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Framework for Improved Sentiment Analysis via Random Minority Oversampling for User Tweet Review Classification

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Abstract: Social networks such as twitter have emerged as social platforms that can impart a massive knowledge base for people to share their unique ideas and perspectives on various topics and issues with friends and families. Sentiment analysis based on machine learning has been successful in discovering the opinion of the people using redundantly available data. However, recent studies have pointed out that imbalanced data can have a negative impact on the results. In this paper, we propose a framework for improved sentiment analysis through various ordered preprocessing steps with the combination of resampling of minority classes to produce greater performance. The performance of the technique can vary depending on the dataset as its initial focus is on feature selection and feature combination. Multiple machine learning algorithms are utilized for the classification of tweets into positive, negative, or neutral. Results have revealed that random minority oversampling can provide improved performance and it can tackle the issue of class imbalance.

Keywords: sentiment analysis (SA); sentiment classification; resampling; random minority oversampling; random majority under sampling; deep learning (DL); machine learning (ML); term frequency inverse document frequency (TF-IDF)

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1. Introduction

Social networking has become a massive influence in our lives. People create new content on applications such as twitter every day and it seems that this trend will continue with substantially more content in the near future. People on twitter create new content which becomes the source for various decision-making procedures in many unique areas. There is a simple reason for it, as we know that user data is an important asset which helps us understand the sentiment of the general public. We can identify problems of one group of people by investigating another group of people.

The way our society functions has been significantly altered by the Internet and related online technologies. Social media applications such as Facebook, Instagram, and Twitter are now commonly used for idea exchange, information sharing, business- and trading-related promotions, political, sociological, and ideological campaigning, and product as well as service promotion [1]. Social media is typically investigated from a variety of angles, such as gathering business intelligence for the promotion of goods and services, keeping an eye out for criminal activity to identify and mitigate cyber threats, and using sentiment analysis to evaluate customer feedback and reviews [2]. Researchers have been studying sentiment analysis extensively in recent years. Several tested techniques have been put forth in the past decade within this context [3].

The primary methods for sentiment analysis are shown below in the Figure 1:

- Lexicon-related [4]

- Machine Learning (ML) related [5]
- Deep learning (DL) related [6]

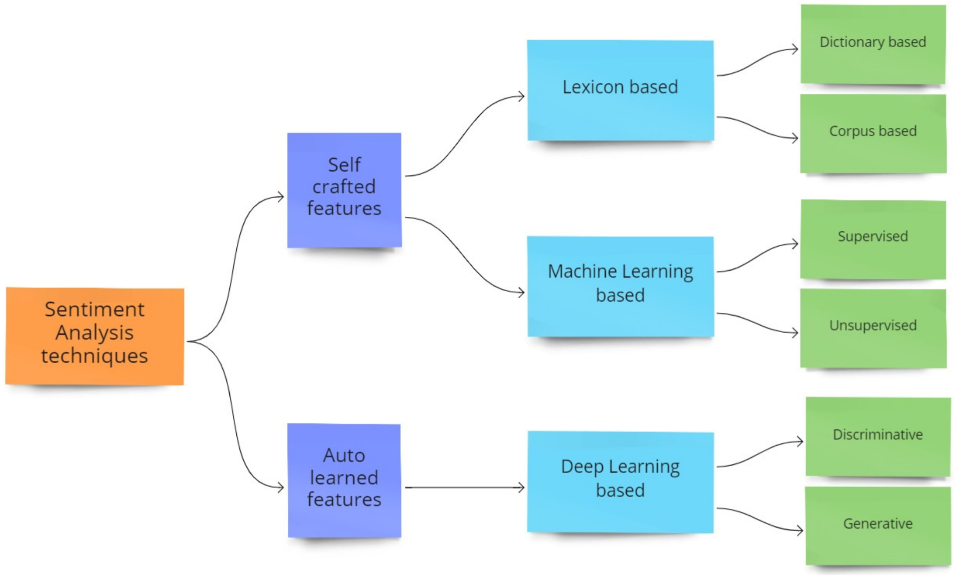


Figure 1. Sentiment Analysis techniques.

The lexicon-related methods [4] depend on categorizing words according to their sentiments. Normal word categorizations include two (+ve and −ve), three (+ve, neutral, and −ve), or five categories (very +ve, +ve, neutral, −ve, and very −ve). The high caliber of sentiment dictionaries that contain the substantial word corpus is categorized in the techniques indicated above, which are necessary for the efficiency of lexicon-related approaches [5]. The requirement to add a sizable number of linguistic resources in order to identify the crucial terms for sentiment analysis is a significant downside [7] of this method.

Both supervised and unsupervised learning techniques are used in the ML-based approach [8,9]. In the former, entire texts are tagged with sentiment categories rather than individual words. It is a complicated, labor-intensive, and error-prone process that calls for properly crafted instructions. In the latter, there is no label available for the tweet text as there are no previous assumptions for the model. The data is simply inserted, and the model learns the structure of the data itself.

In order to speed up text labeling and improve its quality, it seems sensible to develop semi-automatic approaches that use sentiment dictionaries [10]. Our chosen dataset is partitioned into a training set and testing set to accurately test the performance. The TF-IDF metric is then utilized to unsheathe attributes from texts in the following stage. Texts are then categorized using machine learning (ML) methods, such as naive Bayes classifier (NBF), logistic regression classifier (LRC), support vector machine classifier (SVMC), k-nearest neighbor classifier (k-NNC), decision tree classifier (DTC), random forest classifier (RFC), XGBoost, and Gradient Boost classifier (GBC). Unsupervised learning [9] does not use labelled training data and does not call for human involvement. K-means clustering [11] is the unsupervised technique which is utilized most frequently. This technique gathers related data points around centroids, which serve as the clusters' nuclei, and identifies their shared characteristics. Despite not requiring an early preparation of dataset by human specialists, clustering-based techniques are sensitive to the location of central points. Additionally, the clustering method combines instances depending on factors that are implicit in the grouping process. A recent study [12] has focused on a DL-related strategy that aims to improve text classification performance due to its improved results when trained with a large enough data. In order to do this, the employment of various neural networks such convolution based (CNN) and recurrent based (RNN) has been extensively described in the literature [6]. In recent years, transformer-based sentiment analysis such as with DistilBERT has also been researched [13].

The focal point of three above mentioned methodologies is on the current sentiment analysis research. There is a lack of tools, available data, and approaches for sentiment analysis that enable users to play around with, and test various algorithms. The data that is available to test might not be balanced which leads to further issues. This conversation has made it evident that there is an increasing demand for a comprehensive sentiment analysis framework that will close the gap shown in the earlier studies [14].

Furthermore, SA is fraught with difficulties [15]. The first is about ambiguity: in one scenario, a term may be regarded good while yet being considered bad in another. A second problem is diverse methods of expressing thoughts—people do not always communicate their opinions in the same manner. Famously, with sites such as Twitter or blogs, people communicate various viewpoints in the same sentence, which a person can comprehend but a machine cannot. The third one is related to the preprocessing of data and the dataset itself [14,15]. Sometimes the datasets are highly imbalanced in the case of any classification task such as sentiment analysis. So therefore, a complete framework is required to not only handle the imbalanced data but also provide a complete preprocessing method that can lead to a correct handling of the imbalanced data. Therefore, it is important for us to improve the process of sentiment analysis with new techniques, so that unseen data can be predicted with accuracy. In this paper we have made the following contributions:

- Presenting a comprehensive framework for improved sentiment analysis which is specifically designed for imbalanced datasets;
- Handling the imbalanced dataset for multiclass classification problem through the use of random oversampling;
- Selection of best features for sentiment analysis. This task must be performed manually as it is highly dependent on the dataset and it must not be automated;
- Finding the best preprocessing order for the tweet text so that accurate oversampling can be performed without causing the problem of overfitting;
- Finding the actual impact of over-sampling when compared to the results generated with non-oversampled data.

2. Literature Review

The research being completed in the fields of sentiment analysis are covered in this section. There are numerous studies that analyze the opinions expressed by individuals on Twitter and categorize the tweets as good, negative, or neutral. Massive amounts of literature on sentiment analysis are available to be explored; however, as our paper is focused on resampling and machine learning, we will, therefore, primarily focus on those studies. A taxonomy of previous literature is provided in Table 1 which focuses on ML-related as well as DL-related methods for sentiment analysis.

Table 1. Taxonomy of SA literature related to ML and DL methods.

Cite	Technique	Purpose	Positive	Gaps
[16]	Hybrid Lexicon and DL	The sentiment lexicon is employed in order to improve the attributes of sentiment in the reviews. The weighed sentiment characteristics are classified using GRU as well as CNN.	The data has a scale of 100,000 order of magnitude, and it may be commonly utilized in the domain of Chinese SA.	This approach can only classify sentiment into +ve and −ve, which is not useful in domains where required refinement of sentiment is higher.
[17]	ML based	In SA, live tweets from Twitter were utilized to methodically analyze the influence of the issue of class inequality. To address the issue of	Results show that minority up-sampling based technique can handle the issue of class inequality to a great extent.	Not tested for multiclass classification.

		class inequality, the minority up-sampling approach is used here.		
[18]	ML based	To fix the class imbalance, decrease the less significant instances from the majority subgroups.	They identified the mostly misclassified samples based on KNN.	Does not perform well for small datasets.
[19]	ML based	The label discrepancy was reduced by isolating the highly contemporaneous data of the predominant and less dominant labels and analyzing the influence of the labels while resampling.	The algorithm's usefulness has been demonstrated, particularly on datasets with good disparity of majority and minority instances.	The parameters directly impact the performance of the algorithm.
[20]	ML based	SA is performed on customers' feedback about various airlines.	Feature engineering is used to choose the best features, that not only enhances the model's overall effectiveness but also decreases time required for training.	The imbalanced among the classes present in most of the larger datasets might cause overfitting.
[21]	ML based	A feature engineering procedure is applied to identify the major characteristics that will eventually be utilized to train a machine learning-related algorithm.	Improved accuracy over base model through effective feature selection.	May not perform well for imbalanced datasets.
[22]	ML based	Adoption of a hybrid methodology that includes a SA analyzer through algorithms related to machine learning.	A great comparison of sentiment lexicons (Senti-Word-Net, W-WSD, Text-Blob) was presented so that the best might be used for SA.	Only accuracy was used as performance measure and the results were not impressive.
[23]	ML based	Investigating the effect of various classification systems on Turkish SA.	The results concluded that utilizing various classifiers increases the results for solo classifiers.	Various classification systems offer more promise for sentiment categorization, but it is not fully matured.
[24]	ML based	The use of an adequate preprocessing approach may result in improved performance for sentiment classification.	According to research, the combining multiple preprocessing procedures is critical in determining the optimum categorization results.	Imbalanced datasets have not been investigated. That is why our study will focus on that.
[25]	DL based	Utilizing three different feature extraction methods for text analytics through neural networks.	The experiment shows that TF-IDF helps it to achieve higher accuracy with a large dataset.	May not work well with highly imbalanced multiclass dataset.
[26]	DL-based	Using a CNN model to classify investor sentiments from a major Chinese stock forum.	This hybrid model with sentiments outperforms the baseline model. The results support that investor sentiment is a driver of stock prices.	The pretty outstanding forecast accuracy was achieved utilizing solely data from China.
[27]	ML based	To address the class imbalance problem, it proposes a hybrid strategy that combines the Support Vector (SVM) algorithm plus Particle Swarm Optimization (PSO) and several up-sampling approaches.	The study shows that the suggested PSO/SVM technique is successful and surpasses the other alternatives in all parameters tested.	The paper is mainly focused on Arabic language. Other languages may need to be explored.
[28]	Hybrid ML and DL based	KSCB is a novel text SA classification model that combines K-means++ algo with SMOTE for up-sampling, CNN, and Bi_LSTM.	The ablation investigation on both balanced and unbalanced datasets proved KSCB's efficacy in text SA.	KSCB method does not take into account EPI: emotional-polarity-intensity.
[29]	DL based	An oversampling approach for deep learning systems that takes advantage of the famous SMOTE algorithm for class inequality data.	Deep-SMOTE needs no discriminator and yields better artificial pictures that are simultaneously information-rich and acceptable for eye examination.	Deep-SMOTE lacks knowledge related to challenges associated with class and instance level.

[30]	ML based	On Twitter, an aspect-based SA was performed on Telkomsel customers. The data utilized comprises various tweets from consumers who discuss various elements of Telkomsel's offerings on Twitter.	The Word2Vec, Synthetic Minority up-sampling Technique, and Boosting algorithms combined with the LR classifier achieved the best performance.	Data was significantly small to accurately test the performance.
[31]	ML based	For Twitter sentiment analysis, a unique, unsupervised machine-learning approach that relies on concept-based and hierarchical grouping is presented.	The results obtained with this unsupervised learning method are on par with other supervised learning methods.	Boolean and TF-IDF are investigated utilizing unigrams. Bigrams and trigrams may also be investigated. Large datasets can also be explored.
[32]	DL based	Evaluation of SA and emotion identifcation from speech through supervised learning methods, specially speech representations.	Impressive results were obtained through weighted accuracy. Unimodel acoustic examination accomplished competitive results against previous methods.	The model did not perform well for multi-class problems where number of classes were high.

3. Methology

In this section we will present a detailed framework for improved sentiment analysis. We will also discuss all the elements of the framework in an ordered manner. Framework diagram is shown below in Figure 2.

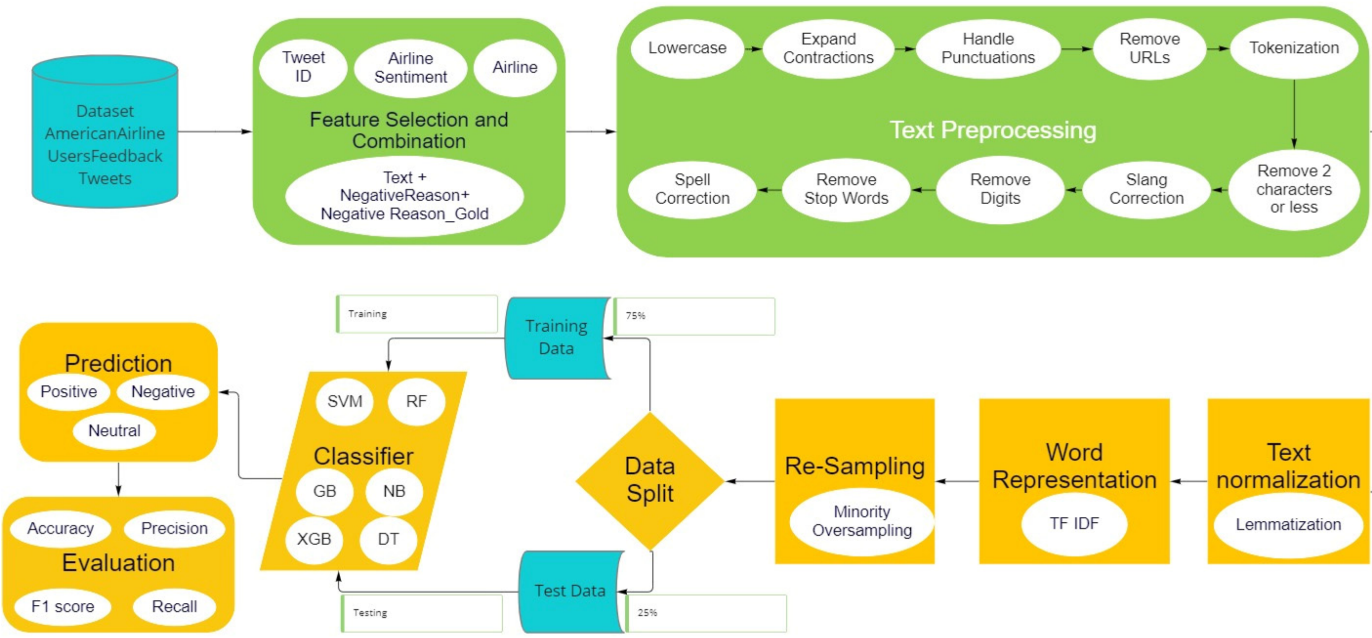


Figure 2. Framework diagram for sentiment analysis through resampling.

3.1. Proposed Framework

In this study, a unified framework that contains all the elements needed for sentiment analysis has been constructed. This modular approach offers many sentiment analysis philosophies with an emphasis on improvements. The suggested framework is made up of various modules that control how the system functions internally. We use a pipeline-based method to automate the entire framework, performing several modules such as feature selection and combination, multistage text preprocessing, text normalization, Word representation and resampling.

3.1.1. Feature Selection and Combination

In order for this framework to effectively perform its task, we need to spend some time on manual inspection of the dataset. Since we are performing sentiment analysis on the US airline dataset (details in Section 4), we need the features which have class labels. In this dataset column, "*airline_sentiment*" contains class labels. We have also chosen column "*tweetID*" for uniquely identifying the tweets. We also combined the features "*text*" which contains the tweets and the feature "*negative reasons*". This was done to enhance tweets sentiment.

3.1.2. Text Preprocessing

The second stage of this framework includes preprocessing of the tweets. This is completed by various functions to remove unwanted text from the data. This results in faster preprocessing of text thus reducing the time complexity of all the upcoming modules of the framework.

- Converting all characters to lowercase

Transforming all words to lowercase is also a very common preprocessing step. This step can reduce the required processing power. For example, for a computer 'good' and 'Good' are two separate words that would need to be processed separately. Table 2 provides an example of this process.

Table 2. Output after lowercasing of sample tweet.

Sample Tweet Input	After Lowercase
it was absolutely amazing, and we reached an hour early. You're great.	it was absolutely amazing, and we reached an hour early. you're great.

- Expanding contractions

A word created by condensing and combining two words is known as a contraction. They include words such as can't (can + not), don't (do + not), and I've (I + have). Expanding contractions can be an effective preprocessing strategy for most NLP tasks. Table 3 provides an example for expanding contractions.

Table 3. Output after expanding contractions of sample tweet.

Sample Tweet Input	Expanding Contractions
it was absolutely amazing, and we reached an hour early. You're great.	it was absolutely amazing, and we reached an hour early. you are great.

- Tokenization

Tokenization is a method where any amount of text is split into tokens, which could be words, sentences or paragraphs etc. Initially, we utilized *StringTokenizer*, but because to its flaws, we chose the far superior *LingPipeTokenizer*. It is vital to note that each document's tokens (keywords) and sentences (list of keywords) are stored in proprietary data structures.

- Removing words less than two characters

Since words of two characters or less do not provide any key information, we have excluded those words from the dataset.

- Removing repeating words

When dealing with twitter data, it is important to remember that most hashtags repeat too often to present any useful information for the training of our classifier. Therefore, removing words that start with '@' can be useful for our dataset. For example, words that mentioned the name of an airline or the name of a person do not provide any information in the context of sentiment analysis, so we have removed these words from the tweets. These words include '@VirginAmerica', '@united', '@SouthwestAir', '@JetBlue', '@USAirways', '@AmericanAir', '@Americ', etc.

- Removing punctuations

Punctuation includes characters such as a full stop, comma, question mark, exclamation mark, semi-colon, colon, ellipsis, brackets, etc. We removed punctuations from the data using *string.punctuation*. Certain punctuations were not removed by the automated function; therefore, a separate string replacement line of code was required to remove some special characters. For example, '@' in words such as @UnitedAirlines. Table 4 provides an example of removing punctuations.

Table 4. Output after removing punctuations from sample tweet.

Sample Tweet Input	Removing Punctuations
it was absolutely amazing, and we reached an hour early. you are great.	it was absolutely amazing and we reached an hour early you are great.

- Removing digits

We have removed numbers because they do not provide any information for our data. However, that is not the case for all NLP tasks. Table 5 provides an example of removing digits from the text.

Table 5. Output after removing digits from sample tweet.

Sample Tweet Input	Removing Digits
is flight 81 on the way should have taken off 30 min ago	is flight on the way should have taken off minutes ago

- Slang correction

This phase entails fixing any slang or acronyms used in internet communications. To convert slang or abbreviations to their original and abbreviated forms, we employ predetermined dictionaries and maps: for instance, GOAT—'Greatest of All Time'; or OML—an abbreviation for 'Oh my lord'. Table 6 provides an example of slang correction.

Table 6. Output after handling slangs and abbreviations.

Sample Tweet Input	Handling Slangs and Abbreviations
your deals never seem to include NYC	your deals never seem to include new york city

- Removing stop-words

A stop word is a commonly used word such as 'the', 'a', 'an', 'in', etc. Since these words do not provide any value in terms of sentiment, they are therefore excluded from the dataset. Table 7 provides an example of stop-word removal from the text.

Table 7. Output after removing stop-words.

Sample Tweet Input	Removing Stop-Words
it was absolutely amazing and we reached an hour early you are great	absolutely amazing reached hour early good

- Spell correction

It can be very useful to include spell correction as a preprocessing step. Since most user tweets contain spelling mistakes, it can create several word features that might belong to the same class. For example, different users might misspell the word "abbreviation" in three different ways thus creating three separate word features that will need to be processed which will consume more time. Table 8 provides an example of spell correction.

Table 8. Output after spell correction.

Sample Tweet Input	Spell Correction
thanks for the good expirince	thanks for the good experience

3.1.3. Text Normalization

Lemmatization is the method of transforming a word to its base form. The method of stemming involves reducing an infected term to its fundamental or root word. Each token is converted to its stem form via the Porter-2 algorithm [27] and stored in the keyword object along with the original token. Lemmatization was applied by using POS tagging and *'WordNetLemmatizer()'*. We chose lemmatization because it provides better results as compared to stemming but takes a lot more time. This was a decision of quality vs. speed, and we chose quality through lemmatization.

3.1.4. Word Representation

We will be using a bag of words model to create features from our text. It is a method of extracting words as attributes from text, such as tweets, for use in a framework, which can be supplied to ML algorithms. It is important to perform this step before the oversampling because it will considerably save processing time. We used TF-IDF vectorizer for creating word embedding because it provided the best results for our model. TF-IDF assesses how significant a word is to a record within a group of records. In order to perform this task, two separate equations are multiplied: the no. of times a word appears in a record and the inverse document frequency of a single word over a group of records.

$$TF = Term\ Frequency$$

$$DF = Docuement\ Frequency$$

$$IDF = Inverse\ Docuement\ Frequency$$

$$N = Total\ number\ of\ documents$$

$$DF_t = Number\ of\ docuements\ that\ contain\ the\ term\ 't'$$

$$TF_{t,d} = Number\ of\ times\ a\ term\ 't'\ occurs\ in\ document\ 'd'$$

$$W_{t,d} = log\left(1 + TF_{t,d}\right) \times \log\left(\frac{N}{DF_t}\right) \quad (1)$$

3.1.5. Oversampling

Various strategies have been put out to address the issue of class imbalance. The oversampling method is the most well-liked of them all. The essential idea behind the strategy is to introduce various ratios of synthetic samples while oversampling the minority class [33]. For binary and multi-class classification tasks, imbalanced classes present a significant challenge in the training of an effective classifier [34,35]. Due to the extreme imbalance between the classes, a majority classifier would produce very accurate results by assigning the most prevalent class to each instance but failing on majority items from the other present classes will lead to a decreased performance in terms of low accuracy and F1-score, which are our main performance criteria. In order to get around this issue, class resampling approaches give us several distinct additional options. In under-sampling techniques, the part of the predominant class is removed from the training data, bringing the size of the training dataset closer to or on par with the minority class. The disadvantage of such a strategy is that the less dominant class is too small to make the other present classes equal to its size, which results in the loss of a significant amount of important and valuable information. A contrasting process is accomplished using the oversampling method. By multiplying the instances of the minority class to the required size, the minority class is made larger to match the size of the predominant class. The benefit of this approach is that it keeps all of the dataset's important data. Numerous algorithms have been presented that are based on oversampling as discussed in the literature review. The most important aspect of proposing an efficient algorithm is to lose the least amount of data possible. The most effective way to solve this issue is through oversampling. As it is visible from Figure 3, that dataset has a lot more tweets that belong to the negative class. Negative sentiment tweets have over 9000 tweets which is about 63% of the dataset, whereas the neutral class is 21% and positive class is only 16%. Our framework addresses the class inequality by oversampling the less dominant classes randomly. One of the most recently used oversampling method is SMOTE [29], but for our framework we chose a random oversampling approach which involves making copies of instances in the less dominant classes, although these instances will not add any new information to the framework, but new instances will be copied from the existing instances.

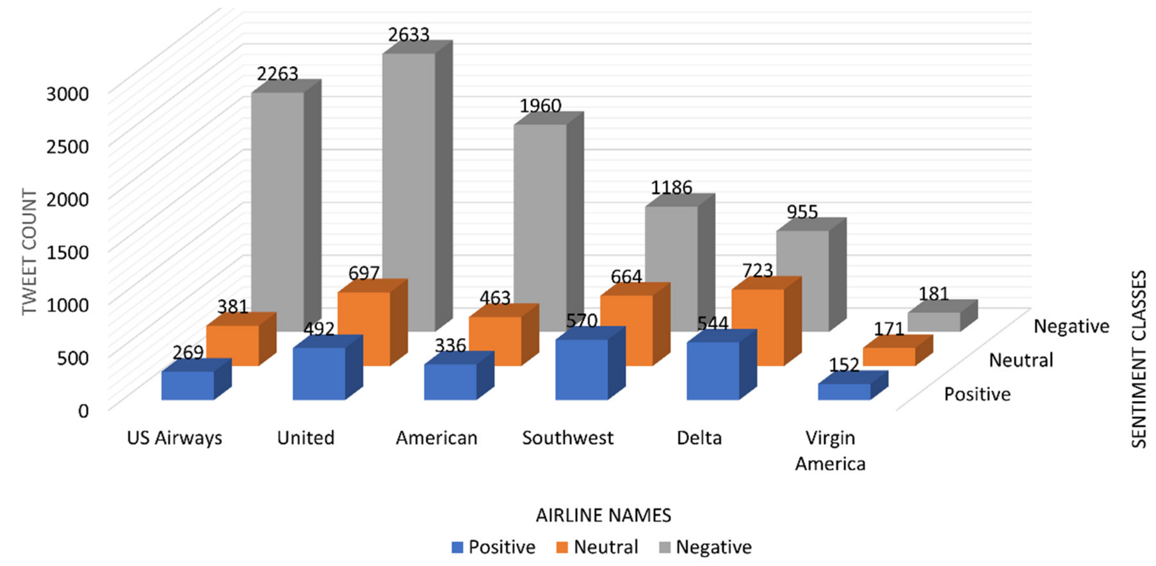


Figure 3. Total number of sentiment tweets for each airline.

3.1.6. Sentiment Classification

We applied six different ML algorithms to test the results with our proposed framework. Machine learning classifiers including Random Forest classifier (RF-C), Multinomial Naive Bayes (MNB-C), Support Vector Machine classifier (SVM-C), Gradient boost, XGB, and Decision Tree Classifier (DTC) have been implicitly used in our experiment on the testing dataset.

4. Results and Discussion

In this section, we will discuss the data that is utilized for the experiments. We will also be outlining our hardware and software configuration for tests. Later, we go over various evaluation criteria and how well our system performed against them. Precision, recall, F-measure, and execution time are just a few of the performance measures we have utilized. We also compare various ML classifiers.

4.1. Dataset

Following dataset was used to check the performance of our model:

- Twitter US Airline Sentiment

This dataset uses tweets to find the satisfaction level of the customers. The dataset conains tweets of six different airlines which include 'VirginAmerica', 'united', 'SouthwestAir', 'JetBlue', 'USAirways', and 'AmericanAir'. We will be using the text of the customers tweets to train the classifier so that predictions can be made on unseen tweet data. We have split the dataset by using 75/25, where 75% is training data and 25% is test data. Table 9 lists the features of the dataset used in this study.

Table 9. Feature description of selected dataset.

Features	Description
Text	Original text of the tweet written by the customer.
Airline	Name of the US airline Company.
Airline_Sentiment_Confidence	A numeric characteristic that represents the confidence rate of categorizing the tweet into one of the three possible categorizes.
Airline_Sentiment	Labels of individual tweets (+ve, neutral, −ve).
Negative Reason	The reason is provided to consider a tweet as −ve.
Negative_Reason_Confidence	The rate of confidence in deciding the −ve reason in relation to a −ve tweet.
Retweet Count	Number of retweets made for a tweet.

Discussion on Dataset

Figure 3 shows the number of tweets for each airline in terms of sentiment classes. It shows that the tweet distribution is not equal with respect to each airline and their sentiment classes. After thoroughly looking at the results of different classification algorithms, it is clear that 'South West' airline have the most positive tweets, but that does not mean that it has the most user satisfaction level, because we also have to look at the negative tweets. If we just look at the positive tweets, then 'South West' can be considered to have the most user satisfaction level. Another way is to calculate the ratio of positive to negative tweets to calculate user satisfaction level. Although virgin America has the least amount of positive to negative tweets ratio but since its data is very small, the ratio cannot be considered. Therefore, the logical conclusion is that the Delta airline can be considered to provide the most user satisfaction level.

We can also extract useful information about the various reasons for unsatisfied customers as shown in Figures 4 and 5 above. However, it is important to remember that this information must be extracted after the preprocessing has been performed. As most of the common keywords before preprocessing are stop-words or other non-useful words, proper preprocessing is hence performed, which results in valuable data which can be used for sentiment analysis.

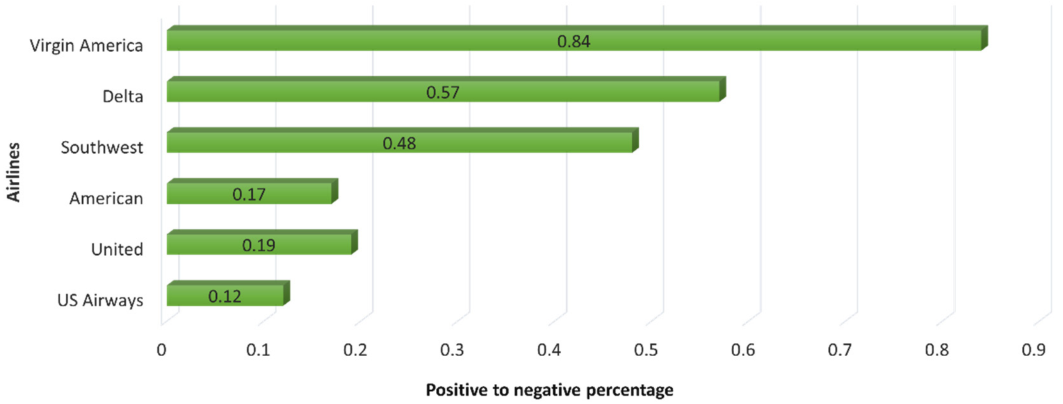


Figure 4. Positive to negative tweet ratio of each airline.

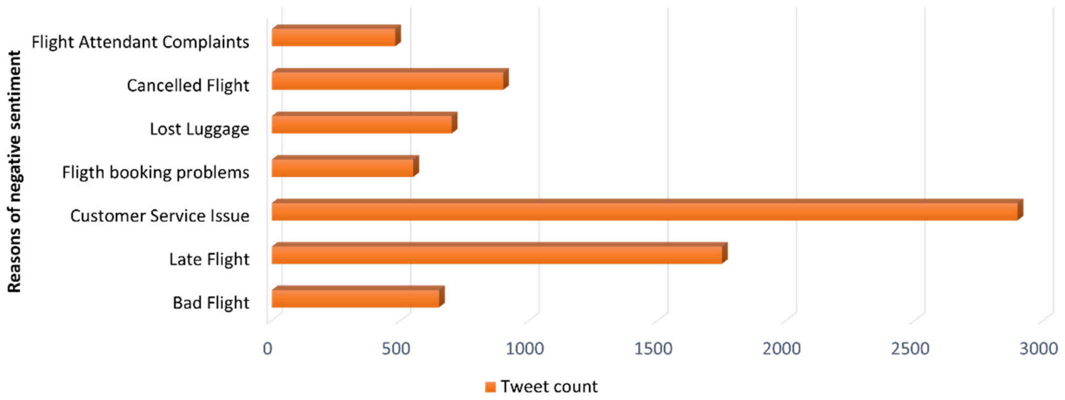


Figure 5. Top seven reasons for unsatisfied customers.

4.2. Experimental Setup

The experimentations were performed on a computer with an AMD Ryzen 5 3rd generation processor running at 4.2 GHz, 16 GB of RAM, and a 512 GB solid state drive. The development of the framework and the experimentation was carried out in python computer programming language using *spyder v5* developed by *spyder project contributors* under MIT license in USA.

4.3. Evaluation Metrics

The main metrics utilized in this study for the evaluation of our framework are accuracy and F1 measure, but we have also included the results with precision and recall for better understanding of the results. These evaluation metrics are consistent with those utilized in another research [36,37]. We have defined the evaluation technique as follows:

- True Positive (*TP*): It produces an output which shows the right prediction made for the +ve class.
- True Negative (*TN*): It produces an output which shows the right predictions made for the −ve class.
- False Positive (*FP*): It produces an output which shows the wrong predictions made for the +ve class.
- False Negative (*FN*): It produces an output which shows the wrong predictions made for the −ve class.

Accuracy: It is usually not a good measure for the imbalanced dataset, but as we have used up-sampling to deal with class inequality problem, accuracy is therefore an accurate measure in this scenario. It is more formally defined as [38,39]:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

Precision: A classification algorithm's capacity to detect only meaningful data items. More formally, the proportion of positively predicted data items to the total number of positively predicted data items. Mathematically, we define it as:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

Recall: A classifier's capacity to discover all relevant examples within a data collection. More formally, the proportion of accurately predicted positive data items in relation to all data items in the actual class. Mathematically, we define it as:

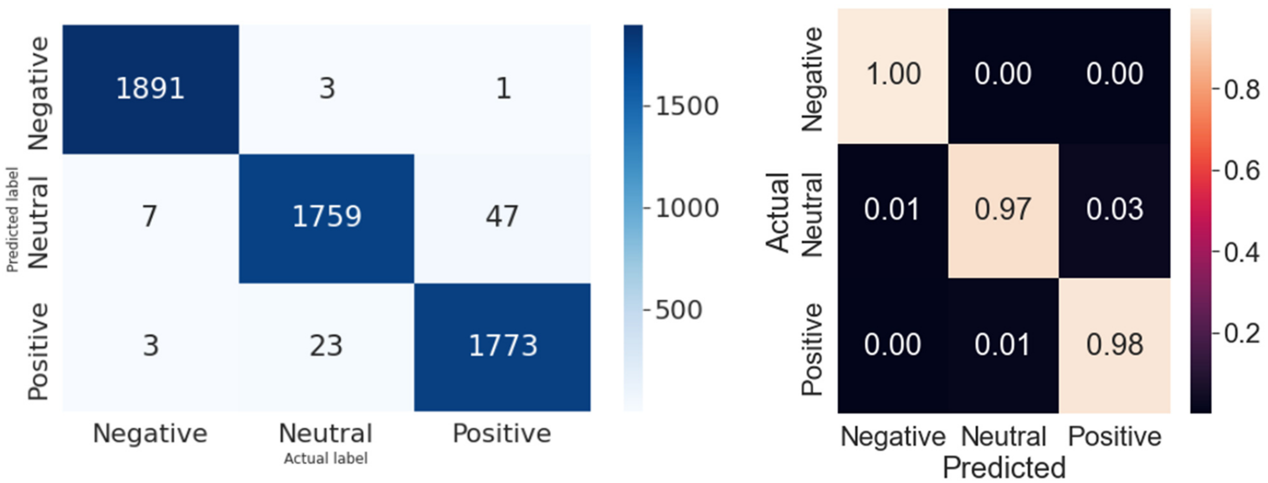
$$Recall = \frac{TP}{TP + FN} \quad (4)$$

F1 Measure: Precision as well as *Recall* are the usual techniques that consider the issue of class inequality. *F1* measure utilizes both to produce a new metric. Mathematically, we define it as:

$$F1 = 2 \times \frac{precision \times recall}{precision + recall} \quad (5)$$

4.4. Classification Results

Random Forest produced the best results with the selected dataset for sentiment analysis with an accuracy of 98.3% and *F1* score of 0.98. The confusion matrix in Figure 6 provides the actual vs. predicted labels of our classifier. Actual labels are presented on the horizontal axis whereas the predictions made by the classifier are shown on the vertical axis. Diagonal values in blue color from top left to bottom right show the ''true positives'' of negative, neutral, and positive sentiment class, respectively. SVM also produced extremely good results with the selected dataset for Sentiment Analysis providing the accuracy of 97.8%. Comprehensive results for each classifier have been provided in figure 7. Table 10 provides a direct comparison of results for each sentiment class.



(**a**) (**b**)

Figure 6. (**a**) Confusion matrix with Random Forest classifier with best predictions; (**b**) Confusion matrix of RF classifier with normalized values.

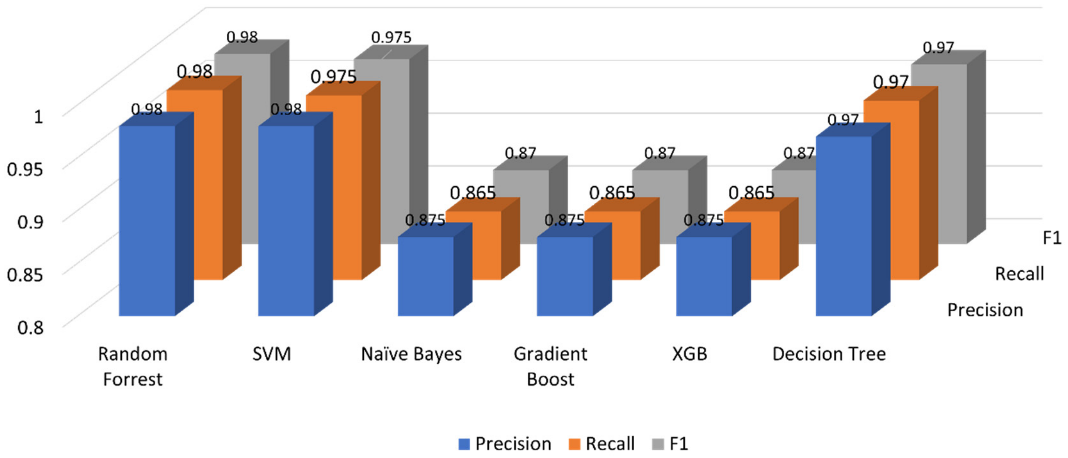


Figure 7. Classifier performance comparison.

Table 10. Classification report for all classifiers:.

	Sentiment Class	Precision	Recall	F1-Score
Random Forest Accuracy = 98.3%	negative	0.99	1.00	0.99
	neutral	0.98	0.96	0.97
	positive	0.97	0.97	0.97
SVM Accuracy = 97.8%	negative	0.99	1.00	0.99
	neutral	0.98	0.96	0.97
	positive	0.97	0.97	0.97
Naïve Bayes Accuracy = 87.4%	negative	0.85	0.94	0.89
	neutral	0.88	0.78	0.83
	positive	0.89	0.90	0.90
Gradient Boosting Accuracy = 87.5%	negative	0.85	0.94	0.90
	neutral	0.88	0.79	0.83
	positive	0.89	0.90	0.90
XGB Accuracy = 96.1%	negative	0.98	0.98	0.98
	neutral	0.97	0.96	0.95
	positive	0.96	0.96	0.97
Decision Tree Accuracy = 96.4%	negative	0.98	0.98	0.98
	neutral	0.97	0.97	0.95
	positive	0.96	0.96	0.97

4.5. Results Comparison: Oversampling vs. No Oversampling

It is clear from the results below that resampling effects the results of each classifier. Using oversampling might be useful but it may cause overfitting, whereas under sampling results in huge loss in accuracy due to underfitting, which is caused by a reduction in the majority class of an already small dataset. Figure 8 presents the direct accuracy comparison between oversampling and no oversampling results. We can see that the results have been dramatically improved when random oversampling is utilized for the data imbalance. For certain classifiers, the improvement is extremely evident. This result was possible because we handled the data imbalance correctly.

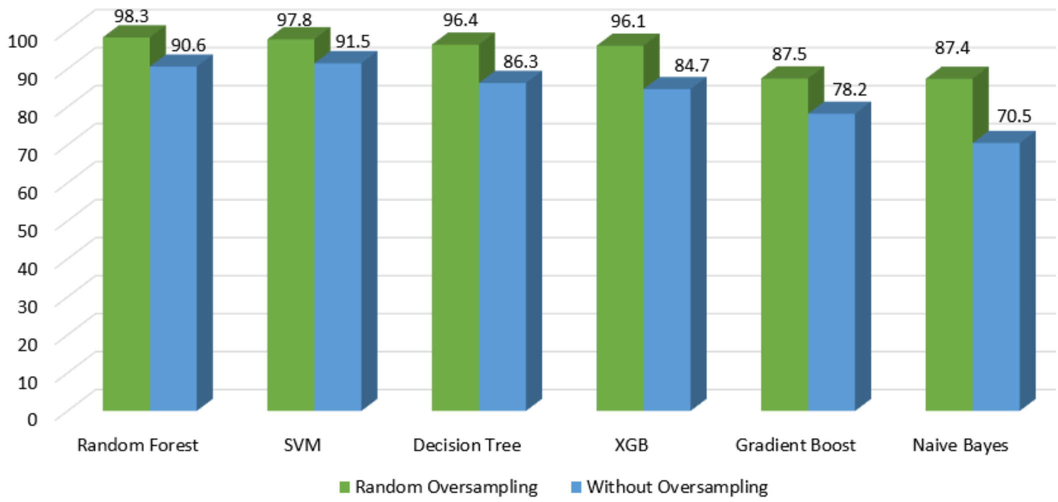


Figure 8. Accuracy comparison with and without oversampling.

5. Result Visualization and Discussion

Our findings and discussion are presented in this section.

The results of Sentiment Analysis depend on several factors such as preprocessing the data. Another important factor is the selection of the classifier to train and test on the given dataset. To choose the best classifier, we have tested the results with many different classifiers such as SVM, naïve Bayes, etc. 'Random Forest' provided the best accuracy out of all the other classifiers. It makes sense since it is an ensemble machine learning algorithm for classification tasks.

5.1. Word Cloud of Positive Tweets after Processing

The word cloud below shows the top words that had an impact in classifying a tweet as positive. We can see that words such as 'thank', 'flight', 'good', 'best', etc., are predominantly visible on the word cloud which represent positive sentiments about the airlines. Figure 9 below shows the top 250 words that were useful in identifying a tweet as positive with respect to sentiment analysis.

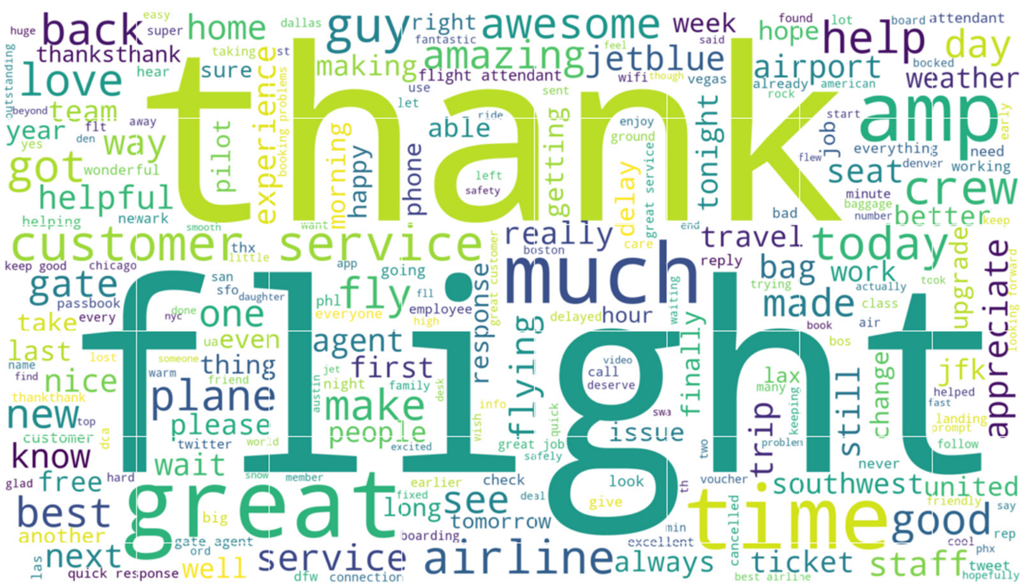


Figure 9. Word cloud of Positive tweets.

5.2. Word Cloud of Neutral Tweets after Processing

The word cloud below shows the top words that had an impact in classifying a tweet as neutral. In the neutral sentiment word cloud, most words do not carry any positive or negative sentiment. Figure 10 below shows the top 250 words that were useful in identifying a tweet as neutral with respect to sentiment analysis.

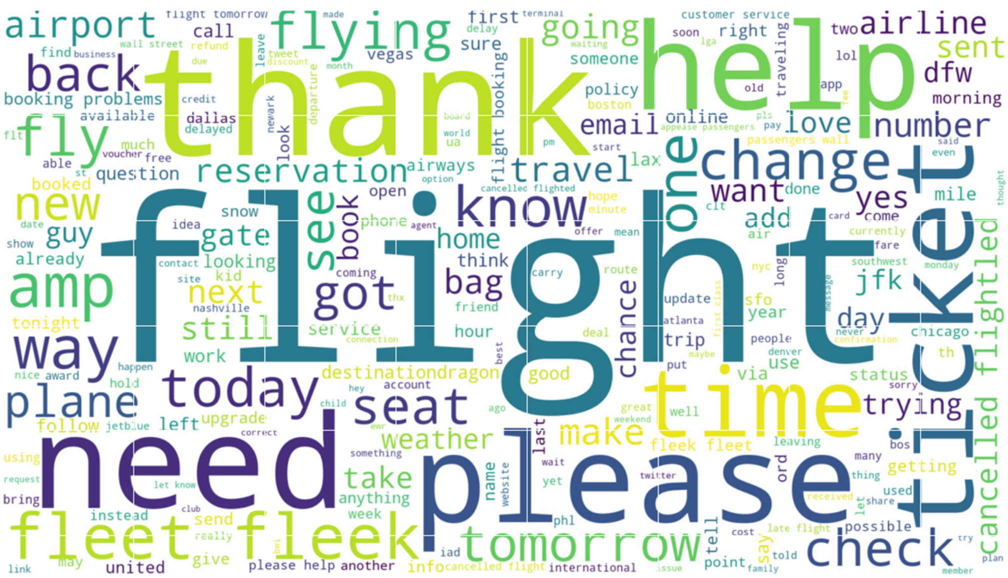


Figure 10. Word cloud of neutral tweets.

5.3. Word Cloud of Negative Tweets after Processing

The word cloud below shows the top words that had an impact in classifying a tweet as negative. We can see that words such as 'customer', 'service', 'issue', 'cancelled', and 'flight' are predominantly visible on the word cloud. Those words describe the reasons for negative feedback. Figure 11 below shows the top 250 words that were useful in identifying a tweet as negative with respect to sentiment analysis.

Figure 11. Word cloud of negative tweets.

6. Conclusions

The design, implementation, and evaluation of our comprehensive SA framework have all been thoroughly covered in this study. The Random Forest classifier offers the best accuracy (above 98%) when utilizing the Twitter dataset. Often, the tweet text alone is not enough to produce good classification results. Therefore, it is important to look at other features of the dataset. In the first dataset, the feature of 'negative reasons' were mentioned for each negative tweet. Therefore, combining the 'negative reasons' and 'negative reasons gold' with the tweet text increased the classification accuracy for the negative class. Although that might cause slight overfitting, but since the words mentioned in the negative reasons might be useful to predict unseen data, it was therefore chosen to be included in the final text.

Handling imbalanced data is an important part for any given dataset as most of the datasets have class imbalance problem. Therefore, it is important to include a resampling technique within your methodology. If the dataset is very large, then we can use under sampling of the majority class. In the other case, if we have a smaller dataset, then we can use oversampling of the minority class. However, if the dataset is highly imbalanced this can cause the classifier to overfit the less dominant class, which can lead to a higher generalization error. Since this dataset is not as highly imbalanced, we therefore chose to include oversampling. We draw the conclusion that our methodology for sentiment analysis has contributed significantly to the field of sentiment analysis. For future directions, we would like to analyze the impact of transformer-based models and create a new transformer-based SA framework for an imbalanced dataset which handles multiclass classification problems. We can also analyze the impact of various graph-based techniques, such as graph neural networks for multi-class classification problems of sentiment analysis.

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