A Comparative Study of TF-IDF and Count Vectorizer under Random State Changes in a Random Forest Classifier for Emotion Detection

Sirirat Kooptiwoot
Department of Psychiatry, Faculty of Medicine, Siriraj Hospital, Mahidol University, Bangkok, Thailand
sirirat.koo@mahidol.ac.th

Suwimon Kooptiwoot
Department of Applied Sciences, Faculty of Science and Technology, Suan Sunandha Rajabhat University, Bangkok, Thailand
suwimon.ko@ssru.ac.th (corresponding author)

Received: 10 November 2025 | Revised: 3 December 2025, 25 December 2025, 9 January 2026, 20 January 2026, and 22 January 2026 | Accepted: 23 January 2026

 DOI: https://doi.org/10.48084/etasr.16158

ABSTRACT

In machine learning processes, parameter settings affect model accuracy. Text-based emotion detection requires stable and accurate models, making parameter choices, such as the random state, increasingly important. Previous studies usually set the random state to 42, claiming that this should be the best for obtaining good accuracy. This study examined random state settings, experimenting with values from 1 to 720 and observing the results in accuracy. In addition, a dataset was employed for emotion detection using the Random Forest (RF) classifier with two vectorizers, TF-IDF and Count. The results show that different random state settings affect model accuracy. In the training subset, the TF-IDF vectorizer offered higher and more stable accuracy than the Count vectorizer. However, the Count vectorized achieved higher accuracy on both the validation and test sets.

Keywords-emotion detection; random forest; TF-IDF; Count; vectorizers; random state

I. INTRODUCTION

Emotion detection is an important topic for human well-being. Emotions out of control can pose dangers both to the subject and the people around him [1, 2]. For example, extreme sadness or anger can lead to severe dangers [3, 4]. Emotion dysregulation, such as depression, is related to suicide ideation [4-6]. Therefore, detecting emotions correctly and promptly can help to find ways to prevent bad situations before they occur. Even in normal situations, companies want to satisfy their customers with their products or services. By promptly detecting the emotions of their customers, they can adjust their services or change the product. Even in personal relationships, people tend to want to be happy and deal with others with happiness, too. Normally, no one wants to make themselves or the other people around unhappy; instead, being aware of their own or other people's emotions, they can adjust their behaviors. In education, during teaching, the teacher needs to detect students' emotions to adjust teaching methods and approaches, achieving better results. Otherwise, having students with undetected bad emotions can lead to poor or ineffective teaching.

Written text is one way to express emotion. Today, social media is widely used all over the world, where people can write anything to express their thoughts, ideas, or opinions. Thus, emotion detection in written text is very important. There are many methods used to detect emotions. For example, deep learning can be used to detect human emotions through text analysis of big data [7, 8]. Naïve Bayes (NB), Support Vector Machine (SVM), and Neural Networks (NN) have been used to develop models for detecting emotions in text [9]. Principal Component Analysis (PCA) can be used with SVM, NB, k-Nearest Neighbor (KNN), Logistic Regression (LR), or Random Forest (RF), and Multilayer Perceptron (MLP) classifiers for emotion detection [10]. Deep learning can also be used to detect contextual emotions in images, even in online learning systems [11, 12]. Convolutional Neural Networks (CNNs) have been used to detect criminal emotions [13] or emotions of the audience of broadcasting services [14].

AI and machine learning have been applied to many applications, such as in examining students' online learning preferences during the COVID-19 pandemic [15], in imaging analyses to better understand the tumor microenvironment and progression [16], and in emotion detection. To extract emotion from text, Natural Language Processing (NLP) plays an important role in understanding the meanings of the text, using different algorithms and methods. For example, in [17], an AraBERT-BiGRU model was used to recognize implicit emotions in Arabic text. In [18], LR, Extra Randomized Tree, Voting, SGD, and LinearSVC were used with feature extraction techniques such as TF-IDF, Bag-of-Words, and N-grams to detect emotion from text. In [19], LSTM was used to recognize emotions in speech and text. During a machine learning process, there are many parameters to set. For example, optimal parameter configuration can minimize LiDAR point cloud errors and maximize accuracy for field conditions in precision agriculture [20], hyper-parameter optimization can maximize CNN performance for olive cultivar classification [21], varying item parameter predictability affects trait estimation accuracy [22], and different parameters and measurement methods can improve measurement accuracy [23]. Machine learning approaches aim to devise models that can be used to correctly predict on new instances. The effectiveness of machine learning methods can be measured using accuracy. The parameter settings have some effect on the accuracy of the model. This study focused on the RF classifier due to its efficiency compared to deep learning, as it performs well on small datasets without requiring GPUs [24]. RF has been widely used in emotion detection and sentiment analysis, either from text or speech [25-28]. Understanding the importance and proper usage of its random state parameter can improve the quality and reliability of machine learning models.

Machine learning for text analysis needs to use a vectorizer so that the machine can understand the meaning of the text. Many vectorizers have been proposed and used in text analysis. This study focuses on two vectorizers that are used in the field: TF-IDF and Count. Text-based emotion detection requires accurate and stable models, since the prediction results are very sensitive and important for taking the right actions in the proper situations, and wrong predictions can have huge implications. As shown in existing works on text-based emotion detection, accuracy cannot reach 100%, despite exploring diverse machine learning algorithms. Examining different vectorizers and parameters can help improve model accuracy [29].

This study focuses on a comparison between the TF-IDF and Count vectorizers under diverse random state settings in the RF classifier for text-based emotion detection. As seen in many studies, the random state is usually set to 42. This study aimed to examine whether different values of random state affect the accuracy of the model and, if so, determine a better random state setting in a specific context. In addition, the objective involved comparing two popular vectorizers, TF-IDF and Count, on the accuracy of an RF classifier on the training, validation, and test sets of an emotion detection dataset [30].

II. METHODOLOGY

This study used the RF classifier, with different random state values and two vectorizers: Count and TF-IDF. Figures 1 and 2 show the processing steps applied for the Count and TF-IDF vectorizer tests. As can be observed, the same steps were applied in the two methods, except for the vectorizer.

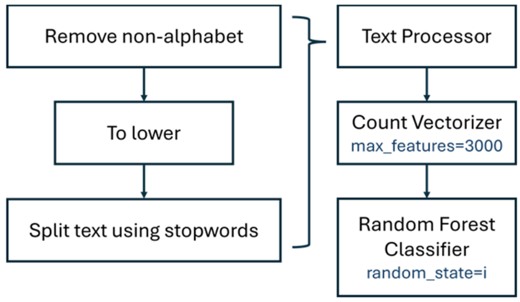

Fig. 1. Processing steps of using Count vectorizer and parameter settings.

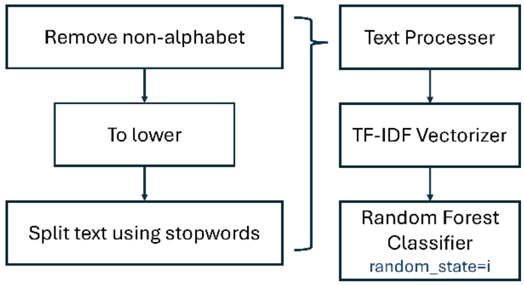

Fig. 2. Processing steps for using the TF-IDF vectorizer.

III. DATASET

The emotion detection dataset is available on [30]. Some samples from the dataset follow:

- i was feeling a little vain when i did this one; sadness
- i cant walk into a shop anywhere where i do not feel uncomfortable; fear
- i felt anger when at the end of a telephone call; anger
- i like to have the same breathless feeling as a reader eager to see what will happen next; joy
- i feel beautifully emotional knowing that these women of whom i knew just a handful were holding me and my baba on our journey; sadness
- i find myself in the odd position of feeling supportive of; love

The dataset was divided into three subsets, training, validation, and test, with the distribution per emotion shown in Table I.

TABLE I. DISTRIBUTION IN TRAINING, VALIDATION, AND TEST SETS

Emotion	Training set	Validation set	Test set
joy	5362	704	695
sadness	4666	550	581
anger	2159	275	275
fear	1937	212	224
love	1304	178	159
surprise	572	81	66

IV. RESULTS

The RF classifier was used with two vectorizers, TF-IDF and Count, with random state changing from 1 to 100. Figure 3 shows the accuracies achieved on the three datasets.

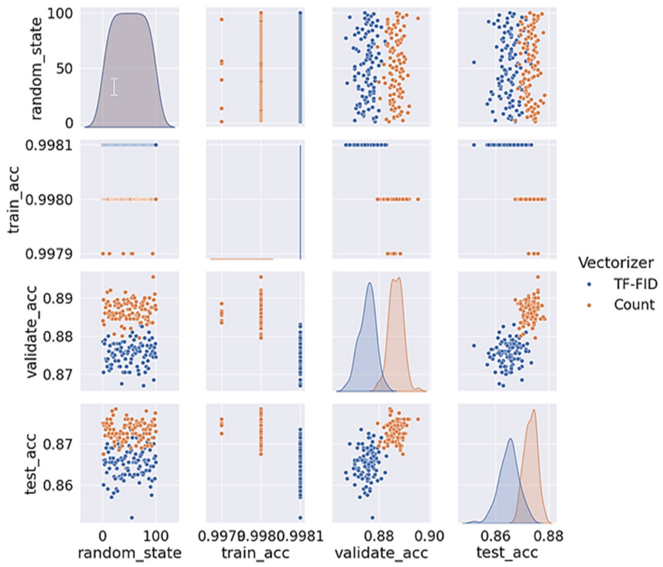

Fig. 3. Accuracy comparison using the Count and TF-IDF vectorizers.

The random state setting was changed from 1 to 720, with Figure 4 showing the accuracies achieved on the three data subsets with RF and the Count vectorizer. The results show that at different random state settings, the accuracies achieved are in the same range, without differing from each other. Compared to the other data sets, accuracy on the training set was the highest, very close to 100%, and the test set had the lowest accuracy.

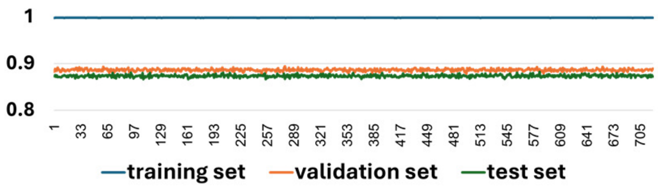

Fig. 4. Accuracy on the three data subsets running the RF classifier with the Count vectorizer and random state from 1 to 720.

Table II shows the minimum, maximum, and range of accuracies using the Count vectorizer on the training, validation, and test sets.

TABLE II. ACCURACY WITH COUNT VECTORIZER

	Training set	Validation set	Test set
Min	0.9979375	0.878	0.8665
Max	0.998	0.894	0.882
Range	6.25E-05	0.016	0.0155

Figure 5 shows a comparison of the accuracy achieved with the Count and TF-IDF vectorizers on the training set. The results show that on the training set, using TF-IDF achieved better accuracy than the Count vectorizer. Moreover, at different random state settings, the accuracies obtained using TF-IDF are quite stable compared to the Count vectorizer. It should be noted that using the Count vectorizer, accuracy dropped in some random state settings. Table III shows details on the accuracy achieved on the training set.

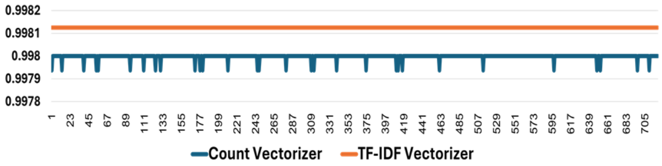

Fig. 5. Accuracies achieved on the training set using the Count and TF-IDF vectorizers across RF random states of 1-720.

TABLE III. ACCURACY ON THE TRAINING SET

	Count	TF-IDF
Min	0.9979375	0.998125
Max	0.998	0.998125
Range	6.25E-05	0

Figure 6 shows a comparison of the accuracy comparison on the validation set for both vectorizers with different RF random state settings. The accuracy obtained using the Count vectorizer at different random state settings is slightly better than that obtained using TF-IDF. Note that the accuracies obtained from both vectorizers are not stable. These results differ from those of the training set. Table IV shows the minimum, maximum, and range of accuracy for both vectorizers on the validation set.

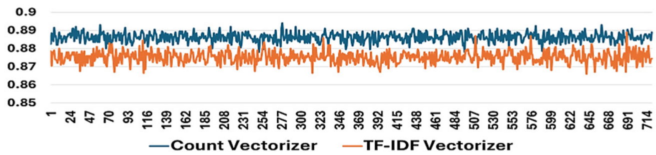

Fig. 6. Accuracies obtained on the validation set using the Count and TF-IDF vectorizers at RF random states of 1-720.

TABLE IV. ACCURACY ON THE VALIDATION SET

	Count vectorizer	TF-IDF vectorizer
Min	0.878	0.866
Max	0.894	0.889
Range	0.016	0.023

Figure 7 shows the accuracy achieved on the test set using both vectorizers with different random state settings, showing that the Count vectorizer outperforms TF-IDF. It should be noted that the accuracy obtained from both vectorizers is not stable across random state settings.

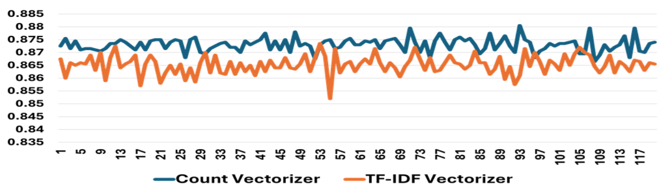

Fig. 7. Accuracy on the test set using the Count and TF-IDF vectorizers at random state settings from 1 to 120.

Working with the test set, the Count vectorizer offers better results, while the accuracy range obtained with the TF-IDF vectorizer is lower and wider, as can be observed in Table V.

TABLE V. ACCURACY ON THE TEST SET

	Count vectorizer	**TF-IDF vectorizer**
Min	0.8665	0.852
Max	0.8805	0.8735
Range	0.014	0.0215

These results show that on the validation and test sets, using the Count vectorizer gives higher accuracies than TF-IDF. However, these results cannot be generalized, as the performance of each vectorizer depends on the specific problem and the data. These results imply that the Count vectorizer can work better if the dataset is smaller and contains fewer unique words, while TF-IDF will work better when the dataset is larger or contains more unique words.

V. DISCUSSION

Random state settings affect the accuracy of machine learning models, as running on different data subsets gives different accuracies. The results of this study show that using the RF classifier with a vectorizer for emotion detection in text, the highest accuracy was obtained on the training set, and the lowest accuracy was obtained on the test set. This shows that the RF classifier overfits the training data using both the Count and TF-IDF vectorizers, especially with the latter.

Using the TF-IDF vectorizer, although at different random state settings, the RF classifier can offer models with quite stable and high accuracies. The results in [31, 32] show that after fine-tuning the hyperparameters, the TF-IDF vectorizer improved performance compared to the Count vectorizer. However, the results in this study show that on the validation and test sets, the Count vectorizer provides better performance than TF-IDF, with TF-IDF being better only on the training set. Both the validation and test sets are smaller than the training set. Thus, there is a question on the dataset size and characteristics where TF-IDF can work better than the Count vectorizer.

TF-IDF vectorizes a word by multiplying its Term Frequency (TF) by its Inverse Document Frequency (IDF). The TF of a word is the number of times it appears in a document compared to the total number of words in the document. IDF shows the proportion of documents in the corpus that contain the word. Words unique in a few documents receive higher importance values than words common across all documents. Working with a larger dataset, TF-IDF can get higher accuracy for to the following reasons.

1. Better Feature Coverage: TF-IDF creates a high-dimensional feature space (every unique word/term becomes a feature). With a smaller dataset, many words appear rarely, so their TF-IDF weights are unstable and do not generalize well. A larger dataset ensures more consistent word frequencies, making TF-IDF vectors more reliable.
2. Reduced Overfitting: RFs are ensemble models that rely on multiple decision trees. With smaller datasets, trees can memorize noise or idiosyncratic word usage, leading to poor generalization. With large datasets, the model sees diverse examples, so the trees learn more general rules about emotion-related word patterns.
3. Balanced Emotion Classes: Emotion detection involves multiple classes (joy, anger, sadness, fear, love, surprise). Smaller datasets may have a class imbalance (e.g., more joy than fear occurrences), which biases the classifier. Larger datasets usually provide more balanced samples, allowing RFs to learn discriminative features across all emotions.
4. Statistical Stability: TF-IDF relies on document frequency statistics. With few documents, IDF values can be skewed (rare words get exaggerated importance). Larger corpora stabilize these statistics, so the model focuses on genuinely informative words rather than random rare terms.

RF is an ensemble method that is based on multiple decision trees, each trained on a bootstrap sample. The random state in the RF classifier controls the randomness in generating these bootstrap samples for each tree. Different random state settings result in different bootstrap samples, which means that each tree in the forest is trained on a slightly different subset of the data. The different data and feature subsets used to train individual trees, due to different random state settings, can lead to different learned patterns and structures of each tree. Although RF aims for diversity among trees to improve generalization, different random states can lead to different levels of diversity and, consequently, different overall ensemble predictions. Changing the random state settings can lead to different predictions on the test set, thus affecting the overall accuracy.

This study worked on three subsets of data, which are the training, validation, and test sets. The results could be different across different datasets, depending on many factors such as the characteristics of the data and the number of unique words in the dataset. Experimenting with other emotion detection datasets with very similar characteristics of the data to those tested in this investigation, the results could be very similar.

VI. CONCLUSION

The results of this study show the accuracy patterns of using the RF classifier with the TF-IDF and Count vectorizers at different random state settings, from 1 to 120 and 720, on three data subsets: training, validation, and test. Comparing the accuracy achieved with the TF-IDF and Count vectorizers shows that using the former achieved better accuracy on the training set, while using the latter provided better accuracy on the validation and test sets. The novelty of this research lies in the investigation of accuracy patterns on the three data subdata sets using the RF classifier with different random state settings and two different vectorizers, Count and TF-IDF. The findings show:

1. TF-IDF does not necessarily offer higher accuracy than the Count vectorizer.

2. Using the same dataset but with different data subsets, it is not necessary that using TF-IDF will help achieve higher accuracies than the Count vectorizer.
3. The Random state setting affects accuracy. Most previous studies did not focus on random state settings in the learning process and accuracy comparison. The findings imply that future research on accuracy comparison should examine different random state settings.
4. TF-IDF offers better results than the Count vectorizer in the training data, as expected, because it is much larger and contains more unique words than the validation and test sets. The Count vectorizer performs better on the validation and test sets, which are smaller and contain fewer unique words. However, there is a need to investigate overfitting issues, especially with TF-IDF, on specific dataset characteristics.

Future research could benefit from these findings, as follows:

1. Some random state settings in RF, with either the TF-IDF or Count vectorizers, could offer better accuracy than that achieved with 42, as seen in previous studies.
2. The TF-IDF vectorizer does not always offer higher accuracy than the Count vectorizer. However, TF-IDF can achieve better accuracy than the Count vectorizer when working with large datasets. Nevertheless, there is always a need to carefully examine overfitting issues.
3. Working with small datasets, the Count vectorizer can help achieve higher accuracy than TF-IDF.

Future research could also evaluate additional models, test different datasets, examine dataset characteristics, or explore other hyperparameters to extend the findings of this study.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGMENT

The authors thank Asst. Prof. Dr. Chinnawat Satsananan, Dean of the Faculty of Science and Technology, Suan Sunandha Rajabhat University, for permission to carry out this research.

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