

Comparison of K-Nearest Neighbor and Support Vector Machine Methods for Sentiment Classification of Public Opinion on the Merah Putih Cooperative

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Abstract

The Merah Putih Cooperative Program is one of the government policies that has generated diverse responses from the public on social media, particularly YouTube. The large number of comments generated makes sentiment analysis an appropriate approach for automatically identifying public opinions. This study aims to compare the performance of the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms in classifying public sentiment toward the Merah Putih Cooperative Program. The research data were obtained by scraping YouTube comments, followed by preprocessing stages consisting of cleaning, case folding, normalization, tokenizing, stopword removal, and stemming. Feature weighting was then performed using Term Frequency–Inverse Document Frequency (TF-IDF) before classification. The dataset was divided into 80% training data and 20% testing data. Model evaluation was conducted using a Confusion Matrix with Accuracy, Precision, Recall, and F1-Score metrics. The results show that KNN with $K = 3$ achieved an Accuracy of 55.81%, Precision of 58.04%, Recall of 55.81%, and F1-Score of 55.27%. Meanwhile, SVM achieved an Accuracy of 61.63%, Precision of 60.49%, Recall of 61.63%, and F1-Score of 57.72%. Based on these results, SVM performed better than KNN in classifying public sentiment toward the Merah Putih Cooperative Program. This study is expected to serve as a reference for selecting sentiment classification methods for social media data and as a basis for further research involving parameter optimization and a larger dataset.

Keywords: Sentiment Analysis, K-Nearest Neighbor, Support Vector Machine, TF-IDF, Merah Putih Cooperative, YouTube.

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Introduction

The Merah Putih Village Cooperative (KDMP) is a strategic government program aimed at strengthening the rural economy through the principles of cooperatives, mutual cooperation, and community empowerment. The program is expected to improve community welfare by developing microenterprises, strengthening food security, expanding access to financing, and optimizing local economic potential. As a national policy, the successful implementation of the Merah Putih Village Cooperative Program is strongly influenced by public acceptance and perceptions. Therefore, public opinion is an important indicator for evaluating the effectiveness of the program's implementation.

The development of social media has provided a space for the public to express opinions, criticism, and support for various government policies, including the Merah Putih Village Cooperative Program. Digital platforms such as YouTube, as well as online news portals, generate thousands of opinions in the form of text data that continue to increase every day. The large volume of data makes manual sentiment identification inefficient, time-consuming, and prone to evaluator subjectivity[1][2]. In addition, unstructured data makes it difficult to group opinions, meaning that the government does not yet have an objective picture of public perceptions of the program.

One solution that can be applied to address this problem is the use of text mining and sentiment analysis techniques. Sentiment analysis enables public opinions to be automatically classified into positive, negative, or neutral categories. However, the success of sentiment analysis is strongly influenced by the classification method used. Each algorithm has different characteristics for recognizing patterns in text data and therefore produces different levels of accuracy. Consequently, a study comparing the performance of several classification methods is needed to identify the most suitable algorithm for analyzing public sentiment toward the Merah Putih Village Cooperative Program[3][4].

This study aims to compare the performance of the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) methods in classifying public sentiment toward the Merah Putih Village Cooperative Program[5]. The comparison is expected to identify the method with the best performance, which can then be used as a reference for developing sentiment analysis systems in the field of public policy.

Previous studies indicate that sentiment analysis of Merah Putih Cooperative reviews and digital financial applications has been conducted by several researchers. Alfian Raidi Noor et al. (2025) conducted a study entitled "Comparison of Support Vector Machine and K-Nearest Neighbor in Sentiment Analysis of the 2024 Presidential Election." The study compared SVM and KNN using three feature extraction techniques, namely TF-IDF, Bag-of-Words (BoW), and Word2Vec.

The dataset consisted of more than 20,000 tweets from social media platform X. The results showed that the combination of SVM and TF-IDF achieved the highest accuracy compared with the other methods. Furthermore, M. Iqbal Fahilla Bukit (2025) conducted a study entitled "Comparison of KNN and SVM Performance in 2024 Election Results Sentiment Analysis"[6][7][8]. The dataset consisted of 506 public opinions from social media. The results showed that SVM achieved 77.45% accuracy, while KNN achieved 75.49%. Both algorithms performed well, but SVM was slightly superior. These studies indicate that Merah Putih Cooperative reviews can be used as a data source for sentiment analysis. However, previous research also shows challenges in sentiment classification, particularly in distinguishing the neutral class and handling class imbalance.

The contribution of this study is to provide a comparative analysis of the performance of the K-Nearest Neighbor and Support Vector Machine methods in classifying public sentiment toward the Merah Putih Village Cooperative Program using TF-IDF feature representation[9].

The results are expected to serve as a reference for academics in developing sentiment analysis research and as input for the government to understand public perceptions of the Merah Putih Village Cooperative Program more objectively, thereby supporting future policy evaluation and improvement strategies[10][11].

Literature Review

Sentiment analysis can be supported by machine learning techniques to identify patterns in public opinions based on social media comment data. This study compares K-Nearest Neighbor (KNN), which performs classification based on data proximity, with Support Vector Machine (SVM), which can construct an optimal separator between sentiment classes. The preprocessing stages include cleaning, case folding, normalization, tokenizing, stopword removal, and stemming, while TF-IDF is used to represent text data before classification. The performance of both methods is compared using Accuracy, Precision, Recall, and F1-Score. Based on the study by Utari and Muhammad Iqbal, SVM performed better than KNN in classifying public sentiment toward the Merah Putih Cooperative Program, with Accuracy values of 61.63% and 55.81%, respectively[1][12].

Research Methodology

The research was conducted systematically through the stages of problem identification, collection of YouTube comment data, literature review, preprocessing, feature weighting using TF-IDF, classification using K-Nearest Neighbor (KNN) and Support Vector Machine (SVM), and evaluation using a Confusion Matrix. The comment data were classified into positive, negative, and neutral sentiments, and the KNN and SVM results were then compared based on classification performance to determine the better method for analyzing public sentiment toward the Merah Putih Cooperative[5][8].

Results

3.1 Dataset

The research dataset consisted of 433 public comments concerning the Merah Putih Cooperative, obtained through YouTube scraping. The data underwent preprocessing, were weighted using TF-IDF, and were classified using KNN and SVM. The performance of both algorithms was compared based on accuracy, precision, recall, and F1-score to determine the best method for classifying positive, negative, and neutral sentiments. Examples of the scraped data are presented in Table 1.

Table 1. Dataset of Scraped YouTube Comments

No	Username	Comment	Number of Likes
1	@AgustinusRomy	Hopefully it will quickly add to the country's losses	0
2	@user-lf5mb5iv5j	If there are many companies in Bandung, they could cooperate with the cooperative so employees can buy everything there and have the payments deducted from their salaries each month	0
3	@Satriobramasta	R 🤔	0
4	@user-ev4br1pe7c	It will not quickly recover its capital if products are sold cheaply; the building/store cost alone is 1.6 billion	0
5	@leaalkaisar	Even if the store is quiet, employees are still paid. If the owners are government officials, it does not matter because they have plenty of money. I would rather buy at the shop next door.	0
6	@AgusSumarna-q5i	Can Nganjuk do it? At my shop I can buy on credit, for example one pack of noodles and one cracker.	0
7	@SeptianiSanti-jw2qn	There is none in my area yet, so I am curious 🤔	0

8	@AdiPratama-e7c	Adi and Mujab lack education	0
....			
43 3	@Iway_sri	HTI 😊 😊	0

3.2 Preprocessing

The preprocessing stage was conducted to clean the Merah Putih Cooperative comment data through Cleaning, Case Folding, Normalization, Tokenizing, Stopword Removal, and Stemming. The preprocessed data were then weighted using TF-IDF and classified using KNN and SVM. The performance of both algorithms was compared based on accuracy, precision, recall, and F1-score to determine the best method. The results of Cleaning and Case Folding are presented in Table 2.

Table 2. Cleaning and Case Folding

No	Cleaning	Case Folding
1	Hopefully it will quickly add to the country's losses	hopefully it will quickly add to the country's losses
2	If there are many companies in Bandung, they could cooperate with the cooperative so employees can buy everything there and have the payments deducted from their salaries each month	if there are many companies in Bandung, they could cooperate with the cooperative so employees can buy everything there and have the payments deducted from their salaries each month
3	R	r
4	It will not quickly recover its capital if products are sold cheaply; the building/store cost alone is 1.6 billion	it will not quickly recover its capital if products are sold cheaply; the building/store cost alone is 1.6 billion
5	Even if the store is quiet, employees are still paid. If the owners are government officials, it does not matter because they have plenty of money. I would rather buy at the shop next door.	even if the store is quiet, employees are still paid. if the owners are government officials, it does not matter because they have plenty of money. i would rather buy at the shop next door.
6	Can Nganjuk do it? At my shop I can buy on credit, for example one pack of noodles and one cracker.	can nganjuk do it? at my shop i can buy on credit, for example one pack of noodles and one cracker.
7	In my area there is still none, so I am curious	in my area there is still none, so i am curious
8	...	...
433	HTI	hti

During preprocessing, normalization and tokenizing were performed to prepare public comments about the Merah Putih Cooperative for sentiment classification. Normalization aims to convert non-standard words, abbreviations, or informal language into more standardized and consistent forms. Tokenizing then divides sentences into words or tokens so that each word can be processed and analyzed using TF-IDF, K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). The results of these two stages are presented in Table 3.

Table 3. Normalization and Tokenizing

No	Normalization	Tokenizing
1	hopefully quickly add to country's losses	['hopefully', 'quickly', 'add', 'to', 'country', 'losses']

2	if in bandung many companies cooperate with the cooperative employees can shop everything later deducted every month salary	['if', 'in', 'bandung', 'many', 'companies', 'cooperate', 'with', 'the', 'cooperative', 'employees', 'can', 'shop', 'everything', 'later', 'deducted', 'every', 'month', 'salary']
3	r	['r']
4	will not quickly recover capital if selling cheaply building/store cost alone billion	['will', 'not', 'quickly', 'recover', 'capital', 'if', 'selling', 'cheaply', 'building/store', 'cost', 'alone', 'billion']
5	although quiet employees still paid owners officials no problem money plenty i prefer buying at shop next door	['although', 'quiet', 'employees', 'still', 'paid', 'owners', 'officials', 'no', 'problem', 'money', 'plenty', 'i', 'prefer', 'buying', 'at', 'shop', 'next', 'door']
6	can nganjuk do it because at my shop i can buy on credit for example noodles crackers	['can', 'nganjuk', 'do', 'it', 'because', 'at', 'my', 'shop', 'i', 'can', 'buy', 'on', 'credit', 'for', 'example', 'noodles', 'crackers']
7	in my area there is still none so i am curious	['in', 'my', 'area', 'there', 'is', 'still', 'none', 'so', 'i', 'am', 'curious']
8	...	...
433	hti	['hti']

After tokenizing, Stopword Removal and Stemming were performed to reduce unnecessary words and simplify word forms. Stopword Removal aims to remove common words that contribute little meaning to sentiment classification, while Stemming converts inflected words into their root forms. The results of these two stages are presented in Table 4.

Table 4. Stopword Removal and Stemming

No	Stopword Removal	Stemming
1	['hopefully', 'quickly', 'add', 'losses', 'country']	hopeful quick add loss country
2	['if', 'bandung', 'companies', 'cooperative', 'employees', 'shop', 'deducted', 'salary']	bandung business cooperative employee shop deduct salary
3	['r']	r
4	['quickly', 'capital', 'sell', 'cheap', 'cost', 'building/store', 'billion']	quick capital sell cheap cost building/store wild
5	['quiet', 'employees', 'paid', 'officials', 'money', 'plenty', 'prefer', 'buy', 'shop', 'next', 'door']	quiet employee paid official money plenty prefer buy shop next door
6	['nganjuk', 'because', 'shop', 'nganjuk', 'example', 'noodles', 'crackers']	nganjuk because shop nganjuk example noodles crackers
7	['area', 'curious']	area curious
8	...	...
433	['hti']	hti

3.3 WordCloud Data Visualization from Processed Data

The WordCloud visualization is used to display the most frequently occurring words in public comments about the Merah Putih Cooperative after preprocessing. The larger the word, the higher its frequency. The WordCloud is generated from the stemming results and therefore displays only root words that have undergone cleaning, normalization, and stopword removal. This visualization is used to identify dominant words and understand topic tendencies before TF-IDF weighting. The resulting TF-IDF weights are then used in

sentiment classification using the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms. The WordCloud visualization of all comment data is shown in Figure 2.



Figure 2. WordCloud

3.4 Data Labeling

Sentiment labeling is the process of assigning a sentiment category to each public comment concerning the Merah Putih Cooperative. In this study, labeling was performed manually by grouping comments into three classes: positive, negative, and neutral. Positive comments contain support or appreciation for the program, negative comments contain criticism or rejection, while neutral comments contain information or opinions that do not show a particular sentiment tendency. The labels were used as target classes in the sentiment classification process. The labeled data were then processed using Term Frequency–Inverse Document Frequency (TF-IDF) weighting and classified using K-Nearest Neighbor (KNN) and Support Vector Machine (SVM). The classification results of both algorithms were compared based on accuracy, precision, recall, and F1-score to determine the method with the best performance in classifying public sentiment toward the Merah Putih Cooperative.

Table 3. Data Labeling

Comment	Sentiment Score	Label
hopeful quickly add loss country	2	Positive
if bandung business cooperative employee shop deduct salary	3	Positive
R	0	Neutral
quick capital sell cheap cost building/store wild	9	Positive
quiet employee paid official money plenty prefer buy shop next door	-1	Negative
nganjuk because shop nganjuk example noodles crackers	0	Neutral
in my area curious	0	Neutral
adi mujab education	2	Positive
prabowo share portion certainly wise	6	Positive
pity for village people's business, truly cruel	5	Positive
operation aims to absorb farmers' crops, fertilizer provision, savings and loans to help the people	8	Positive
which DPR member represents the village? who defends this phenomenon? cooperative kills shop businesses; whose voice is heard? hopefully officials will help	0	Neutral

stress	4	Negative
look at the village, buy	-4	Positive
KPK intervenes; KPK audits criminal elements of corruption; KPK arrests	5	Negative
corrupt material	-9	Negative
if members borrow money for the cooperative savings and loan program	-3	Negative
Alfa/Indomaret stores, shop, complaint	-3	Neutral
Merah Putih operation, corruptors; government program aimed at corruptors	0	Positive
not good	3	Neutral
moal baleg	0	Netral

3.5 Sentiment Classification

In this study, the dataset that had undergone preprocessing and sentiment labeling was divided into two parts: training data and testing data. The data were divided using an 80:20 scheme, with 425 data points (80%) used as training data to train the sentiment classification model and 107 data points (20%) used as testing data to evaluate the model's ability to classify previously unseen data. Thus, the total data used in this study was 532 data points.

Table 4. Training and Testing Data

Data Type	Number of Data	Percentage
Training	341	79.86%
Testing	86	20.14%
Total	427	100%

3.6 KNN Implementation

K-Nearest Neighbor (KNN) is one of the supervised learning methods used in this study to classify public sentiment toward the Merah Putih Cooperative. KNN classifies test data based on their proximity or similarity to a number of the nearest training data points. The data used at this stage were preprocessed and sentiment-labeled data represented numerically using Term Frequency–Inverse Document Frequency (TF-IDF) weighting.

The KNN method was applied using data divided into 80% training data and 20% testing data. Training data were used as a reference for determining sentiment classes, while testing data were used to assess the model's ability to classify data not previously used during training. The data were divided using stratification so that the proportions of positive, negative, and neutral sentiment classes remained consistent in the training and testing sets.

The KNN classification process was performed by determining the parameter K, which represents the number of nearest neighbors used to determine the class of a data point. The value of K can be determined by testing several values to obtain the parameter that provides the best performance on the research data. The proximity between data points was then calculated based on TF-IDF feature values. Test data were classified according to the most dominant class among the K nearest neighbors.

In general, the KNN implementation in this study consisted of the following stages:

1. Use the TF-IDF matrix as the input features for the classification process.
2. Determine the training and testing data using an 80:20 ratio.
3. Determine the value of K, or the number of nearest neighbors.

4. Calculate the proximity between test data and training data based on TF-IDF features.
5. Select K training data points with the shortest distance to the test data.
6. Determine the sentiment class based on the majority class among the K nearest neighbors.
7. Generate sentiment predictions as positive, negative, or neutral classes.
8. Evaluate the KNN classification results using a confusion matrix, accuracy, precision, recall, and F1-score.

The KNN classification results were then compared with the actual sentiment labels in the testing data. These results were used to measure KNN's ability to classify public sentiment toward the Merah Putih Cooperative. The resulting evaluation values were then compared with the classification results of Support Vector Machine (SVM) to determine which method provided better classification performance on the research dataset.

3.7 Model Evaluation

Model evaluation was conducted using a Confusion Matrix to measure the performance of the K-Nearest Neighbor (KNN) algorithm. Based on the testing results, the best K value was K = 3, with Accuracy of 55.81%, Precision of 58.04%, Recall of 55.81%, and F1-Score of 55.27%. These results indicate that KNN correctly classified more than half of the test data, but still made errors, particularly for data with similar sentiment characteristics. The precision value indicates reasonably good predictions, while recall indicates that the model's ability to recognize data in each class still needs improvement. The KNN Confusion Matrix is shown in Figure 4.

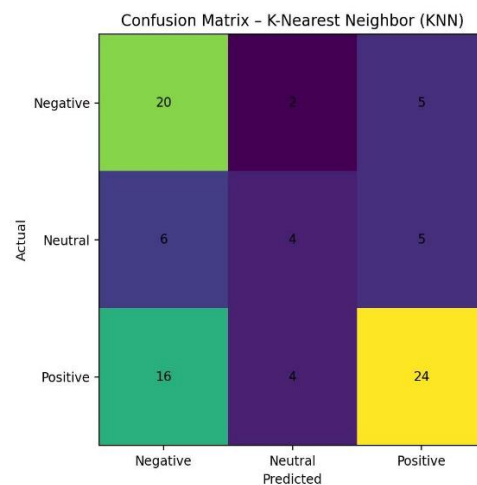


Figure 4. KNN Confusion Matrix

3.8 SVM Implementation

The Support Vector Machine algorithm was applied using TF-IDF representation with an 80% training and 20% testing data split. The testing results produced an Accuracy of 61.63%, Precision of 60.49%, Recall of 61.63%, and F1-Score of 57.72%. These results indicate that SVM has better ability than KNN to distinguish sentiment classes. The highest recall was obtained for the positive class at 86.36%, while the neutral class had the lowest recall at 13.33%, indicating that misclassification still frequently occurred. The SVM Confusion Matrix is shown in Figure 5.

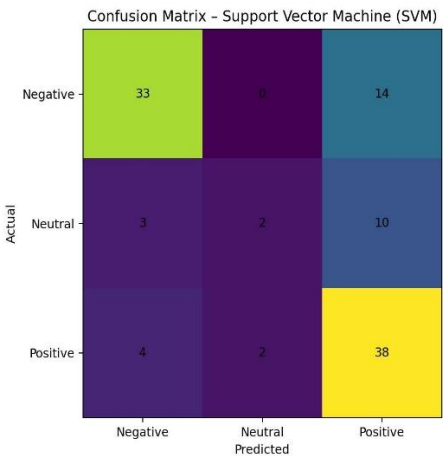


Figure 5. SVM Confusion Matrix

3.9 Comparison of KNN and SVM Algorithms

The comparison shows that SVM achieved higher Accuracy, Precision, Recall, and F1-Score than KNN. KNN achieved an Accuracy of 55.81%, whereas SVM achieved 61.63%. Therefore, SVM was more effective in identifying public sentiment patterns toward the Merah Putih Cooperative Program in this research dataset.

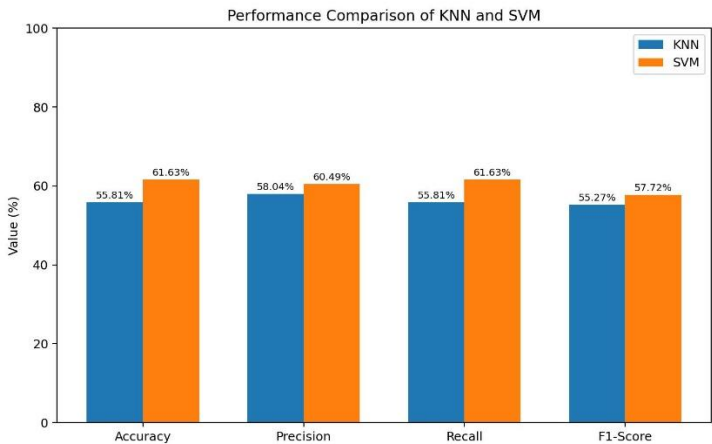


Figure 6. Performance Comparison Diagram

3.10 Discussion

Based on the research results, the K-Nearest Neighbor (KNN) algorithm with $K = 3$ achieved an Accuracy of 55.81%, Precision of 58.04%, Recall of 55.81%, and F1-Score of 55.27%. Meanwhile, the Support Vector Machine (SVM) algorithm achieved an Accuracy of 61.63%, Precision of 60.49%, Recall of 61.63%, and F1-Score of 57.72%. These results show that SVM performed better than KNN in classifying public sentiment toward the Merah Putih Cooperative Program. The differences in evaluation values indicate that SVM was better able to recognize patterns in TF-IDF-weighted data, resulting in more accurate classification than KNN.

These results are consistent with the study by Alfani Raidi Noor et al. (2025), which compared Support Vector Machine and K-Nearest Neighbor algorithms in sentiment analysis of the 2024 Presidential Election. That study used more than 20,000 data points from social media platform X and showed that the combination of SVM and TF-IDF produced better performance than KNN and other feature extraction methods. The consistency of the results indicates that SVM has better ability to classify high-dimensional text data because it can construct an optimal hyperplane to separate each sentiment class more effectively.

In addition, these results are consistent with the study by M. Iqbal Fahilla Bukit (2025), which compared KNN and SVM performance in sentiment analysis of the 2024 election results using 506 public opinion data points. The study reported that SVM achieved 77.45% accuracy, while KNN achieved 75.49%, making SVM the superior method. Although the accuracy in the present study was lower, the overall trend was the same: SVM provided better classification performance than KNN. Differences in accuracy may have been influenced by differences in dataset size, the characteristics of YouTube comments, sentiment-class distribution, labeling procedures, and preprocessing stages used in each study.

The accuracy in this study, which remained in the range of 55–61%, indicates that the classification process still faced several challenges. One influencing factor is the characteristics of social media comments, which contain non-standard language, abbreviations, emojis, and ambiguous sentences, making them difficult to clearly separate into positive, negative, and neutral classes. In addition, this study used three sentiment classes, making the classification problem more complex than studies using only two sentiment classes. These conditions may cause the model to misclassify comments, especially those with similar characteristics across classes.

Overall, the results show that Support Vector Machine is more suitable than K-Nearest Neighbor for classifying public sentiment toward the Merah Putih Cooperative Program in this research dataset. Nevertheless, the performance of both algorithms can still be improved by increasing the amount of data, balancing class distributions, optimizing model parameters, and applying better feature extraction or representation techniques. Thus, this study provides empirical evidence that SVM has better classification capability than KNN for public sentiment analysis of the Merah Putih Cooperative Program, while also serving as a reference for future research.

CONCLUSION

Based on the research results, it can be concluded that the K-Nearest Neighbor (KNN) and Support Vector Machine (SVM) algorithms can be applied to classify public sentiment toward the Merah Putih Cooperative Program based on YouTube comments. The research stages included data collection through scraping, preprocessing (cleaning, case folding, normalization, tokenizing, stopword removal, and stemming), feature weighting using TF-IDF, and model classification and evaluation using a Confusion Matrix. The evaluation results show that KNN with $K = 3$ achieved an Accuracy of 55.81%, Precision of 58.04%, Recall of 55.81%, and F1-Score of 55.27%. Meanwhile, SVM achieved an Accuracy of 61.63%, Precision of 60.49%, Recall of 61.63%, and F1-Score of 57.72%. Based on all four evaluation metrics, SVM performed better than KNN in classifying public sentiment toward the Merah Putih Cooperative Program. This study demonstrates that Support Vector Machine is a more effective method for sentiment classification on this dataset. Nevertheless, the accuracy obtained indicates that there is still room for performance improvement. Therefore, future research may consider using a larger dataset, balancing class distributions, optimizing algorithm parameters, and applying more optimal feature-selection or feature-representation techniques to improve classification results.

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