Student sentiment Analysis Using Classification With Feature Extraction Techniques

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Abstract: Technical growths have empowered, numerous revolutions in the educational system by acquainting with technology into the classroom and by elevating the learning experience. Nowadays Web-based learning is getting much popularity. This paper describes the web-based learning and their effectiveness towards students. One of the prime factors in education or learning system is feedback; it is beneficial to learning if it must be used effectively. In this paper, we worked on how machine learning techniques like Logistic Regression (LR), Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT) can be applied over Web-based learning, emphasis given on sentiment present in the feedback students. We also work on two types of Feature Extraction Technique (FETs) namely Count Vector (CVr) or Bag of Words (BoW) and Term Frequency and Inverse Document Frequency (TF-IDF) Vector. In the research study, it is our goal for our proposed LR, SVM, NB, and DT models to classify the presence of Student Feedback Dataset (SFB) with improved accuracy with cleaned dataset and feature extraction techniques. The SFB is one of the significant concerns among the student sentimental analysis.

Keywords—Sentiment Analysis, Web-Based Learning System (WBLS), Logistic Regression (LR), Support Vector Machine (SVM), Naive Bayes (NB), Decision Tree (DT), Bag of Words (BoWs) and Term Frequency Inverse Document Frequency (TF-IDF) Vector

1. INTRODUCTION

Learning circumstances are nowadays progressively complex, and students have to take additional accountability for their learning. In the current era, computer-based learning is playing an important role. Along with this, the internet has brought a huge revolution to in web-based learning system (WBLS). The WBLS is increasing popularity, the progression of web-based learning has not been without defies. Since its early commencement in the 1960s, online education has been repetitively panned for its superficial absence of quality control, particularly the insufficiency of high-quality teachers, so it’s prime important that how much students are satisfied with learning content. In this paper we will study models of how the quality of web-based learning system can be achieved, further instead of question-based student satisfaction feedback, we will propose an opinion based student feedback in which a web panel will ask for an opinion (Text) based on that written text we will analyze the student opinion for any course. In this study, we generated the dataset by the student’s reviews or feedback through WBLS. The
link to the web portal is http://elearningit.in The data was collected for the six months, the name of the dataset is the Student Feedback (SFB) dataset. The SFB data set is a text-based dataset and data pre-processing and cleaning is a challenging task in Text and Data Mining (TDM) and Machine Learning (ML) [1], [2]. TDM is a cycle of finding designs in enormous data sets involving methods collections including machine learning, statistics, and database systems. TDM is an interdisciplinary subfield of data mining and Web-Mining (WM) and measurements with a general objective to extricate data (with intelligent methods) from a data set and change the data into a conceivable structure for additional utilization. The ML and DM are strongly co-related to each other. In this work we have been used first pre-processes the text data and cleaned white-spaces, numbers, punctuations, stop word, etc. We also used lemmatization and spelling correction. The main task of the Feature Extraction Technique (FET) to remove irrelevant or useless features from the dataset [1], [3]. In this work, we Proposed FETs like BoW and TF-IDF. Preprocessing of the text dataset is the first important step for TDM [4]. In this paper, the preprocessed text is converted into the vector using techniques like BoW and TF-IDF. The ML techniques namely LR, NB, SVM, and DT are used for the classification of the SFB dataset. The classification performance is compared for uncleaned SFB Dataset and preprocessed SFB dataset for both FETs BoW and TF-IDF. The outcomes are compared in terms of Accuracy, Sensitivity, Specificity, and F1-Score. The word cloud is also used for the frequency analysis of SFB datasets.

Further, in the next section of the paper in section II, we will discuss some literature focus on sentiment analysis and web-based learning quality measurement models.

2. LITERATURE SURVEY

KhinZezawar Aung, Nyein NyeinMyo [5] proposes the level of teaching evaluation method based on the lexicon-based approach. This method analyzes automatically the students’ feedback comments to strongly negative, or moderately negative, or weakly negative, or strongly positive, or moderately positive, or a weakly positive or neutral category using two lexicons. A heuristic technique is used to calculate the semantic orientation score of combining words for automated students' feedback comments analysis.

Krenare Pireval, Ali Shariq Imran, FisnikDalipi [6] facial recordings are analyzed to find seven emotional engagement attributes and three sentiment engagement attributes using facial expression software. The author also proposed some recommendations based on extensive comparison of features among different LMS that will provide better content personalization and customization, thereby improving learning outcomes.

Mohammed Atif [7] Author presented an enhanced framework for sentiment analysis that can be utilized for universities. In proposed method is to use the datasets (students’ responses) accumulated to build the classifier. Input datasets are preprocessed first by classification of comments using the value of “Overall student views on course”.

B. Vamshi Krishna, Ajeet Kumar Pandey, and A. P. Siva Kumar [8] proposed a model is used to analyze user opinions and reviews posted on social media websites and helps users in decision making to buy products and organizations to recommend products online. Fuzzy sets are used with a variable degree of membership and degree of polarity of the expressed opinions, F-Score:- 0.36.

Y. Wang, J. Zhang [9] presented an automatic keyword extraction method based on a bi-directional long short-memory (LSTM) recurrent neural network (RNN). Compared to an LSTM
network, a bi-directional LSTM (BLSTM) network contains two parallel layers that propagate both forward and backward, thus allowing it to obtain information on the sequential series from both the past and future. Each forward or backward layer functions in a similar way to a regular LSTM.

Accuracy: 93%

Ngoc Phuong Chau, Viet Anh Phan, Minh Le Nguyen [10] the association between all words in a sentence, and all sentences in a document is captured by LSTM and GRNN, respectively. A document sentiment classification experiment is conducted on a multi-domain sentiment dataset. The elimination of outliers leads to higher performance in this model. In the experiment, the proposed method achieves improvements in terms of accuracy in a range of 0.14% - 6.93% over the LSTM + GRNN model.

Mazen El-Masri, Nabeela Altrabsheha, Hanady Mansourb, Allan Ramsay [11] proposed tool can be used to analyze any topic given by the user, as the tool was trained by Twitter data which consists of a wide range of domains. The tool is useful for intermediate or experienced users. Compared between the performance of the lexicon-based and machine-learning methods.

Thorsten Joachims, Laura Granka, Bing Pan, Helene Hembrooke [12] examined the reliability of implicit feedback generated from click-through data in the WWW search. Analyzing the users’ decision process using eyetracking and comparing implicit feedback against manual relevance judgments, we conclude that clicks are informative but biased.

BACKGROUND OF STUDY
The success of outcome-based learning is completely dependent on, the major factor that is student satisfaction, there is a traditional way to attain student satisfaction that we can rate the Learning Management System (LMS) course in four categories as depicted in Fig.-1. In the following way, we found that there is a contradiction if someone gave a Rate as 3 which is good for any course but he/she has given comment as course content is not up to the mark. Then we have developed the Web-Based Learning System (WBLS). It more convinces easy, understandable to used for anywhere in both PC and Smart Phone.

![Course feedback](image)

For the investigation and research of student opinion in WBLS emphasis on comment given by the student, henceforth we need a machine learning algorithm for classification the student sentiment from student text review.

3. Proposed Framework
Figure 2 shows the proposed framework for the research work. The data set collection, pre-process the data set, reduced data set with Feature Extraction Technique, the partition of data set into training and testing, training and testing of classifiers, and compare the performance of classifiers.

In the first section, we have collected the SFB dataset from our developed web-portal, student opinion for sentiment analysis of WBLS enhancement and advancement in technology. The applied the text pre-processing techniques like removing numbers, punctuations, converts all characters into lowercase, Tokenization, removing stop words and lemmatization to eliminate the noise and inconsistent data and prepare the smooth dataset. Then we used two different kinds of FETs methods like BoW and TF-IDF to extract the feature from the SFB dataset and obtained the spars matrix from the data set. The data partitioned...
techniques like Hold-Out is used to divide the data set into training and testing with different data partitions. The proposed classification models have been trained and tested the SFB and with a subset of SFB dataset. In the last section, we have compared the classifiers in terms of parameters like Accuracy, Sensitivity, Specificity, F1-Score, and Word Cloud for frequency analysis.

3.1. About Dataset
In this paper, we used the student feedback dataset (SFB). It was collected through a web portal named http://elearningit.in which is mainly made for the UG-PG level Students of the college of the various stream from the Chhattisgarh region of India. The data collected from January 2020 to June 2020. In this web portal students get enrolled in any of the courses available in the web portal and after completion of the course students give their feedback about the course, content, and the LMS. If they are satisfied they provide positive comments and if not satisfied then provide negative comments. The original dataset consists of 549 comments of students. Based on the comments dataset can be divided into two class labels Positive comments and Negative comments. The positive comments are labeled as class label -1 and for negative comments, the class label is 0.

3.2 Text Preprocessing
The feedbacks taken by the students are in form of natural language i.e. in the English Language as the machine learning model doesn’t understand input in form of the text so we first need to convert it in a form that the machine learning model can understand.

Before converting the text into number or vectors the very first step that we need to follow is preparing data to be sent in the model. As there are many challenges involved with text data, it contains lots of noise as people usage punctuations, slangs, emoticons, and spelling mistakes are also there. For eg they use sorrryyyy, veryyy, gr8, sooooo much, this kind of word which machine cannot make sense out of it and some word which is most frequently used like I, you, he, she, is, am, the, these kind words called stop words which don’t carry any emotion so it is always good to remove these words to increase the accuracy of the model.

The preprocessing steps which are carried in this SFB dataset are:

i. Removing Numbers and Punctuations
ii. Converts all Characters into Lowercase
iii. Tokenization
iv. Removing Stop Words
v. Lemmatization
vi. Removing the words having Length <=2
vii. Filtering long word repeated letters > 2
viii. Spelling correction

3.3 Feature Extraction Techniques
Feature Extraction Techniques (FETs) have a significant role in text dataset classification; it is straightforwardly affecting the accuracy of text classification. It depends on VSM (vector space model, VSM), in which a text is viewed as a dot in N-dimensional space [13]. For converting the text into features some feature extraction techniques

![Figure 2 Proposed Frameworks](image)
need to be applied. When we use methods like CountVectorizer (bag-of-words) or TF-IDF to create features, we take into account all the tokens occurring in the dataset and these tokens determine the dimensions which are nothing but the number of features.

In this paper we used two of the most basic and ubiquitously used formats:

3.3.1 Count Vector (Bag of words)

The Bag of Words (BoW) model is the simplest form of text representation in numbers. This model is used to convert the text into a bag of words, which keeps a count of the total occurrences of most frequently used words. In this model, a text (for example, a sentence or documents) is represented as the bag (multiset) of its words, ignoring syntax and even word request yet keeping assortment [14], [15]. The bag-of-words model is most commonly used in methods of document classification where the frequency of each word is used as a feature for training a classifier.

3.3.2. TF-IDF Vector

Term Frequency–Inverse Document Frequency (TF-IDF) is mathematical methods based on statistical analysis which represent that a word is how significant to a document in a collection or corpus. The TF-IDF is frequently utilized as a weighting factor in the text mining method. The value of TF-IDF increases proportionally to the number of times a word appears in the document but is counteracting by the frequency of the word in the corpus [4], [16]. Term Frequency Inverse Document Frequency (TF-IDF) methods were quite popular for a long time, before more advanced techniques like Word2Vec or Universal Sentence Encoder. In TF-IDF, instead of filling the BOW matrix with the raw count, we simply fill it with the term frequency multiplied by the inverse document frequency. It is intended to reflect how important a word is to a document in a collection or corpus.

3.4 Text Classification

Classification is one of the critical texts mining appliances and its technique of ordering the content dataset into decided text classes. Classification is supervised learning which comprises two stages: training and testing. In the training phase, a classifier trained using the training data set, and the trained model tested using the testing data set [17]. There are four classification methods utilized in this work for the classification of the SFB dataset.

- **Naïve Bayes:**
  
  Naïve Bayes is a simple method that uses all the attributes and permits them to contribute to take the decision, taking into account the features as equally important and independent of each other, considering the class. This is unrealistic in real-life data; the attributes are not equally important or independent. However, this assumption results in a simple scheme, which, when put in practice, works astonishingly well. The scheme is called Naïve Bayes classifiers, although there is nothing “Naïve” about its use in appropriate circumstances. The Naive Bayes (NB) classifier used in this study is Multinomial Naïve Bayes classifier (MNNB), it is called Naïve Bayes classifier because it is a Bayesian classifier that makes a simplifying (naïve) assumption about how the features interact [18].

- **Decision Tree:**

  The Decision Tree (DT) [19] can be said to be a map of reasoning procedure. It is utilized a structure like resembling that of a tree to define a dataset and solutions can be visualized by following different pathways through the tree. In this study, we have used CART as a DT. In 1984, L. Breiman, J.
Friedman, R. Olshen, and C. Stone, all statisticians published the book Classification and Regression Tree (CART). The CART and ID3 were developed independently of each other, but almost the same time, they followed the equally learning process. CART is a non-restrictive DT method used to build model either classification or regression trees, based on whether the dependent variable is categorical or numeric. It constructs a binary DT by isolating the record at each node, according to a function of a single attribute [20].

- **Logistic Regression:**
  The logistic regression is an overall measurable model that was initially evolved and advocated basically by Joseph Berkson, beginning in Berkson (1944) [21]. In insights, the logistic model is utilized to show the probability of a specific class or occasion existing, for example, great/terrible, pass/fail. In simple words, it predicts the probability of occurrence of an event by fitting data to a logit function. Since it predicts the probability, its output values lie between 0 and 1. The logistic regression model itself just models the probability of yield regarding input and doesn't perform statistical classification (it's anything but a classifier), however, it very well may be utilized to make a classifier, for example by picking a cut off worth and classifiers to contributions with probability more prominent than the cut off as one class, underneath the cut off as the other; this is a typical method to make a binary classifier. The coefficients are for the most part not processed by a closed-form expression, in contrast to direct least squares [22].

- **SVM:**

A Support Vector Machine (SVM) [23], [24] is another strategy for the classification of both direct and nonlinear text data. It depends on the idea of decision planes that describe decision limits. A decision plane is one that isolates between a lot of items having different class participation. An SVM is a supervised machine learning model that uses classification algorithms for two-group classification problems. After giving an SVM model set of labeled training data for each category, they're able to categorize new text. So you're working on a text classification problem.

3.5 Performance Evaluation
On the classification of text dataset, in this work have two or binary classes. Then the classification on the test has four promising groups’ shown in table 1.

| Hypothesized class or predicted class | Actual class or Observation | Class +Ve | Class -Ve |
|--------------------------------------|----------------------------|-----------|-----------|
| Actual +Ve                           | TP(+Ve,+Ve)                | FN(-Ve,+Ve) |
| Actual -Ve                           | FP(-Ve,+Ve)                | TN(-Ve,-Ve) |

The different parameters used for classification performance are shown in figure 3 in the equation (1) to (4).

\[
\text{Accuracy (ACY)} = \frac{TP + TN}{TP + TN + FP + FN} \\
\text{Sensitivity(SNY)} = \frac{TP}{TP + FN} \\
\text{Specificity (SPY)} = \frac{TN}{TN + FP} \\
\text{F1-Score (F1-S)} = \frac{2TP}{2TP + FP + FN}
\]
4. Result and Discussion

The experiment conducted on the analysis of this research work we have used Python programming version 3.7.3 using Jupyter Notebook under Anaconda 3. The result and discussion section have been divided into four different sections according to work nature and outcomes. In this paper, we have used the following terms as Unclean SFB (USFB) for raw SFB dataset and for pre-processed or Cleaned SFB or Normalized SFB dataset (NSFB).

Then the SFB dataset has a Data Partition Technique (DPT) in two ways using the hold-out method. The first Data partition named DP1 is divided into 70% for Training and 30% for Testing in models and the second Data Partition DP2 is divided into 80% for Training and 20% for Testing in models% (DPT1-Training 70%, Testing 30%, and DPT2-Training 80%, Testing 20%).

4.1 Preprocessing of SFB dataset

Working with text generally involves converting it into a format that our model can understand, which are mostly numbers. In the initial stage of the data pre-processing we have done different kinds of pre-processing steps such as removed numbers and punctuations, converted all uppercase to lowercase, tokenization, removed stop words, lemmatization, removed the words having Length 2 or less, converted list to strings. The SFB dataset can be categorized into two parts according to the actual class Label Positive and Negative Review. Of the total 549 comments, 446 have positive and 103 have negative comments.

4.2 Feature Extraction Technique

Here CountVectorizer of Sklearn library of python Language is used to create count vectors from the cleaned text. It takes a word from each text. After counting the words, it forms a Sparse matrix. A sparse matrix is a matrix that has very few non-zero elements. The count of words matrix creates the data frame. In the Data frame, each row represents the given text in ‘data’ (which I have taken as input string in code) and columns represent the unique words from the given string of list, and values shown in the Data Frame table are the occurrence of words. Just like Count Vector, TF-IDF can also be very easily implemented in Python using Sklearn.

4.3. Machine Learning Classifiers (MLC) performance

The confusion matrix obtained by proposed MLC algorithms (LR, NB, SVM, and DT) is shown in Table 2.

| ML-C | BOW | DPT1 | DPT2 | TF-IDF | DPT1 | DPT2 |
|------|-----|------|------|--------|------|------|
| USFB | TP  | 25   | 1    | 131    | 3    | 19   | 131  | 87    | 4    | 29   | 0    | 132  | 1    | 21   | 0    |
|      | FN  | 9    | 24   | 5     | 127   | 3    | 19   | 2    | 86    | 4    | 29   | 1    | 131  | 1    | 21   | 0    |
| USFB | TP  | 17   | 16   | 17    | 115   | 10   | 12   | 9    | 79    | 4    | 29   | 1    | 131  | 2    | 20   | 0    |
|      | FN  | 16   | 17   | 13    | 119   | 9    | 13   | 4    | 84    | 5    | 28   | 1    | 131  | 1    | 21   | 0    |
| NSFB | TP  | 20   | 13   | 8     | 124   | 11   | 11   | 4    | 85    | 15   | 18   | 3    | 129  | 7    | 15   | 0    |
|      | FN  | 24   | 9    | 39    | 93    | 17   | 5    | 15   | 73    | 25   | 8    | 28   | 104  | 17   | 5    | 14   |

The confusion matrix received by the MLC methods are shown in Table 2 with different Data Partition Technique DPT- (Training 70%, -Testing 30%) and DPT2-(Training 80%, Testing 20%) in the case of
USFB and NSFB dataset. The TP is achieved highest by DT with the FETs as BoW in the case of DPT1 and DPT2 with the NSFB dataset. In the same way, TP is achieved highest by DT with the FETs as TF-IDF in both cases of DPT1 and DPT2 with NSFB dataset. The TN is maximum with LR by the FETs as BoW in the event of DPT1 with the USFB dataset. Also TN is acquired most by LR with the FETs as BoW on the DPT2 with the NSFB dataset. The TN is acquired maximum by LR with the FETs as TF-IDF in the case of DPT1 with USFB dataset. The TN is acquired maximum by LR, NB, and SVM with the BoW in case of DPT1 and DPT2 for both USFB and NSFB dataset. The TP is achieved maximum by DT with the FET BoW for DPT1 with the NSFB dataset and for DPT2 it acquired maximum by DT with the USFB dataset. In case of TF-IDF the FP is maximum for DT in the case of DPT1 with USFB dataset. And The FP is acquired maximum by SVM with the FET as BoW for DPT2 with the NSFB dataset. The FN is maximum for BoW in the event of DPT1 with USFB dataset. The FN is acquired maximum by LR with the BoW in DPT2 with USFB and NSFB dataset. In case of TF-IDF the FN is acquired maximum by LR in the case of DPT1 for both USFB and NSFB dataset. The FN is acquired maximum by LR for BoW in case of DPT2 for both USFB and NSFB dataset.

Table 3 Performance of MLC classifiers with Bow in SFB dataset

| MLC | DPT1 | DPT2 |
|-----|------|------|
|     | ACY  | SNY  | SPY  | F1-S | ACY  | SNY  | SPY  | F1-S |
| LR  | USFB | 84.24| 24.24| 99.24| 38.09| 81.82| 13.63| 98.86| 23.6 |
|    | NSFB | 82.42| 27.27| 96.21| 38.30| 80.91| 13.63| 97.72| 22.7 |
| NB  | USFB | 80.00| 51.52| 87.12| 50.75| 80.91| 45.45| 89.77| 48.67|
|    | NSFB | 81.82| 48.48| 90.15| 51.61| 84.55| 40.90| 95.45| 51.44|
| SVM | USFB | 86.67| 51.52| 96.21| 61.82| 85.45| 40.91| 96.59| 53.02|
|    | NSFB | 87.27| 60.61| 93.94| 38.09| 86.36| 50   | 95.45| 59.35|
| DT  | USFB | 70.91| 72.73| 70.45| 50   | 81.82| 77.27| 82.95| 62.78|
|    | NSFB | 78.18| 81.82| 77.27| 60   | 85.45| 40.91| 96.59| 53.02|

The table 3 shows the performance of MLC algorithms using BoW FST in SFB dataset. In this table the Accuracy (ACY) is shown for two cases 1. Uncleaned dataset i.e USFB and for Normalized dataset i.e. NSFB dataset. From above dataset we get 86.67% Accuracy for USFB while 87.27% Accuracy for NSFB dataset from DPT1. With DPT2 we obtained the ACY of 85.45% from USFB dataset and 86.36 % ACY from NSFB dataset. In the term of F1-S, the DT is obtained the highest F1-S of 62.78% with DPT2 from USFBD dataset.
The comparison of the model performances (especially LR, NB, SVM, and DT models) on the foundation of the ACC graph 3(a) and 3(b). The outcome of the classification models ACC graph 3(a) of proposed ML-C models obtained the good quality of ACC with the cleaned NSFB compared to the USFB dataset. The classification result shows that the SVM model is better than other models used in the analysis in the case of used FETs as Bow in DPT1. The outcome of the classification models ACC graph 4(b) of proposed ML-C models obtained the good quality of ACC with the cleaned NSFB compared to the USFB dataset. The classification result shows that the SVM model is better than other models used in the analysis in the case of used FETs as Bow in DPT1.

Table 4 Performance of ML-C classifiers with TF-IDF in SFB dataset

| ML-C | DPT1 | | | | DPT2 | | | |
|------|------|--|---|---|---|---|---|---|
|       | ACY  | SNY | SPY | F1-S | ACY  | SNY | SPY | F1-S |
| LR    | USFB | 82.42 | 12.12 | 100 | 21.43 | 80.91 | 4.55 | 100 | 9.52 |
|       | NSFB | 81.82 | 12.12 | 99.24 | 20.87 | 80.91 | 4.55 | 100 | 9.52 |
| NB    | USFB | 81.82 | 12.12 | 99.24 | 20.87 | 81.82 | 12.12 | 99.24 | 16.51 |
|       | NSFB | 82.42 | 15.15 | 99.24 | 25.41 | 82.42 | 15.15 | 99.24 | 9.52 |
| SVM   | USFB | 86.67 | 42.42 | 97.73 | 55.55 | 86.36 | 31.82 | 100 | 48.48 |
|       | NSFB | 87.27 | 45.45 | 97.73 | 58.36 | 87.27 | 36.36 | 100 | 52.94 |
| DT    | USFB | 78.18 | 75.76 | 78.79 | 58.08 | 82.73 | 77.27 | 84.09 | 64.06 |
|       | NSFB | 81.82 | 78.79 | 82.58 | 63.44 | 85.45 | 77.27 | 87.50 | 67.89 |

Table 4 Performance of ML-C classifiers with TF-IDF in SFB dataset. The ML-C Classifiers ACC are shown without normalized USFB and NSFB dataset. The SVM classifiers obtained the ACC of 86.67% with USFB datasets for DPT1. In the same way, the SVM classifiers obtained the ACC of 86.36% with USFB datasets for DPT2. Also the SVM classifiers obtained the ACC of 87.27% with preprocessed NSFB datasets for both DPT1 and DPT2. In the terms of F1-S, The DT is obtained the highest F1-S of 67.89% with the NSFB dataset for DPT2.
The comparison of the model performances (especially LR, NB, SVM, and DT models) on the foundation of the ACC graph 4 (a) and 4(b). The outcome of the classification models ACC graph 4 (a) of proposed ML-C models obtained the best accuracy with the cleaned NSFB as compared to the USFB dataset. The classification result shows that the SVM model is better than other models used for analysis in the case of FET as TF-IDF for DPT1. The outcome of the classification models ACC graph 4(b) of proposed ML-C models obtained the good quality of ACC with NSFB as compared to the USFB dataset. The classification result shows that the SVM model is better than other models used for analysis in the case of FET as TF-IDF for DPT2.

4.4. Word Cloud Visual Representation of SFB dataset

A word cloud is a collection or cluster of words shown in different sizes. It is a very important technique to represent the student comments that have big value or less value in WBLMS. The comments have the biggest word show the highest frequency of word each means this word is most prominent. The multiple visualizations in the form of word clouds. Sometimes, the quickest way to understand the context of the text data is using a word cloud of the top 100-200 words. Here we created Word cloud for our most frequently used words.

Figure 4(C) The word cloud of SFB dataset.

Figure 4(C) Represented the word cloud of the SFB dataset. In this figure, we got the idea that the highest frequency word is thanks in the SFB dataset. Then the good is the second frequently used word. With the help of the above word cloud, we can conclude that the feedback received has more no of positive words like thanks, good, great, helpful etc. It means the WBLMS system is useful
for the student in learning and understanding the concept. The content used in the WBLMS system gives a satisfactory result of the review analysis of student feedback.

5. CONCLUSION

In this paper, an SFB sentiment classification model is proposed to identify the student’s sentiment as Positive and Negative by the feedback given by them in our web portal WBLMS. The feedback collected in WBLMS forms a raw dataset. These comments show the strength and weaknesses of the web portal WBLMS. The Obtained raw SFB dataset is first pre-processed. After that, we used two feature extraction techniques Bow and TD-IDF to covert the raw text into feature vectors. The Bag of Words (BOW) converts the collection of text documents to a matrix of feature vector counts that gives the no of occurrences a word appears in an SFB dataset. The TF-IDF method represents that a word is how significant to a document as in an SFB dataset. Based on the SFB dataset, the comments are classified as positive, negative. The model is examined for FETs, BoW & TF-IDF to examine the classification performance. Our research consists of two parts: first, the uncleaned SFB dataset is converted into feature vector using FETs BoW and TF-IDF, and then Preprocessing is applied to the raw SFB dataset and we get a normalized NSFB dataset for both BoW and TF-IDF FETs. Second:Classify the outcome matrix with different ML methods: LR, SVM, NB, and DT using 80%,20% and 70%, 30% data partition. The experimental results show that SVM ML Classifier performed best in the case of both BoW and TF-IDF FETs. SVM ML-Classifier achieves the best result 87.27% accuracy in the case of DPT1(70%, 30%) data partition with BoW model and TF-IDF also got same accuracy of 82.27% for both DPT1 and DPT2.

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