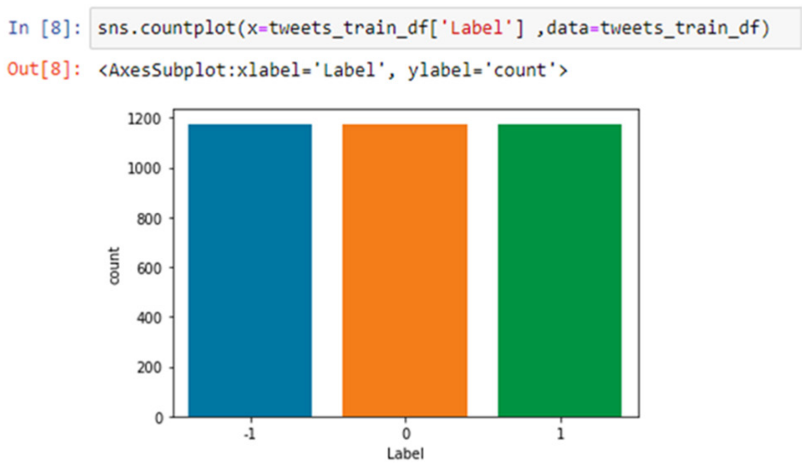

Fig. 3. Balanced comments

3.3 Comments preprocessing

Lowercasing. In this step, all the uppercase letters used in the document were converted into lowercase letters. The purpose of performing this step is to treat the words like "Wow" the same as "wow". Lowercasing helps dictionaries in reducing the number of words for labeling.

Comments cleaning. Stop words are the words that are often used in English but they do not add any value to the meaning of the sentence. All the stop words, URLs, and other unnecessary characters from the document were eliminated to make the proposed model more efficient. This step includes.

- removed URLs from the text
- removed hashtags, usernames, and mentions

- removed stop words
- removed numbers
- removed unnecessary spaces
- removed punctuations marks and symbols

Lemmatization. The process of lemmatization with the help of morphological and vocabulary analysis removed the inflectional ending of the words in the document and assigned it a lemma (canonical forms available in dictionaries).

Tokenization. Tokenization is the process of splitting a text document into small chunks of words to build a word vector. A Word vector is also called a bag of words. Figure 4 shows how the original comment was transformed into a clean comment.

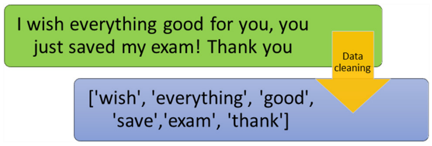

Fig. 4. Comment after lowercasing, cleaning, lemmatization, and tokenization

Vectorization. Vectorization was performed using the count vector function to the number of times a particular word appears in the comments. count vectorizer only focuses on word count without considering the sentence structure.

In this study, the strategy was adopted as found during the literature survey. SentiStrngth used raw comments without any data preprocessing. TextBlob used cleaned comments without vectorization and data annotation, while, Naïve Bayes Classifier used annotated cleaned and vectorized comments. In Naïve Bayes, after all the preprocessing, the data set was divided into two subsets 80 percent data for training and 20 percent data for testing.

4 Tools and interpretation

Humans often use emotions to convey their feelings to others. Text classification has become an elementary and critical task as a result of the increased usage of texts digitally as well as the growing need to access them in flexible ways. Numerous techniques that utilize machine learning and statistical theory have already been applied to text classification in recent years. A lot of researchers are continuously working on sentiment detection through different techniques. For this study, three methods were employed for sentiment analysis of YouTube educational videos. The experiment for each method is discussed below.

4.1 SentiStrength

SentiStrength is a lexicon-based approach. It contains a list of words with positive or negative sentiment scores and has rules to deal with linguistics. SentiStrength can simultaneously measure the positive and negative sentiments expressed in a single text [27]. It assigns a pair of scores (p, n) to a text, where p represents a positive sentiment strength score and q represents a negative sentiment strength score also p and q are integers that lie in the ranges "$1 \leq p \leq 5$" "$-1 \leq n \leq -5$".

Getting a score of 1 means the sentence is not positive while 5 means the text is extremely positive. −1 shows text is not negative while −5 shows it is extremely negative. For Sentiment analysis with the help of SentiStrength, the comments were first copied from excel to notepad as SentiStrength works with text files. Then the SentiStrength was run for sentiment detection and classification. SentiStrength also has a feature of translation and emotional rationale but these two options were disabled as the researcher only wanted to work with polarity.

Comments were classified further according to their positive and negative strengths. Labels were assigned to comment based on the following rule. Positive comments were labeled as 1, negative comments were labeled as −1 and neutral comments were labeled with 0. Table 1 shows how labels were assigned to comments according to SentiStrength scoring based on the following rule;

$$\begin{cases} comment\,label = 1 & |p| > |n| \\ comment\,label = 0 & |p| = |n| \\ comment\,label = -1 & |p| < |n| \end{cases}$$

Table 1. Labeling of comments based on SentiStrength results

Positive Score	Negative Score	Label
1	−2	−1
1	−1	0
1	−2	−1
1	−1	0

4.2 TextBlob

TextBlob is a lexicon-based approach and all lexicon-based approaches require a dictionary that has stored words with their polarities that are positive negative, or neutral. A comment is made with a bag of words. A polarity score is assigned to the comment by using any pool operation like taking the average of each word's score. [28] TextBlob measures the polarity and subjectivity of a text. Polarity represents how positive or negative a piece of text is, while subjectivity tells how opinionated a piece of text is. TextBlob returns the polarity (p) and subjectivity (s) in the following ranges "$-1 \leq p \leq 1$" and "$0 \leq s \leq 1$" −1 shows the text is extremely negative while 1 shows the comment is extremely positive. A higher subjectivity score shows the comment contains more opinions than factual information.

TextBlob was first installed and imported in python then a python code was written in Jupyter Notebook to extract the polarity of the comment using the TextBlob library. After getting the results comments were further classified and labeled using the following rule. Table 2 represents how comments were assigned with the labels according to their polarity results using following rule.

$$\begin{cases} comment\,label = 1 & p > 0 \\ comment\,label = 0 & p = 0 \\ comment\,label = -1 & p < 0 \end{cases}$$

Table 2. Labeling of comments based on TextBlob results

Polarity	Label
−0.083333333	−1
0.24672619	1
−0.25	−1
−0.145833333	−1

4.3 Naïve Bayes classifier

The Naïve Bayes classification method is a supervised machine learning method that is based on the Bayes theorem [35]. The Naïve Bayes algorithm uses the given data or evidence from the past to predict the future probability [24]. Equation (3) gives the working of Naïve Bayes

$$P(C|X) = (P(X \mid C).P(C))/(P(X)) \tag{1}$$

$P(C|X)$ is posterior probability
$P(X \mid C)$ is the likelihood
$P(C)$ is the prior probability
$P(X)$ is the evidence
With help of the code, the data was cleaned tokenized and vectorized. After preprocessing the data was split into 80 percent training and 20 percent testing data using a machine learning library Scikitlearn. Scikitlearn also helped in training the Naïve Bayes classifier model and analyzing its performance.

5 Results and discussion

5.1 SentiStrength

As SentiStrength simultaneously measures the positive and negative sentiment strength of a single piece of text. Table 3 shows the number of comments SentiStrength classified for each positive score. Similarly, Table 4 shows the number of comments against each negative score.

The Tables 3 and 4 show that the majority of the comments received a SentiStrength score of 1 (not positive) or −1 (not negative). Additionally, the comments had more words with high positive strength in comparison with negative strength. Very few comments got scores of −3, and −4, and no comment got a negative score of 5. After achieving SentiStrength scores for all the comments, the comments were categorized into positive, negative, and neutral groups based on the rule we discuss in above section 4.1. Figure 5 demonstrates the classification.

Table 3. Positive score count

Positive Score	Count
1	1731
2	1144
3	551
4	94
5	5

Table 4. Negative score count

Negative Score	Count
−1	2662
−2	582
−3	204
−4	76
−5	0

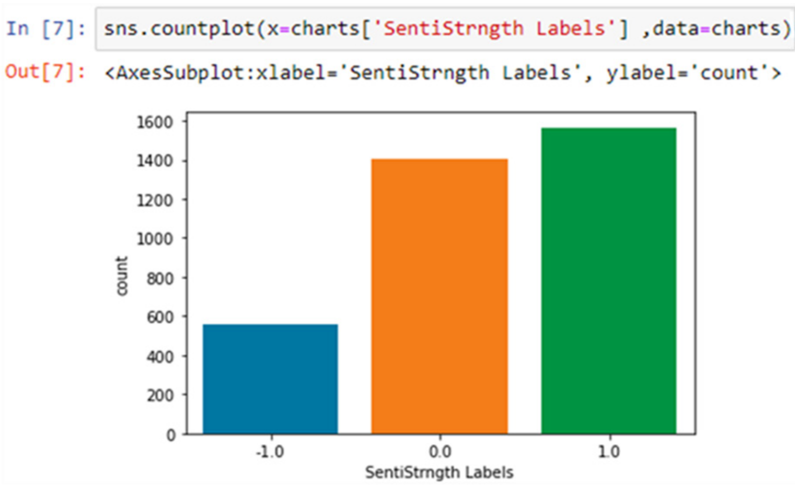

Fig. 5. SentiStrength labels classification

5.2 TextBlob

TextBlob gauges the text's subjectivity and polarity. For this investigation only the polarity of the data is needed, thus subjectivity findings were disregarded initially. Figure 6 represents how many comments TextBlob assigned for each score as the Text-Blob scale lies between −1 to 1.

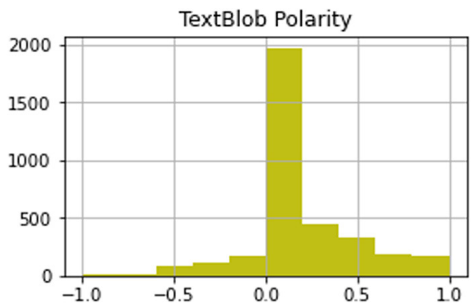

Fig. 6. TextBlob polarity result

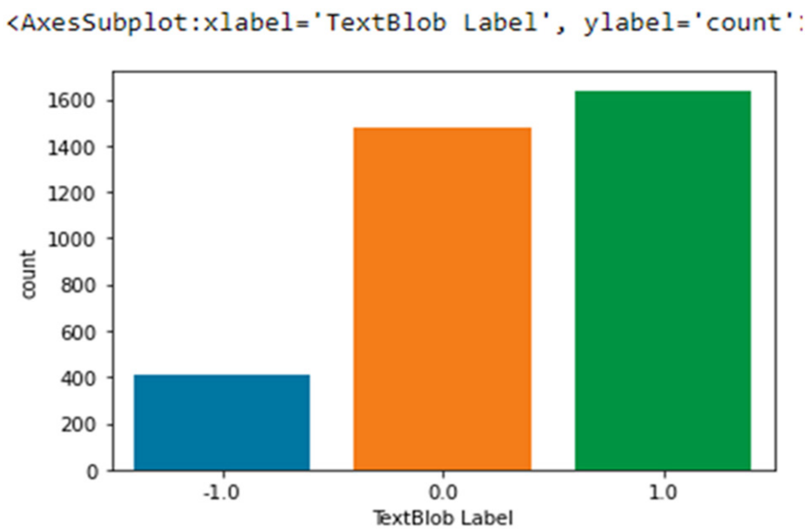

Fig. 7. TextBlob labels classification

Figure 6 shows that TextBlob assigned 0 (neutral) to the most number of comments but when we observed the positive scores collectively they exceed neutral comments as depicted in Figure 7.

5.3 Naïve Bayes Classifier

For Naïve Bayes Classifier, the data were divided into training and testing purposes after being cleaned and prepped. The model was created, and then it was used to analyze the test data. The labels assigned by Naïve Bayes Classifier are represented in Figure 8. The Naive Bayes results also indicated that viewers have found the videos beneficial as the highest number of comments were classified as positive.

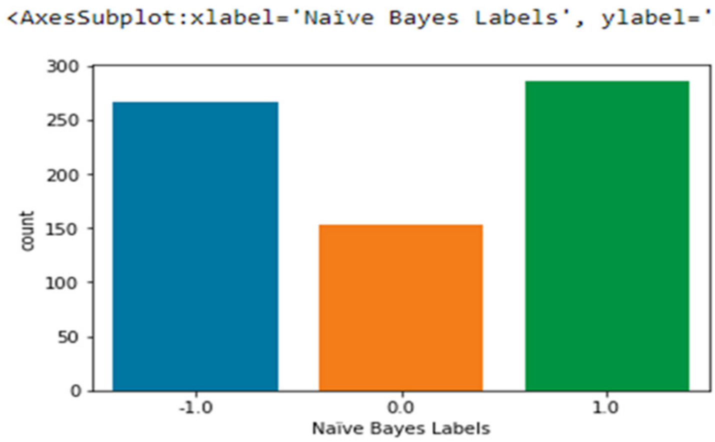

Fig. 8. Naïve Bayes labels classification

5.4 Discussion

Fig. 9. Word clouds for positive, negative, and neutral comments

It is evident from Figure 9 that the in the Word cloud of all comments "Thanks" is the word that appeared the most in comments, understand, video, love, much, need, sir, etc. words are mostly used by people to post their opinions under comments. In the Word Cloud for positive comments a lot of positive words can be seen like Thank, love, nice, amazing, great, wow, awesome best, helpful, etc. In the Word Cloud for negative comments, It can be observed that negative comments are mostly related to volume, voice, sound, video, etc. some positive words like thank, good video, and great can also be noticed because some negative comments contain a positive part too. For instance, "Love the enthusiasm!! Awesome video! The Audio kept cutting out about every minute or so on my end." Or "Good explanation! But it was very basic. You skipped a lot of important points". In the Word Cloud for neutral comments it can be observed that the words like sir, world, video, world, command, and question are widely used. All the word clouds show that the words with positive sentiments like "thank" "good" appear in the highest frequencies even in negative and neutral comments.

The three approaches we used in the study, are contrasted in Table 5 and Figure 10. The table clearly shows that all strategies produced essentially identical outcomes. All three methods classified the highest percentage of the comments as positive.

Table 5. Comparison table

Method	Label	Percentage
SentiStrength	Positive	44.39716
	Negative	15.74468
	Neutral	39.85816
Textblob	Positive	46.46809
	Negative	11.65957
	Neutral	41.87234
Naïve Bayes Classifier	Positive	40.56738
	Negative	37.7305
	Neutral	21.70213

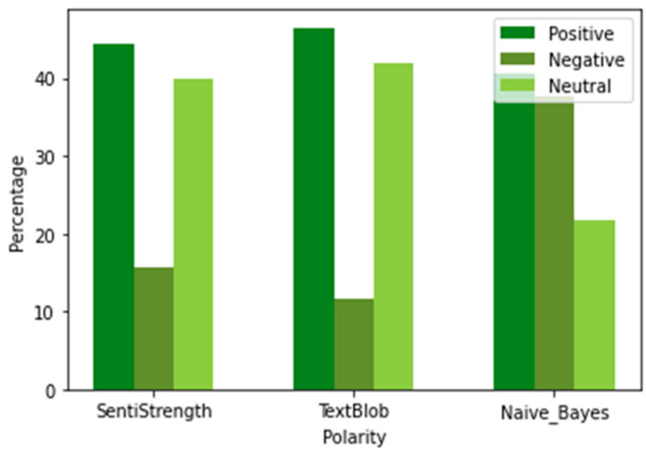

Fig. 10. Percentages of labels for each method

The positive versus negative ratio was visualized for all three methods in Figure 11 neutral comments were not compared because they were mostly related to students' queries. TextBlob results also suggest that out of 1476 neutral comments 135 comments are not subjective this means more than 90 percent of the neutral comments do not contain any opinion so they can be ignored while studying the satisfaction of the students. Only positive comments and negative comments defined students' satisfaction. The comparison showed that the greatest number of comments were classified as positive. The results suggest that students are satisfied with YouTube educational videos. They take YouTube educational videos positively and consider them helpful learning tools.

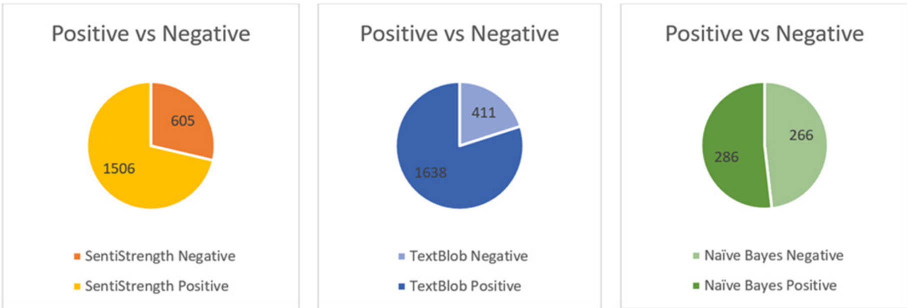

Fig. 11. Positive and negative ratios for each method

6 Conclusions

This study was conducted to analyze the sentiments expressed in comments under YouTube educational videos. Three sentiment analysis methods – SentiStrength, TextBlob, and Naive Bayes classifier were used. The findings from all three approaches indicate that a majority of the comments were positive. Very few comments were classified as negative using all three approaches. The experiment leads us to believe that YouTube has enormous potential for use in education. Students can benefit from the educational content on YouTube in their educational careers. YouTube has a wide range of instructional topics so caution is required when selecting YouTube videos.

7 References

[1] R. Kim, L. Olfman, T. Ryan, and E. Eryilmaz, "Leveraging a personalized system to improve self-directed learning in online educational environments," *Comput Educ*, vol. 70, pp. 150–160, 2014, https://doi.org/10.1016/j.compedu.2013.08.006

[2] C. S. Lee, H. Osop, D. Hoe-Lian Goh, and G. Kelni, "Making sense of comments on YouTube educational videos: A self-directed learning perspective," *Online Information Review*, vol. 41, no. 5, pp. 611–625, 2017, https://doi.org/10.1108/OIR-09-2016-0274

[3] N. Marchal, H. Au, and P. N. Howard, "Coronavirus news and information on YouTube: A content analysis of popular search terms," 2020.

[4] S. Saurabh and S. Gautam, "Modelling and statistical analysis of YouTube's educational videos: A channel Owner's perspective," *Comput Educ*, vol. 128, pp. 145–158, 2019, https://doi.org/10.1016/j.compedu.2018.09.003
[5] Y. Chtouki, H. Harroud, M. Khalidi, and S. Bennani, "The impact of YouTube videos on the student's learning," in *2012 International Conference on Information Technology Based Higher Education and Training, ITHET 2012*, 2012. https://doi.org/10.1109/ITHET.2012.6246045
[6] C. Snelson, "YouTube across the disciplines: A review of the literature," 2011. [Online]. Available: http://www.watchknow.org
[7] S. Chelaru, C. Orellana-Rodriguez, and I. S. Altingovde, "How useful is social feedback for learning to rank YouTube videos?," *World Wide Web*, vol. 17, no. 5, pp. 997–1025, 2014, https://doi.org/10.1007/s11280-013-0258-9
[8] E. D. Liddy, "Natural Language Processing," in Encyclopedia of Library and Information Science, 2nd Ed. NY. Marcel Decker, Inc. 2001. [Online]. Available: https://surface.syr.edu/istpub
[9] N. M. Sham and A. Mohamed, "Climate change sentiment analysis using lexicon, machine learning and hybrid approaches," *Sustainability (Switzerland)*, vol. 14, no. 8, 2022, https://doi.org/10.3390/su14084723
[10] P. Gonçalves, M. Araújo, F. Benevenuto, and M. Cha, "Comparing and combining sentiment analysis methods," in *COSN 2013 – Proceedings of the 2013 Conference on Online Social Networks*, 2013, pp. 27–37. https://doi.org/10.1145/2512938.2512951
[11] J. Feine, S. Morana, and U. Gnewuch, "Measuring Service Encounter Satisfaction with Customer Service Chatbots using Sentiment Analysis," in Proceedings of the 14th International Conference on Wirtschaftsinformatik (WI2019), Siegen, Germany, February 24–27. 2019. [Online]. Available: http://ksri.kit.edu
[12] H. T. Son, N. T. Ha, P. Thi, and M. Khuyen, "Measuring students' satisfaction with higher education service-An experimental study at Thainguyen University," 2018. [Online]. Available: www.ijbmm.com
[13] M. Z. Asghar, I. Ullah, S. Shamshirband, F. M. Kundi, and A. Habib, "Fuzzy-based sentiment analysis system for analyzing student feedback and satisfaction email of 2nd," 2019, https://doi.org/10.20944/preprints201907.0006.v1
[14] J. Ohliati and B. S. Abbas, "Measuring students satisfaction in using learning management system," *International Journal of Emerging Technologies in Learning*, vol. 14, no. 4, pp. 180–189, 2019, https://doi.org/10.3991/ijet.v14i04.9427
[15] S. Al-Otaibi et al., "Customer satisfaction measurement using sentiment analysis," 2018. [Online]. Available: www.ijacsa.thesai.org; https://doi.org/10.14569/IJACSA.2018.090216
[16] D. Kang and Y. Park, "Review-based measurement of customer satisfaction in mobile service: Sentiment analysis and VIKOR approach," *Expert Syst Appl*, vol. 41, no. 4 PART 1, pp. 1041–1050, 2014, https://doi.org/10.1016/j.eswa.2013.07.101
[17] Z. Gang and L. Chenglin, "Dynamic measurement and evaluation of hotel customer satisfaction through sentiment analysis on online reviews," *Journal of Organizational and End User Computing*, vol. 33, no. 6, pp. 1–27, 2021. https://doi.org/10.4018/JOEUC.20211101.oa8
[18] R. F. Alhujaili and W. M. S. Yafooz, "Sentiment Analysis for YouTube Educational Videos Using Machine and Deep Learning Approaches," in *2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information, ICETCI 2022*, 2022, pp. 238–244. https://doi.org/10.1109/ICETCI55101.2022.9832284
[19] R. Al-Maroof et al., "The acceptance of social media video for knowledge acquisition, sharing and application: A comparative study among YouYube users and TikTok users' for medical purposes," *International Journal of Data and Network Science*, vol. 5, no. 3, pp. 197–214, 2021, https://doi.org/10.5267/j.ijdns.2021.6.013

[20] C. M. Wang, J. H. Ye, and J. N. Ye, "Hands-on making leather goods: Learning from youtube videos," *International Journal of Information and Education Technology*, vol. 11, no. 6, pp. 269–276, 2021, https://doi.org/10.18178/ijiet.2021.11.6.1522
[21] K. M. Tahat, W. Al-Sarayrah, S. A. Salloum, M. Habes, and S. Ali, "The Influence of YouTube Videos on the Learning Experience of Disabled People During the COVID-19 Outbreak," in *Studies in Systems, Decision and Control*, vol. 378, Springer Science and Business Media Deutschland GmbH, 2022, pp. 239–252. https://doi.org/10.1007/978-3-030-77302-1_13
[22] G. Giray, "An assessment of student satisfaction with e-learning: An empirical study with computer and software engineering undergraduate students in Turkey under pandemic conditions," *Educ Inf Technol (Dordr)*, vol. 26, no. 6, pp. 6651–6673, 2021, https://doi.org/10.1007/s10639-021-10454-x
[23] A. Almobarraz, "Utilization of YouTube as an information resource to support university courses," *Electronic Library*, vol. 36, no. 1, pp. 71–81, 2018, https://doi.org/10.1108/EL-04-2016-0087
[24] I. Amarasekara and W. J. Grant, "Exploring the YouTube science communication gender gap: A sentiment analysis," *Public Understanding of Science*, vol. 28, no. 1, pp. 68–84, 2019, https://doi.org/10.1177/0963662518786654
[25] Slamin, Universitas Negeri Jember, Institute of Electrical and Electronics Engineers. Indonesia Section, Institute of Electrical and Electronics Engineers. Indonesia Section. Computer Society Chapter, and Institute of Electrical and Electronics Engineers, *Proceedings, 2019 International Conference on Computer Science, Information Technology, and Electrical Engineering (ICOMITEE 2019): October 16th-17th 2019, Jember, Indonesia*.
[26] C. Harbour and C. C. Tisdell, "How do Australasian students engage with instructional YouTube videos? An engineering mathematics case study," In AAEE2016 Conference. [Online]. Available: http://aaee.net.au/wp-content/uploads/2018/10/AAEE2016-Tisdell-Instruction_YouTube_video_Australian_student_engagement.pdf
[27] *2018 2nd East Indonesia Conference on Computer and Information Technology (EIConCIT)*. IEEE, 2018.
[28] V. Bonta, N. Kumaresh, and N. Janardhan, "A comprehensive study on lexicon based approaches for sentiment analysis," 2019. [Online]. Available: www.rottentomatoes.com; https://doi.org/10.51983/ajcst-2019.8.S2.2037

8 Authors

Samia Naz earned a bachelor's degree in Mathematics from the University of Karachi, and has recently completed her master's degree in Applied Mathematics from NED University of Engineering & Technology. Her research intrests are Artificial Intelligence, Machine Learning, and Data mining and Statistics.

Dr Saman Hina is an Associate Professor in the Department of Computer Science & IT at NED University of Engineering and Technology, Pakistan where she is serving from 2006. She received her Masters from the same University and completed her PhD

from University of Leeds, UK in 2013. Her PhD research was in AI in general and Natural Language Processing in particular. Other research interests include areas of Artificial Intelligence and its applications in inter-disciplinary domains.

Dr Ubaida Fatima received the B.E. in Biomedical Engineering (2011) and MS in Applied Mathematics (2014) degrees from NED University of Engineering and Technology. Completed her PhD degree in Applied Mathematics (2015–present) at NED University of Engineering and Technology. Research interest are Big data analysis, Social network analysis, Artificial intelligence, Data mining, Fuzzy Logic and Statistics.

Huma Tabassum is currently pursuing PhD (Computer Science) from NED University. She holds MS (Computer Science) and BE (Computer & Information Systems Engineering) degrees. Her research interests include Learning Analytics, Natural Language Processing, Data Mining, and Machine Learning.

Article submitted 2023-01-30. Resubmitted 2023-03-01. Final acceptance 2023-03-01. Final version published as submitted by the authors.