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# Sentiment Analysis of Students' Feedback before and after COVID-19 Pandemic

**M. Umair[1], A. Hakim[1*], A. Hussain[1] and S. Naseem[2]**
[1]Researcher, Department of Computer Science, MNS University of Agriculture, Multan, Pakistan.
[1]Assistant Professor, Department of Computer Science, MNS University of Agriculture, Multan, Pakistan.
[1]Assistant Professor, Department of Computer Science, MNS University of Agriculture, Multan, Pakistan.
[2]Lecturer, Department of Statistics, MNS University of Agriculture, Multan, Pakistan.

(Corresponding author: A. Hakim)

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**ABSTRACT: COVID pandemic has impacted most of the higher education institutes by shifting to online teaching. Due to this shift, there has been increasing use of e-text, online learning management systems, social media apps, and micro-blogging platforms used by students to provide feedback and comments about a course and online classroom experience before and during the pandemic. This feedback is important for the education institutes and can be used to improve the teaching and learning experience. One of the major problems is to extract useful information out of several comments and feedback. This study presents a hybrid approach of student sentiment analysis based on feedback of classes collected through Google survey forms and WhatsApp social media platforms before and during the pandemic. For classification and comparative analysis, Support Vector Machine, and Naïve Bayes algorithms have been used and an average accuracy of 85.62% has been achieved using Support vector machine with K-fold cross-validation.**

**Keywords:** COVID-19, Opinion mining, Sentiment analysis, online feedback, Natural language processing, COVID.

**Abbreviations:** COVID, Coronavirus Disease; AI, Artificial Intelligence; ML, Machine Learning; LMS, Learning Management System; LIWC, Linguistic Inquiry Word Count; NB, Naïve Bayes; MNB, Multinomial Naïve Bayes; RF, Random Forest; SGD, Stochastic Gradient Descent; SVM, Support Vector Machine; NLTK, Natural Language Toolkit; VADER, Valence Aware Dictionary and Sentiment Reasoner; NLP, natural language processing; GSP, Generalized Sequential Pattern; TD-IDF, Term Frequency-Inverse Document Frequency; BOW, Bag of Words.

## I. INTRODUCTION

Sentiment Analysis, also known as Opinion mining or Opinion AI is one of the leading research areas due to the increasing use of e-text, online learning management system (LMS), and microblogging platforms including *Twitter*, *WhatsApp*, *Facebook*, *AnswerGarden*, *Poll Everywhere*, and online blogs. People use these platforms to express their thoughts and opinion regarding any product, place, or event throughout the world. This feedback is very critical for concerned organizations to satisfy their customers. One of the major problems is to extract useful information out of feedback and comments to improve the quality of products or services.

Sentiment Analysis is the process of classification of data in different categories such as positive, negative, or neutral class. In this work, we gathered student feedback in two different scenarios of before and during the COVID pandemic from WhatsApp groups and Google forms. An analysis has been performed on student's textual comments in both scenarios using sentiment analysis to identify their opinion about the quality of teaching and learning. One of the objectives of this system is to help university faculty and administration to find gaps between students learning and tutor teaching quality.

Sentiment analysis is mostly done using three techniques: lexicon-based approach, machine learning approach, and a hybrid technique that uses both lexicon and machine learning techniques [1, 2]. In the lexicon-based technique, a pre-defined dictionary is used where words are already weighted according to their sentiments. The most common tools for performing lexicon-based analysis are SenticNet, SentiStrength, and Linguistic Inquiry Word Count (LIWC) [3]. In the machine-learning approach, the common algorithms for sentiment classification are Naïve Bayes (NB), Multinomial Naïve Bayes (MNB), Random Forest (RF), Stochastic Gradient Descent (SGD), Support vector machine (SVM), and hybrid techniques using a combination of these algorithms.

Due to the COVID-19 pandemic situation, almost all higher education institutes were shifted from face-to-face or blended to fully online teaching, and many students faced difficulties regarding online learning. To facilitate them, it is critical to design a system that takes feedback from students and provide an overall class opinion to teachers and administrators to revise their teaching and assessment methodology. This can be done by converting textual data into positive, negative, and neutral classes using Natural language processing algorithms. It will help to determine students' level of understanding and any difficulties they are facing after each class and to classify text-based data into positive, negative, and neutral feedback to evaluate tutor performance.

In this work, we have performed classification and analysis of student's feedback before and after COVID-19 pandemic using machine learning techniques. Data is collected through online google forms, LMS, and

Whatsapp group messages of selected courses. Annotation of student's feedback on classes before and during pandemic has been performed using open-source tools: *TextBlob* and *VADER* [4]. These tools were integrated with the Natural Language Toolkit (*NLTK*) Python library using Jupiter notebook.

VADER (Valence Aware Dictionary and sEntiment Reasoner) is a rule-based and vocabulary-based sentiment analysis tool adapted to the sentiment expressed on social media and other types of data [5]. VADER is different from other emotional analysis tools because it does not classify text in discrete categories of positive, negative, or neutral. Instead, VADER generates a composite score between -1 and +1, which indicates a range of positive, negative, or neutral. TextBlob is a Python library for processing textual data that provides a simple Application programming interface to perform common natural language processing (NLP) tasks like speech part tagging, noun phrase extraction, emotional analysis, classification, and translation. It generates a result score between -1 and +1. Score grading for both TextBlob and VADER is such that all values less than zero are considered as negative, zero consider neutral and values above zero considered as positive. For classification, Naïve Bayes, and Support Vector Machine [6] have been used due to their high accuracy on textual data [7].

This paper is divided into five sections. Section 2 presents the background to the related literature of sentiment analysis and opinion mining. It also discusses the main approaches and techniques for sentiment classification. The proposed methodology is described in Section 3. Results and discussions are presented in Section 4 followed by a conclusion and future work that is discussed in Section 5.

Sentiment analysis of text data on the Internet can be useful in many applications such as product reviews, political campaigns, popular topics, and educational improvements, but it is most often applied to feedback analysis [8]. Feedbacks are received from several domains, including advertising [9] , movies [3, 10, 11, 12], products [4, 10, 13], automobiles, tourism, smartphones [7, 14] , and education-learning [15-17]. We focus on an overview of previous work related to the sentimental analysis of educational related data.

An opinion is someone's feelings, beliefs, or judgments about an important issue in a particular situation and is generally considered subjective. Studies have shown that opinions have a major impact not only on facts but also on individual decisions, as well as on communities, such as organizations and government sectors. The terms sentiment analysis and opinion mining often used interchangeably in the field of text data mining which extracts opinions from evaluation texts and classifies the polarity of opinions into positive or negative rankings based on the valency of the text results [18].

In the field of education, very few studies have focused on sentiment analysis of online learning such as [19-23], and only one feedback study was conducted on the classroom related data [24]. In [25], authors used two pattern mining algorithms Apriori and Generalized Sequential Pattern (GSP) to extract comment words from student feedback data sets for evaluation of tutor performance. The results of the evaluation showed that GSP performs better than Apriori in the extraction of opinion words.

In [26], authors claimed to detect polarity (positive, negative, and neutral) on Facebook comments related to e-learning. The positive class consisted of happy and excited emotions, and negative class included emotions such as anger, sadness, and profanity. The method was evaluated on 1000 positive and negative text messages and Facebook statuses.

Most of the sentiment analysis techniques focused on after-class feedback and classified students' feedback into discrete categories. In this work, we are performing comparative analysis of student's feedback in blended and fully online learning in two scenarios of before and after COVID pandemic respectively.

## II. MATERIALS AND METHODS

The proposed framework for this research (as shown in Fig. 1) consists of five phases: Dataset collection and preprocessing, data annotation/polarity calculation, feature extraction, classification, and visualization

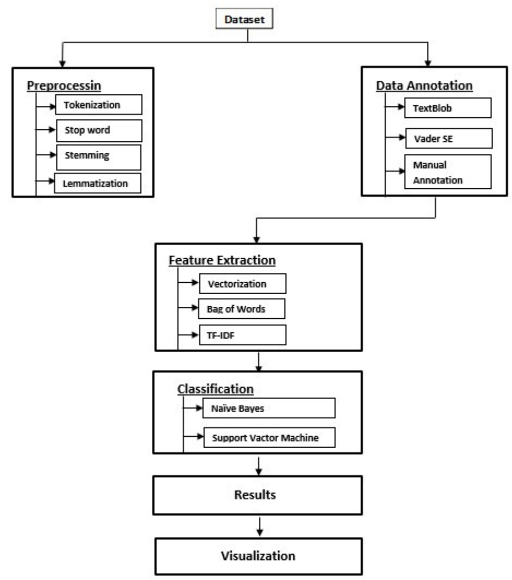


**Fig. 1.** Proposed Framework for Sentiment Analysis.

*A. Data Collection*

For data collection purposes three different sources were used. The first was before the COVID-19 pandemic, where classes were conducted in traditional or blended mode. Feedback of undergraduate and postgraduate students was collected during and after each class of the selected courses from Department of Computer Science at MNS-University of Agriculture. A google questionnaire form is designed with the coordination of the Supervisor. The others source was feedback collected using an online Google form provided to students at the end of the class.

During COVID-19 pandemic scenario, all classes were shifted to fully online mode. We extracted feedback from students' *WhatsApp* groups (see Appendix-I for details). The students sent textual comments/messages expressing their opinions and feedback about the lecture. An un-labelled dataset of around 2000 instances was collected from all sources. Word Cloud of all words in the dataset is shown in Fig. 2.

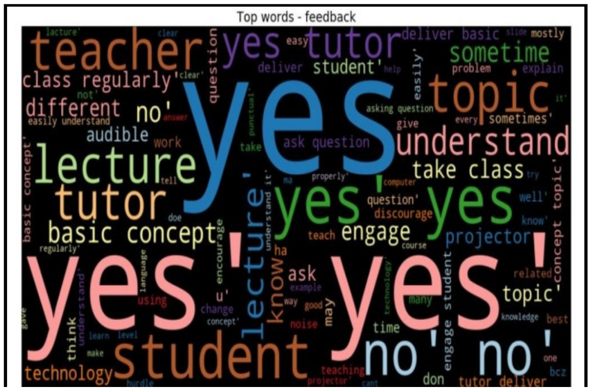


**Fig. 2.** Word cloud of the dataset.

There were several challenges in classification of sentiments for instance, the data collected from *Whatsapp* messages was unstructured that made it hard to annotate and classify data using machine learning techniques. Students' feedback data was noisy, for instance, the feedback "Today's lessons are understandable and the topic is awesome". There were several deviations of spelling of the same word, awesome word can be seen in many different ways as- "awsem, awssuumm, awsomee". The process of data cleaning is discussed in the next section.

**Pre-processing**

Input data pre-processing is a significant step before the classification process. At this stage, the dataset is first normalized and then prepared for the classification algorithm training, so that proposed algorithms work efficiently and achieve actual results consuming less time [32]. We have used pre-processing parameters: stemmer, stop-words handler, lowercase or uppercase conversion, and tokenizer [9, 27, 28, 29], for cleaning up junk data and increasing data accuracy by reducing data errors. There are pros and cons of pre-processing, such as without pre-processing, the system may lose the importance of words, while on the other hand, the loss of important data might occur due to the extensive pre-processing. An open-source web application Jupyter Notebook has been used for data statistical modelling, numerical simulation, data visualization, data cleaning and transformation, and machine learning model implementation. Jupyter Notebook Anaconda 3 has been used for data pre-processing and model implementation using python language.

**Data Annotation**

Polarity detection of textual data has been performed using two methods: *TextBlob* and *VADER*. TextBlob annotated our total dataset into 650 negative feedbacks, 900 neutral feedbacks, and 450 positive feedbacks as shown in Table 1. The problem with *TextBlob* annotations is that if feedback received from a student is in the form of 'yes'or 'no' for any question, instead of annotating it as 'positive' or 'negative' based on the context, *TextBlob* annotates it as 'neutral'. To perform context-aware annotation, we used Vader sentiment analysis that annotated our total dataset into 633 Negative feedbacks, 793 Neutral feedbacks, and 574 positive feedbacks as shown in Table 2.

**Table 1: Dataset annotation using TextBlob.**

| Before COVID | | During COVID | |
|---|---|---|---|
| **Class** | **Feedback** | **Class** | **Feedback** |
| Negative | 160 | Negative | 490 |
| Neutral | 400 | Neutral | 500 |
| Positive | 240 | Positive | 210 |
| ***Total*** | ***800*** | ***Total*** | ***1200*** |

**Table 2: Dataset annotation using Vader.**

| Before COVID | | During COVID | |
|---|---|---|---|
| **Class** | **Feedback** | **Class** | **Feedback** |
| Negative | 134 | Negative | 499 |
| Neutral | 450 | Neutral | 343 |
| Positive | 323 | Positive | 251 |
| ***Total*** | ***800*** | ***Total*** | ***1200*** |

**Feature Extraction**

annotating the dataset using two different techniques, we applied vectorization, Term Frequency – Inverse Document Frequency TF-IDF, and Bag of word techniques for feature extraction.

**Vectorization:** As we know Machine Learning (ML) algorithms operate best on numeric values, where rows represent instances and columns represent features into two-dimensional feature matrices. To perform ML in text, the document needs to be converted into a vector representation to apply numerical machine learning. The numerical representation of the document gives the ability for performing meaningful analysis of ML algorithms.

Term Frequency-Inverse Document Frequency (TF-IDF): In the pre-processing phase, TF-IDF provides a numerical statistic to state the importance of a word in a document that helps in sentiment analysis (Pang & Lee, 2008). Frequency evaluation of commonly use words has been performed in the TF-IDF phase to identify important words in the dataset. In the dataset, the most frequently used words are 'yes', 'no', 'excellent', 'bad', 'sad', or 'happy'. The number of occurrences of a term/word in a given document is referred to as term frequency.

**Bag of words (BOW):** Extracting information is a key phase in text mining, which serves as the starting point in many data mining algorithms. Extracting entities and their relationships from the text may reveal meaningful semantic information in the text data rather than a general representation of the text bag, and it is necessary to understand the hidden knowledge in the text data. For feature extraction, we have used a common technique called a bag of word approach (BOW). Using this approach, a list of unique words in the dataset is created which is referred to as vocabulary. This approach performs analysis of the histogram of words within the text by considering each word as a characteristic assign a value of 1 if the word is present and 0 if the word is absent in the vector representation of data.

**Classification**

After feature extraction, we used Naïve Bayes, and a Support vector machine (SVM) for classification. Both are the famous machine learning algorithms for supervised based approach and in the literature, both are followed by different researchers [7, 30] for classification purpose. Both perform batter accuracy for text classification rather than other supervised machine learning classifiers after comparisons [31].

SVM classifier works best for classifying sparse text data by defining rectilinear partitions in the data set and divides the set into different classes. SVM also uses kernel functions to transform data in a certain way, so that Hyperplane distribution classes can be allocated efficiently. On the other hand, Naïve Bayes classifier is the most commonly used text mining classifier which uses Bayes theorem to calculate the possibility of the given label related to a particular feature

## III. RESULTS AND DISCUSSION

To analyze the classifier's performance with a sentiment analysis framework using both TextBlob, and Vader annotated dataset, three measures have been taken (Recall, Precision, and F-Measure) to evaluate the performance of the proposed method.

***TextBlob*** **Annotated dataset classification results**

To optimize results and overcome the model overfilling problem we work on k-fold cross-validation in this model we calculate the best value of K by using hyper-parameter tuning using Grid Search for maximum results for both *TextBlob* annotated dataset and Vader annotated dataset, In this validation we use K as 5 which provides maximum result scores after applying hyper-parameter tuning using Grid Search technique on *TextBlob* annotated dataset and analyze the results which are the mean scores for recall, precision, and F-Measure score are 70.0%, 71.0%, and 69.0% with 70.8% accuracy using SVM and 69.8% accuracy by using Naïve Bayes, see Table. 3 class wise (negative, neutral, positive). Figure 3 shows classification results after TextBlob annotation through pie chart showing 63% neutral responses, 29% positive (high positive + positive), and 8% negative (high negative + negative) responses in the entire dataset.

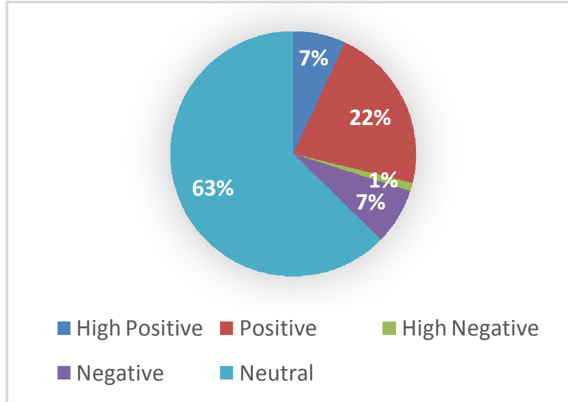


**Fig. 3.** Classification results of TextBlob annotated data.

**Table 3: Results for TextBlob Annotated Dataset using train-test split using SVM.**

| Class | Precision | Recall | F-Measure |
|---|---|---|---|
| **Negative** | 0.61 | 0.72 | 0.70 |
| **Neutral** | 0.50 | 0.57 | 0.53 |
| **Positive** | 0.71 | 0.69 | 0.70 |

***Vader*** **Annotated dataset classification results**

One of the issues of using TextBlob annotation is that if feedback received from the student says only 'Yes' or 'No' for any question, instead of annotating it as positive or negative it shows that the given feedback is 'neutral'. That's why the neutral value graph also shows more percentage. To deal with this problem we move forward to Vader sentiment analysis whose annotation result is more authentic as compared to TextBlob. To optimize results and overcome the model overfitting problem we work on k-fold cross-validation in this model we use the value of k as 15 which provides maximum result scores after applying hyper-parameter tuning using Grid Search technique using both algorithms (SVM and Naïve Bayes). The obtained results are mean scores of 73.3% accuracy using Naïve Bayes, and 85.6% accuracy using Support vector machine which is higher than Naïve Bayes. According to the results the Precision, Recall, and F-Measure of Support vector machine is 85.0%, 83.0%, and 82.0%. The results are presented class-wise (negative, neutral, positive) as shown in Table 4.

**Table 4: Results for *TextBlob* Annotated Dataset using train-test split using SVM.**

| Class | Precision | Recall | F-Measure |
|---|---|---|---|
| **Negative** | 0.71 | 0.99 | 0.83 |
| **Neutral** | 0.55 | 0.60 | 0.63 |
| **Positive** | 0.97 | 0.94 | 0.53 |

Fig. 4 shows pie chart of all Vader annotated feedback after classification showing 42% neutral responses, 41% positive, and 17% negative responses in the entire dataset.

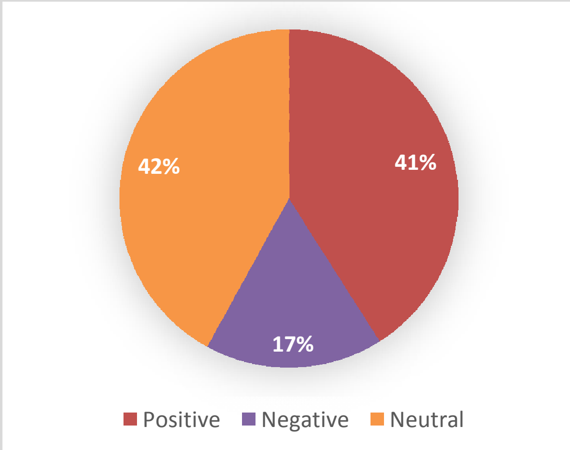


**Fig. 4.** Pie chart of all polarity values (annotated using Vader).

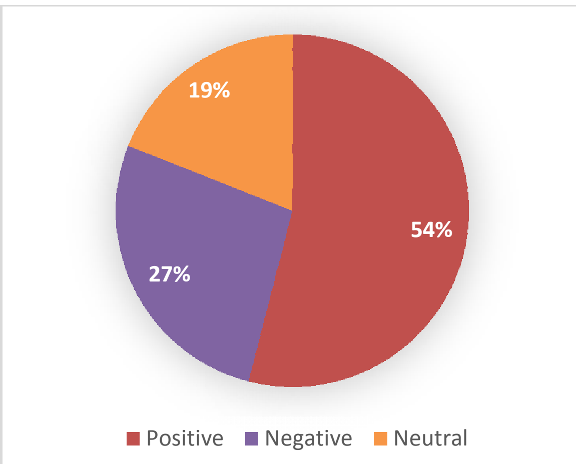


**Fig. 5.** Pie chart of manual annotation.

After TextBlob and Vader, we also annotated our dataset based on expert opinion of three human experts. Fig. 5 shows that human experts assign 54% positive responses, 19% neutral responses, and 27% negative responses in the entire dataset.

A comparison table to compare annotation percentage of TextBlob, VADER sentiment analysis, and manual annotation is shown in Table 5. The difference between TextBlob, VADER, and manual annotation polarity distribution is because of TextBlob and VADER use different libraries and lexicons for the polarity distribution process. VADER sentiment analysis is most applicable to social media and even educational text. It relies on a dictionary of emotional words. Each word in the dictionary is divided into positive or negative numbers.

**Table 5: Comparison of dataset annotation using different methods.**

| Annotation Methods | Positive comments (%) | Negative comments (%) | Neutral comme nts (%) |
|---|---|---|---|
| TextBlob | 29 | 8 | 63 |
| VADER | 41 | 17 | 42 |
| Manual Annotation | 54 | 27 | 19 |

## IV. CONCLUSION

The purpose of this research is to propose a comparative analysis of student's feedback before and during the COVID pandemic when all educational institutes have been shifted from face-to-face learning to a fully online learning system. Student's feedback has been collected through different online platforms including WhatsApp and google forms. We applied both Naïve Bayes and Support vector machine supervised machine learning algorithms for classification and compared their performance on the given dataset. Support vector machine works best for text-polarity classification in our study. It was found that there are more negative instances of feedback during fully online classes as compared to that in the blended teaching mode (Table 2). The findings can help tutors in designing strategies for teaching improvement in fully online classes after each class.

## V. DISCUSSION &FUTURE SCOPE

Due to COVID-19 pandemic, most of the universities around the world have shifted to blended learning or fully online learning systems. In this scenario, there is a need to get informed about the students' sentiments and their opinion when the student-teacher interaction is minimal. There is a potential to merge the proposed system with real time facial expression analysis to develop an information board for the tutors. The results presented in their paper shows the performance of different annotation methods and classification techniques for sentiment analysis out of textual data. Based on results, it is recommended to use VADER for annotation and SVM for classification of textual data. We are also working on automated detection of learner's engagement by analyzing their facial expressions. We plan to compare the results of both systems to find the difference (if any) between the written (through comments/text messages/forms) and expressed (through face) sentiments of the students. The comparative analysis could be applied in the quality assurance program at the university to determine and improve the student-tutor relationship.

**Conflict of Interest:** There is no conflict of interest relevant to publication of this paper.

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