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Hybrid Feature Selection Technique with an Enhanced TF-IDF and SVM-RFE in Sentiment Classification based on Hotel Review

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Abstract. A hybrid feature selection technique is implemented on a hotel review dataset to observe the sentiment classification performance is presented in this paper. This technique is proposed to overcome the issue of unable to accurately calculate the feature importance in existing techniques. Therefore, an enhanced Term Frequency-Inverse Document Frequency (TF-IDF) is proposed by having variance threshold while reducing features and to avoid non-significant features or significant features from being removed. Subsequently, a hybridization of the TF-IDF and Supports Vector Machine (SVM-RFE) known as TF-IDF+SVM-RFE is implemented. The TF-IDF+SVM-RFE aims to measure features importance by selecting the significant features to be classified. Hotel Review dataset from Kaggle database is used to observe the classification performance of this proposed technique. The classification performance is observed based on accuracy, precision, recall and F-measure. Based on the experiment, the proposed technique able to be outperformed other related technique with 91.74%, 91.51%, 91.92% and 91.70% for the accuracy, precision, recall and F-measure respectively. Ultimately, the proposed technique able to reduce 38.53% of the total features from 17896 to 11000 that being used in the classification. This reduction rate is significant in optimally utilizing the computational resources and maintaining the efficiency of the classification performance.

Keywords: Sentiment Classification, Sentiment Analysis, Feature Selection, Computational Intelligence

1. Introduction

Sentiment classification has been widely used to replace traditional methods of processing public opinion that has been expressed in text documents, whether it is positive or negative. The example of sentiment classification is classifying rumors, spam detection, forecasting stock market and product or service quality classification [1-4]. Thus, we focus on the sentiment classification for service reviews which is hotel reviews to be classified based on a text document.

Lexicon-based and machine learning-based (ML) are the two approaches in sentiment classification. However, we focus on the ML-based approach in this paper. It is because ML-based approach has been proved that able to produce better classification performance not only in sentiment classification, but in many other problems [5-9]. This paper will focus on the feature selection technique that has been implemented in the selected approach. Feature selection is a crucial part in sentiment classification with the aim to select the significant features to be classified to avoid a distraction to the performance efficiency.

There are three approaches in ML-based approach namely, filter, wrapper and hybrid. Hybrid approach is a combination of filter and wrapper approach which is the focus in this paper. This hybridization able to overcome drawbacks in the filter and wrapper approach. The hybrid feature selection technique implemented in this paper is an enhanced technique known as TF-IDF+SVM-RFE that we have proposed recently [5]. For the TF-IDF, we proposed an enhanced TF-IDF by using a threshold based on a variance score for each feature in order to determine which feature will be eliminated and which feature will be considered as a significant feature. This enhancement is proposed due to some issues in existing TF-IDF, for instance, only 0.001% less significant features are able to be reduced using lowest term frequency threshold, boost TF-IDF only considered the most frequent features to be classified without measuring the feature importance and TF-IDF has been implemented as feature refinement not to filter the features [1,10,11]. Based on the enhanced TF-IDF, we do the hybridization with SVM-RFE to overcome problems in the existing feature selection techniques, namely, Chi-Square that failed to re-evaluate the features that have been evaluated by the TFIDF since it does not involve any learning algorithm which lead to the evaluation is less accurate [12]. In addition, there is a study that integrates TF-IDF with Next Word Negation to handle word negation issue, however, it leads to the increment of features to be evaluated [13]. Therefore, we implemented the TF-IDF to measure the important of a feature based on the variance scores, and the SVM-RFE that will rank the features by selecting significant features from a whole text document.

Hotel reviews dataset from Kaggle has been used to evaluate the performance of our proposed technique. The aim of this evaluation is to measure the performance efficiency based on accuracy, precision, recall, and F-measure. We also observe how much this technique able to reduce the number of features and at the same time able to maintain its efficiency. The next sections will discuss about the related works, the methodology of this technique, the experiments and results that have been obtained and the conclusion.

2. Related Works

There are a lot of studies that have implemented feature selection technique for the sentiment classification. However, we focus on the existing research that implemented hybrid feature selection for sentiment classification. A previous study on product review sentiment classification proposed by Larasati et al. attempt to improve the sentiment classification accuracy in movie review dataset using SVM as a classifier and Chi-Square Statistic and TF-IDF as feature selection techniques [12]. Without the feature selection, the accuracy only reached 68.7%, and the proposed feature selection techniques with 80.2%. Nevertheless, it only measures accuracy as sentiment classification performance which is insufficient in assessing a classification model. Iqbal et al. introduced a feature reduction based on the Genetic Algorithm (GA) for sentiment classification [14]. The proposed technique examines three sentiment datasets, namely, the UCI ML dataset for sentiment scoring, Twitter labelled sentiment analysis dataset, and the geopolitical dataset related to the 2016 United States Presidential Election. In testing the UCI ML dataset, non-GA and GA-based feature selection performed equally with close to 80% accuracy using NB classifier. However, they claimed that GA optimization could reduce only 40% features from the initial feature set.

Muthia proposed the hybrid of information gain and genetic algorithm as feature selection techniques [15]. The hybrid feature selection is aimed to increase the accuracy of Naïve Bayes classifier for hotel review classification. The hotel review dataset is the review of Hotel Royal at Queens in Singapore derived from www.tripadvisor.com. The accuracy of Naive Bayes classifier has improved about 4.5% from 78.50 % to 83%. However, accuracy and ROC are insufficient to measure the efficiency and efficacy of the proposed technique since precision and recall play a significant role in sentiment classification.

Farisi et al. conducted a comparison between two feature selection techniques for classifying English hotel review [16]. The first feature selection technique is frequency-based feature selection whereby it will remove feature that has low word appearance frequency. The second feature selection used to remove feature with the minimum difference of positive and negative value. The first feature selection outperformed the second feature selection in F1-score. However, it is only 0.181% difference.

Following that, Apriliani et al. works on developing the hybrid feature selection technique by combining decision tree and information gain [17]. The proposed DT+IG technique focuses to enhance sentiment analysis for the evaluation of hotel services. The hotel review dataset is retrieved from the https://www.google.com/maps. It contains text data in the form of a collection of public thoughts and comments for hotel services in Indonesia's Central Java province. From the experimental results, it shows that the best accuracy obtained is 88.54%. However, accuracy is insufficient to measure the efficiency and efficacy of the proposed technique since precision and recall play a significant role in sentiment classification.

Based on these related works, it can be concluded that most of the studies have implemented different feature selection techniques to improve the classification performance. However, the less related research considered the ML-based approach in hybrid feature selection technique, in particular the hybridization of filter and wrapper approach. Although there are studies that implemented the hybrid feature selection technique, it does not improve the performance significantly. This situation happens due to most of the techniques did not focus in measuring the features importance and selecting the significant features to be classified. We can see that it is important to obtain a good performance with less features to be classified. Therefore, it is crucial to design an effective feature selection technique that can fulfil the needs. Thus, in our proposed technique, TF-IDF will measure the important of a feature in the text document, and SVM-RFE will evaluate and rank the features by selecting the significant features using SVM score and recursive feature elimination.

3. Methodology

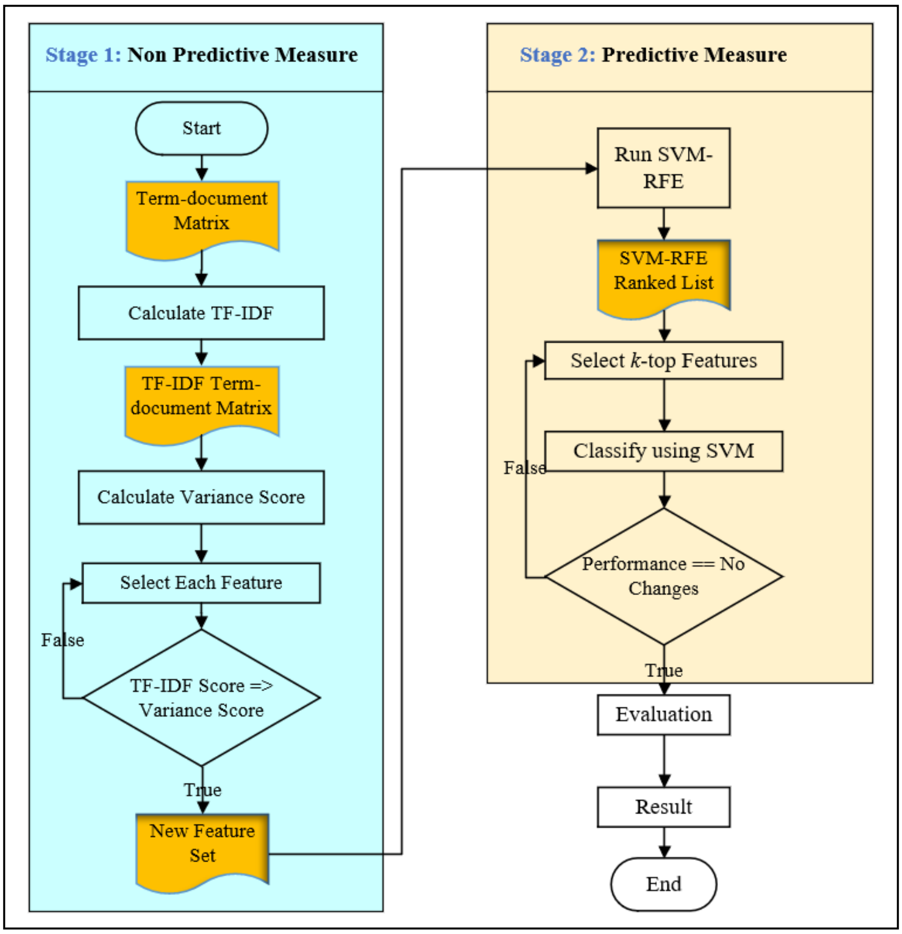

Fig. 1: TF-IDF+SVM-RFE Feature Selection Framework

There are 5 main phases in sentiment classification that we implemented in this paper. The phases are data acquisition, pre-processing, feature selection, classification, and evaluation. However, our focus to be discussed in detail in this section is the feature selection phase. Basically, for the data acquisition, we acquire the data from a benchmark database known as Kaggle. The data normally has been labelled by an expert. For the pre-processing phase, we implement 5 processes. The processes are tokenization, stop-word removal, short-word removal, stemming and term-document matrix conversion. Sentiment text is always in an unstructured format that contains text, symbols, numbers, typos and many more. As a result, it complicates the process of extracting actual information. Therefore, a classifier readable data format is required which will be generated in this phase. Thus, the aim of this phase is to produce a classifier-readable data format known as term-document matrix (TDM). Table I shows the example of TDM that has been produced from this phase. TDM will be used for the next feature selection and sentiment classification phase. The feature which words in the text document is represented by FN which is F1 to F9, for example, F1 represents the feature/word 'slow', F2 represents the feature/word 'great'. DN which D1 to D4 is the document of the sentiment text. The value in the table indicates the frequency of the feature appears in the document. For example, F3 appears 1 time in D1, F4 appears 2 times in D3. Note that class label 1 and 0 indicate that the sentiment text is positive and negative, respectively.

The most important phase in this paper is the feature selection phase. Fig. 1 shows the framework of the feature selection phase technique. This phase is divided into 2 stages. Stage 1 is a non-predictive measure to calculate and identify feature importance using the enhanced TF-IDF. Whereas, stage 2 is a predictive measure to re-evaluate the remaining features that have been extracted from the stage 1.

TABLE I. THE EXAMPLE OF TDM

Document, D_N	***Feature, F_N***									**Class Label**
	F_1	***F_2***	***F_3***	***F_4***	***F_5***	***F_6***	***F_7***	***F_8***	***F_9***	
D_1	0	0	1	0	1	0	1	0	0	1
D_2	1	0	0	0	0	0	0	1	1	0
D_3	1	0	0	2	0	1	0	1	0	0
D_4	0	1	0	0	1	0	1	0	1	1

TABLE II. THE EXAMPLE OF TF-IDF TERM-DOCUMENT MATRIX

Document, D_N	***Feature, F_N***								
	F_1	***F_2***	***F_3***	***F_4***	***F_5***	***F_6***	***F_7***	***F_8***	***F_9***
D_1	0	0	0.200	0	0.100	0	0.100	0	0
D_2	0.100	0	0	0	0	0	0	0.100	0.100
D_3	0.075	0	0	0.301	0	0.150	0	0.075	0
D_4	0	0.150	0	0	0.075	0	0.075	0	0.075

In the stage 1, TF-IDF for the term-document matrix is calculated using a standard formula for TF and IDF to produce TF-IDF term-document matrix. Where TF defines as frequency of a feature or term appear in a sentiment text document, FFTD over the total number of a feature appears in all sentiment text document, TFTD. Whereas IDF is logarithm of the total number of documents, TD divided by is the number of documents with the feature in them, NDF. It assesses feature's ability to distinguish between categories. Note that, the categories are the defined class label of the sentiment text document. Table II shows the example of TF-IDF term-document matrix after the TF-IDF calculation based on TDM in Table I.

Next step is to calculate variance score for each feature in the TF-IDF term-document matrix as in Table II, where we need data point for the samples represented by the TF-IDF score in the TF-IDF term-document matrix. The sample mean and the total number of features are also required to calculate the variance score. For instance, the variance from features in Table II is 0.080. Subsequently, the comparison of TF-IDF score and the variance score for each feature is made. Therefore, all the features more than the variance score, in this example is more than 0.080 will be selected as the new features, and the features below that score will be removed. Table III shows the example of TF-IDF term-document matrix after the comparison is done. For example, F1 in D3, and F5, F7 and F1 in D4 have been removed. Algorithm 1 in Fig. 2 describes the whole process of the TF-IDF in the stage 1.

Next, the stage 2 will be implemented. SVM-RFE is used in the second stage of the predictive measure to re-evaluate the features importance in the TF-IDF matrix. In the SVM-RFE algorithm, the SVM works as a classifier to train and evaluate the features. Whereas RFE algorithm is a search strategy for feature selection method that fits the training model by discarding the weakest feature(s) until the desired number of features that give high performance is reached. Finally, the features are ranked. The higher the feature in the rank, the significant the feature.

TABLE III. THE EXAMPLE OF TF-IDF TERM-DOCUMENT MATRIX

Document, D_N	***Feature, F_N***								
	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9
D_1	0	0	0.200	0	0.100	0	0.100	0	0
D_2	0.100	0	0	0	0	0	0	0.100	0.100
D_3	0	0	0	0.301	0	0.150	0	0	0
D_4	0	0.150	0	0	0	0	0	0	0

The process of selecting features started by defining several numbers of k-top features from the ranked features. The ranked features are divided into several groups of *k-top* features. The size of *k-top* features is determined by the size of the feature set. The performance of the *k-top* features will be evaluated using the classifier. This process is repeated until the performance produced a consistence result. Later, the *k-top* features with higher performance will be selected as the result. Fig. 3 shows the algorithm 2 that describes the SVM-RFE in the stage 2.

```
Algorithm 1: TF-IDF
Input:    TDM matrix, TDM array(i x j)
i = document, j = term
Output:   TF-IDF term-document matrix

      1:  Read TDM line by line and store in array, i x j
      2:  Calculate term frequency, TF
          For every document, i
          2.1: Calculate term, j for all documents
          2.2: Sum all terms in the sentiment text document
          collection
          2.3: Compute TF using (1)
      3:  Calculate IDF
          For every term, j
          3.1: Identify non-zero frequency document
          If not zero
          3.3: Compute IDF using (2)
      4:  Calculate TF-IDF
          4.1: TF-IDF = TF x IDF
      5:  Calculate variance score for the feature using (3)
      6:  Compare TF-IDF with variance score
          6.1: If TF-IDF => variance score: select the feature
          Else
          6.2: remove the feature
      7:  End
```

Fig. 2: TF-IDF Algorithm

```
Algorithm 2: SVM-RFE
Input:    Initial feature subset, S=1,2,3,…,n
Output:   Ranked list according to the smallest weight criterion, R

      W:  Weight vector
   Rank:  Ranking criteria
      1:  Set R= {}
      2:  If S = not {}, do 2 to 10
      3:  Train SVM using S.
      4:  Compute W SVM weight vector formula
      5:  Compute Score = W².
      6:  Sort rank; NewRank = sort (Score)
      7:  Update rank; Update R = R + S(NewRank)
      8:  Eliminate the feature with the smallest rank.
      9:  Update S = S - S(Newrank_lowest)
     10:  end if
     11:  End
```

Fig. 3: SVM-RFE Algorithm

4. Results and Discussions

For the experiment, Hotel Review dataset from Kaggle is used to observe the performance of the proposed technique. The dataset consists of 6449 samples with 3235 samples are positive sentiments and 3214 samples are negative sentiments. From the total of samples, we use 80% of the samples which is 5159 samples for the training and the rest which is 1290 for the testing. The total features that we extracted from the Hotel Review samples is 17896. Table IV provides the example of sentiments in the Hotel Review dataset.

We conducted the experiment in two phases. The first phase is to observe the classification performance without the proposed technique and the second experiment is with the proposed technique. For both experiments, we use the same platform which is Intel i-7 with MATLAB software, LIBSVM as the library for SVM model. The 5-fold cross-validation is used with the parameter C is set to 1 in utilizing the SVM. For the performance measurement, we use accuracy, precision, recall and F-measure to observe the efficiency of the proposed technique.

TABLE IV. THE EXAMPLE OF SENTIMENTS IN HOTEL REVIEW

Sample	Review in Text	Class Label
1	I hated inn terrible, room-service horrible staff un-welcoming, décor recently updated lacks complete look and management staff horrible.	0
2	Great time group 5 April great time the beach great food good overall great time, downfall opinion resort big, prefer resort walk end minutes not wait trolley.	1

4.1 Experiment 1

In this experiment, all 17896 features that being extracted from the samples are used to be classified. This experiment provides a baseline for comparison with the proposed technique. Table V summarizes the result from this experiment based on the accuracy, precision, recall and F-measure.

TABLE V. THE PERFORMANCE RESULTS IN EXPERIMENT 1

Measurement	Performance	Number of Features
Accuracy	91.74%	17896
Precision	91.51%	
Recall	91.92%	
F-measure	91.70%	

Based on the result, classifier correctly classified the sentiment as positive and negative sentiment at 91.74%. Whereas the precision score obtained is 91.51% which indicates that 91.51% of the estimated positive sentiment is correctly identified. The recall score shows that 91.92% is correctly identified out of the actual positives. Lastly, the F-measure score of this review is 91.70%.

4.2 Experiment 2

In this experiment, we implement the proposed technique to observe the classification performance. The proposed technique identified the significant feature set that divided into several groups of top features (k-top) depending on the feature size. Each group of k-top features will result in either no change, an increase, or a decrease in performance. In this experiment, we can determine which k-top features group is the most effective in classifying the sentiments. Besides, we set to eliminate 50% of the features at a time. When the remaining feature is less than 100, it eliminates one feature at a time. The 50% feature elimination percentage is set to speed up the evaluation process. Table VI summarizes some significant results from this experiment based on the accuracy, precision, recall and F-measure.

TABLE VI. THE PERFORMANCE RESULTS IN EXPERIMENT 2

k-top features	Performance Measures (%)			
	Accuracy	Precision	Recall	F-measure
5000	91.33	90.02	93.06	90.63
6000	91.45	90.15	93.54	91.25
7000	92.02	90.15	93.70	92.32
8000	92.67	91.62	94.50	92.07
9000	93.00	91.64	94.23	93.20
10000	93.82	91.11	95.01	93.31
11000	**94.06**	**92.63**	**95.68**	**94.12**
12000	94.05	92.05	94.78	93.08
13000	93.81	92.00	93.67	93.21

Based on Table VI, the best accuracy, precision, recall, and F-measure scores obtained are 94.06%, 92.63%, 95.68%, and 94.11% respectively, when the 11000-top features are selected. Compared with the baseline experiment in Table V, it is about 2.32%, 1.12%, 3.76% and 2.42% difference for accuracy, precision, recall, and F-measure, respectively. In terms of feature reduction, 6896 features are removed to achieve the best classification performance. It is about a 38.53% reduction from the original feature size.

We also did a comparison of our proposed technique performance with the existing technique that tested their experiment based on hotel reviews sentiment. All the chosen existing techniques in this comparison had implemented their own feature selection techniques.

Based on the comparison, the proposed technique outperformed other existing technique that implemented feature selection in classifying hotel reviews sentiment. Thus, it is reasonable to conclude that the proposed feature selection technique aids in improving classification performance while also reducing feature size for the hotel review dataset.

TABLE VII. COMPARISON: PROPOSED TECHNIQUE VS EXISTING TECHNIQUES

Technique	Performance Measures (%)			
	Accuracy	Precision	Recall	F-measure
Muthia [15]	83	85.11	86.00	-na-
Farisi et al. [16]	-na-	-na-	-na-	91.4
Apriliani et al. [17]	88.54	-na-	-na-	-na-
Proposed Technique	94.06	92.63	95.68	94.12

5. Conclusion

The proposed technique is a hybridization of the non-predictive measure in stage 1 and the predictive measure in stage 2 in classifying the sentiment of hotel review. In this technique, we implemented the feature selection technique to select the significant features to be classified. It is because sentiment reviews normally in high dimensionality data and unstructured. Thus, there is high possibility that the features consist of significant and insignificant features. The insignificant features will distract the performance. Therefore, it is crucial to be removed prior the classification process.

We implemented an enhanced feature filtering in the non-predictive measure whereby a threshold based on a variance score in added into the TF-IDF in order to measure the features importance. Later, the selected features will be re-evaluated and eliminated in the predictive measure based on the top list of features named k-top features. The k-top features indicates that the features are the most important features that have been selected. The features will be evaluated in the classifier to observe the classification performance.

The classification performance is observed based on the accuracy, precision, recall and F-measure using Hotel Review. The results show that our proposed technique able to outperform other related techniques. Most important, this proposed technique able to reduce the total features from 17896 to 11000 which is 38.53% of the reduction percentage to obtain the promising results. It shows that the proposed technique able to optimally utilize the computational resources while maintaining the classification efficiency.

As for future work, the result of this research motivates us the following future directions. First, the proposed feature selection technique will be tested on a larger dataset to measure its efficiency and effectiveness. Another research direction will focus on determining the best threshold in selecting features from the TF-IDF feature list.

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