

Donation Intention Classifications Task in Non-Profit Organizations Based on Document Classification Techniques

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Abstract

In contemporary society, non-profits make up for what companies and the government lack. Fundraising and donor communication skills are crucial for success. This research uses natural language processing techniques to analyze donation messages, employing BERT embeddings combined with SVM, XGBoost, LLM model, and Voting Classifier. Results show that BERT significantly improves accuracy. The study recommends expanding the dataset and incorporating different platforms to enhance model precision, optimize fundraising strategies, and improve donor interactions, ultimately encouraging social contributions.

Keywords: Non-Profit Organizations, Natural Language Processing, BERT, Intent Detection

1 Introduction

In recent years, non-profit organizations (NPOs) have carried out significant social missions; their operating funds mainly come from donations from the public, forming "public funds" to support various initiatives and humanitarian aid work.

In an era of rapid development of artificial intelligence, investigating how to employ technology to increase fundraising efficiency has become a new challenge for NPOs. [Tseng \(2023\)](#) using precise text analysis on NPOs, can create targeted and successful fundraising strategies by better understanding the needs and intents of donors. Therefore, this research selects donation messages in online donations on NPO official websites as the research topic. This study develops a tool to automatically classify donation messages so that NPOs can automatically analyze many donation messages, accurately capture donors' concerns, needs, and opinions, and provide effective fundraising strategies and communication methods. To begin with, data pre-processing on donation messages will be performed to remove noise

and perform multi-label classification according to classification standards. The pre-trained BERT, Support Vector Machine (SVM), XGBoost, and LLM model in natural language processing (NLP) for feature extraction and classification. After training, the model's prediction performance was evaluated based on the Macro-average F1 score. Secondly, it is hoped that this research can provide NPOs with tools to process and analyze many donation messages efficiently. In addition, the research also established a rich data set of donor message intentions, laying the foundation for future model training and optimization. We expect that these tools and methods can help NPOs more effectively understand and respond to the needs of donors, provide more precise goals and directions for future fundraising strategies, leading to more effective social services and welfare provision.

2 Related Work

2.1 Research on Donations to NPO

In recent years, the COVID-19 pandemic has greatly impacted the charity sector in various countries, and Taiwan has not been immune. In the post-epidemic era, it is crucial for NPOs to increase the frequency of continuous donations. Research shows that for every 1% increase in fundraising, donations will decrease by 0.84%. Therefore, reducing the churn rate and increasing the "renewal rate" play an important role in the long-term stable development of the organization ([Marudas et al., 2012](#)). Donation behavior is affected by many factors, including age, income, gender, region, and education level. Research shows that economic status is a key factor, with donation amounts positively correlated to annual income ([Wang, 2023](#)). Not only that, according to statistics, men's total donation amount is relatively high, but women's donation willingness and frequency are higher. Therefore ([Chen, 2014](#)) believes that gender may be a potential factor in developing donation strategies.

In addition to introductions from relatives and friends, advertising, and tax saving, Yang (2023) pointed out empathy can trigger altruistic donation behavior. Hsiao (2020) discovered in his research that there is a significant positive correlation between the convenience of contribution and willingness to give. Highlights the value of diversified donation methods and channels.

As Taiwan enters an aging society, middle-aged and elderly people have become the main donor group. Nonetheless, NPOs will eventually need to cultivate potential donors from Generation Z. Targeting Generation Z donors, gifts and rewards are used to encourage donations and marketing techniques for placing fundraising gifts. These flash marketing strategies help attract cooperation and strengthen corporate social responsibility (Hsueh, 2014).

2.2 Message Analysis in Social Media Applications

With the rapid development of Internet technology, social media has become an indispensable platform for information exchange. NPOs can use these platforms to strengthen information dissemination, interaction, fundraising, and volunteer management, increasing public awareness, support, resource collection, and social influence. Facebook messages have become important for governments, businesses, and NPOs to understand users' emotions and opinions. According to Kuang (2015) research, message analysis can identify opinion leaders with a 70% chance of success and can discern between positive, neutral, and negative emotions with a 90% accuracy rate; Lee (2023) noted that LINE's ecology makes information transmission more convenient. Nonetheless, the age group of LINE users is relatively high, prompting NPOs to focus on engaging younger potential donors. In contrast, Instagram attracts many young users and combines pictures and short videos to become an important social media platform. Lin (2020) found that users often use emojis to express their feelings and appreciation of food.

Overall, NPOs need to understand the characteristics and limitations of each platform and formulate appropriate fundraising strategies to promote fundraising activities and improve donation efficiency.

2.3 Application of Deep Learning and Machine Learning in Sentiment Analysis

With the rapid development of deep learning and machine learning technologies, text classification and sentiment analysis fields have advanced dramatically in recent years. BERT (published by Google in 2018) has brought breakthrough development in sentiment analysis. Based on the Transformer architecture, it can consider the contextual information of words at the same time and achieve good results when applied to multi-category, multi-label, and multi-output classification. In addition, machine learning has demonstrated excellent capabilities in sentiment analysis problems. Support vector machine (SVM), as a powerful supervised learning model, is often used to solve classification and regression analysis problems. Lin (2020) used SVM to predict the rise and fall of the foreign exchange market using news headlines, showing its successful application in financial markets. Another machine learning algorithm, Extreme Gradient Boosting (XGBoost) (Chen & Guestrin, 2014), is an efficient gradient-boosting tree algorithm. Huang & Wang (2023)'s research used the post data set of China's Sina Weibo during the COVID-19 period for sentiment analysis, utilizing XGBoost to determine the correlation between the word vector sparse matrix and the user's mental health status. The findings indicate that the epidemic has an extremely negative impact on people's psychology.

This study further explores the application and advantages of voting classifiers. Integrating multiple models improves performance while addressing bias and overfitting issues. Yang (2022) applied a voting classifier in Taiwan stock market futures trading to predict the closing price trend of Taiwan stock futures, which improved transaction efficiency. Based on the above, machine learning and deep learning have boundless promise in the NLP domain. They can offer more precise perceptions of people's feelings and actions, serving as valuable references. This research aims to develop an automatic message classifier to classify donation messages into ten categories. The tool will enable fast, accurate analysis of donation messages, supporting fundraising strategies across different contexts while capturing and analyzing social and emotional trends and behavioral intentions.

2.4 Large Language Models for Text Classification

Although large language models (LLM) have made significant progress in natural language processing, especially with zero-shot and few-shot tasks (Sun et al., 2023), LLM was used to predict donation intention by classifying challenged benchmarks. This is consistent with previous difficulties encountered using LLM in structured or hierarchical tasks, where the complexity and nuances of the label space constitute limitations. Auto-regressive-based LLMs like GPT (Touvron et al., 2023; OpenAI, 2024) generate text one token at a time conditioned on previous inputs. Despite LLMs being powerful API-accessible tools that let you make heuristic-based hints without any training task-specific, they may not always get accurate classification, specifically in more complex or less sophisticated tasks. Sun et al. (2023), LLM does well in flat classification problems. Still, it is unsuitable for tasks with highly structured label spaces, such as the hierarchical donation intention classification task used in this study. Said results suggest that, while LLM is a promising approach for some NLP tasks, the structure of labels in more complex or nuanced contexts could demand further tuning the need to complement the classification model with other methods.

3 Method

This study proposes to create a dataset for the donation intent classification, which is collected from donation websites for NPOs, and define the label of donation intent by human annotation. Finally, we apply several machine learning and deep learning models to train and predict the donation intent. The research framework is shown in Figure 1.

3.1 Dataset

In this section, we describe the process of collecting donation information from the donation database of NPOs official website. These messages reflect donors' remarks, feedback, and needs during the donation process, typically showing support for organizations, events, or service projects. The messages range in content and length and contain emojis, Chinese, and English. Some may be brief expressions of gratitude, while others can be more in-depth and sentimental assessments. The data collection covers 2020/01 to 2023/07. The original

data from the NPOs official website contains 22,994 messages.

3.2 Data Preprocessing

In this study, following the collection of donation messages from NPOs, we manually processed the data to ensure the quality of the training set and consistency in feature extraction. This involved reviewing each message and removing irrelevant characters, duplicate content, and unusual conditions to ensure data consistency and accuracy; we carried out the following data noise-cleaning tasks: (1) Emoji emoticons and special symbols: They will be deleted if there is no semantic change or is redundancy. (2) HTML special tags and syntax, such as `
`, to prevent sentence fragmentation or different semantics. (3) Punctuation: Delete as it adds nothing to the message's original meaning. (4) Duplicate messages: Removed to avoid negatively impacting the training process. While emoticons often convey emotional intent, we removed these symbols to maintain consistency and clarity in our analysis, especially when they were used to repeat the emotional expression of an existing message. After data processing, 4717 messages were finally

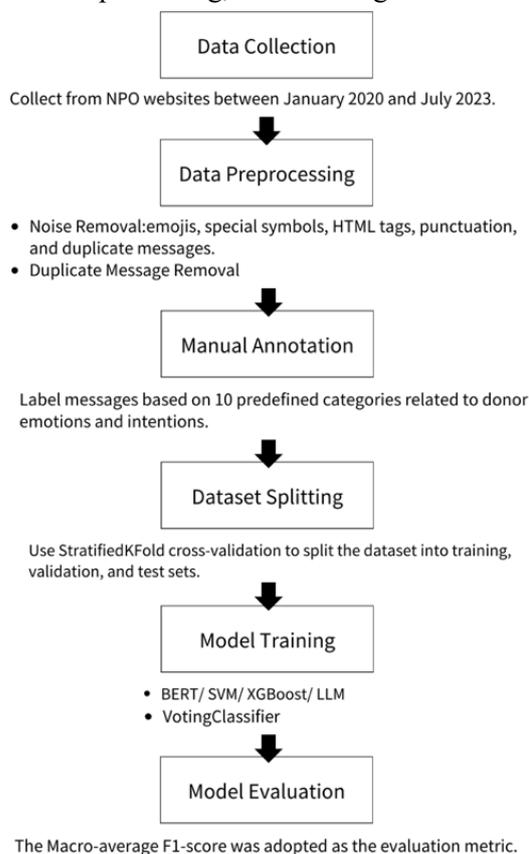


Figure 1. Research Process Flowchart

Categories Type	Definition	Example
Support Again	Supporters who have donated may clearly indicate their continued support for the organization in their messages, or update the authorization information due to changes in card information.	"I have donated before and am willing to continue to support."
Environmental Protection	Donors' actual actions and expectations for environmental protection, may want to switch from paper to electronic forms to expressing their support for environmental protection through digital channels.	"No need for paper DM"
Personal Information	Donors are concerned about privacy protection and ensure that donors' personal and financial flow information are properly protected to prevent data leakage or improper use, and whether the donation will be made public. (Those who leave their name, address or phone number in the donation message also fall into this category.)	"Who am I? What is my phone number and company name?"
Taxation	Donors want to know whether their donations are eligible for tax deductions and how to obtain relevant tax receipts or documents. There are also issues related to tax savings.	"Can this donation be used for tax filing?"
Giveaways	When people donate to charities, some organizations will provide gifts in full to express their gratitude and encourage for the donation. Donors may have questions about the gift.	"I want to ask for a thank you gift" or "I don't need any gifts"
Gratitude	Donors may express their gratitude and appreciation to the charity and praise it for supporting rural and disadvantaged groups or share their own experiences of benefiting from the organization.	"I sincerely thank you for your work, you did a great job!"
Encouragement and expectations	Donors may leave messages to express their support and expectations for the charity and full of expectations for the organization's future and encourage the organization to make greater contributions to social welfare.	"Thank you for your hard work! Come on!"
Care and blessings	Donors may express blessings and good wishes in their messages, hoping that underprivileged groups would be able to overcome obstacles and lead fulfilling lives.	"I pray for these children that their lives will be filled with joy and success."
Hope	Through words of encouragement, donors convey positive energy and encourage underprivileged groups to face challenges, establish and achieve success.	"Seeing the hard work of children in rural areas, I hope my donation can bring them more opportunities."
Empathy	Donors convey empathy, identification, and understanding with underprivileged populations in their communications. They will also express their recognition for the charity's development plans.	"I have also faced difficulties, and I understand their situation."

Table 1. The Definition and Examples of Ten Donation Intentions.

selected for this study's data set. Using the labeling criteria to complete the manual token samples, the statistics show that 4192 messages belong to 1 category, 502 messages belong to 2 categories, and 23 messages belong to 3 categories.

3.3 Manual Annotation

This study summarizes the message analysis and further establishes a classifier of donation intention. The classifier has designed ten category labels, covering the emotional expression and specific intentions of donors, including "Support Again," "Environmental Protection," "Taxation," "Gifts," "Personal Information," "Empathy," "Hope," "Gratitude," "Cheers and Expectations," and "Care and Blessings." These labels reveal their personal motivations, identification with the organization, and expectations for feedback. The distribution and proportion are shown in Table 2. It also enhances the organization and donation connections, fostering a more sustainable and stable support base. To make the manual annotation process more efficient and accurate, the definition of each category needs

to be further refined, and examples should be provided. Further refined and examples provided, as shown in Table 1

Since a donation message may contain two or more categories, this study adopts a multi-label tagging method so that messages with multiple meanings can be labeled under different categories.

Label	Annotations	Proportion
Support Again	942	18.0%
Environmental Protection	153	2.9%
Personal Information	316	6.0%
Taxation	228	4.3%
Giveaways	269	5.1%
Gratitude	701	13.4%
Encouragement and Expectations	720	13.7%
Care and Blessings	611	11.7%
Hope	694	13.2%
Empathy	608	11.6%
Total	5242	100%

Table 2. Label Distribution and Proportion

3.4 Experimental Design

In recent years, with the advancement of deep learning, NLP models based on neural networks, especially BERT, have achieved remarkable success in various NLP tasks. This study used the pre-trained BERT model and supervised learning methods to classify donation message data and established a classifier for the donation intention classification problem. To ensure the validity and generalization ability of the model, we used the StratifiedKfold stratified cross-validation method to divide the dataset into five folders with fixed randomness (random state is set to 42). Three approaches were used for model training: deep learning, LLM, and machine learning.

For deep learning, the "bert-base-chinese" pre-trained BERT model was used, and parameters such as learning rate, epochs, and batch size were adjusted to build a binary classification model. Additionally, the GPT-4o-mini LLM model was used for message classification, enhancing classification accuracy through semantic understanding and natural language generation.

In the machine learning part, after tokenization with Jieba, TF-IDF and Word2Vec techniques were applied to transform the text while tuning the regularization parameter (C) and kernel function of SVM, as well as the learning rate, max depth, and the number of decision trees in XGBoost to improve classification accuracy and performance. The research also built an integrated model (VotingClassifier), combining SVM and XGBoost, adjusted the parameters, and used Soft Voting to calculate the prediction probability of each classifier and select the result.

The model performance was evaluated using the Macro-average F1-score, providing a comprehensive analysis of the effectiveness of different methods.

3.5 Evaluation Metric

In this study, the donation intent classification problem belongs to a multi-label task. Therefore, we build ten classifiers for ten donation intents. Each intent category is trained and estimated independently. The Macro-average F1-score measurement metric to evaluate the model's prediction performance of each classifier. The macro-average F1-score calculates the F1-score for each donation

intent category and then uses the average of these scores as the performance indicator of the model. This ensures that the ten categories of donation intention are treated as equally important, regardless of the information between categories and the imbalance problem. Macro-average F1-score calculates the F1 score of each category and averages all F1. N is the total number of ten categories. $F1Score_i$ is the F1 score of the i -th category, which is the average precision and recall. The formula is as follows:

$$MacroAverage\ F1Score = \frac{1}{N} \sum_{i=1}^N F1Score_i$$

In the results and analysis, comparisons will be made with other models, and Macro-average F1-score will be unified as the final evaluation index.

4 Experimental Results

This research aims to achieve the best combination of performance and efficiency through fine parameter adjustment of deep learning and machine learning models. We conducted extensive performance testing on the BERT model, adjusting parameters such as learning rate and epoch to achieve the optimal configuration. At the same time, the GPT-4o-mini as an LLM model was used for message classification, enhancing classification performance through background definition and semantic understanding. The SVM and XGBoost algorithms were used, and the Kernel type, C parameters, max depth, and number of n_estimators were experimentally adjusted to find the best parameter combination. In addition, the VotingClassifier integrated model was established by combining these two algorithms, and the soft voting method was used to calculate the average value of the predicted probability, which improved the stability and accuracy of the model.

The experimental design of this study significantly improved the prediction accuracy of the model and the robustness of the results, and provided key parameter settings for each model to achieve optimal performance.

4.1 Prediction Performances

For each category in the dataset, the data was divided into five independent folders, each containing training and testing data. On the BERT model, the Macro-average F1-score is 0.9806, and the

classification prediction result is 0.8792, which exceeds all test models. The second is the SVM model, which is verified that the F1-score is 0.8731 and the test is 0.8095; the XGBoost model is verified at 0.8408 and the test is 0.7653; while the VotingClassifier model is verified as F1-score is 0.7965, the test is 0.7945; the LLM model performed with a verified F1-score of 0.4989 and a test F1-score of 0.3391. It can be seen that it performs best in BERT classification performance. As shown in Table 3.

Model	Macro-average F1-score	
	Validation Set	Training Set
BERT	0.9806	0.8792
LLM	0.4989	0.3391
SVM	0.8731	0.8095
XGBoost	0.8408	0.7653
Voting Classifier	0.7965	0.7945

Table 3. Classification Effectiveness of Different Classifiers

4.2 BERT Result Analysis

During the training process of the BERT model, we set the learning rate to $1e-5$ and the epoch to 13, and obtained the best Macro-average F1-score: 0.9806 on the verification set, as shown in Figure 2. The figure shows that the model with the learning rate set to $1e-5$ performs best. As the epoch increases, the F1-score gradually increases and reaches the highest at the 13th epoch, stabilizing and maintaining a high score level. Comprehensive observation, setting the learning rate to $1e-5$ can achieve the best results because it achieves a good balance between fast learning and stability of the model.

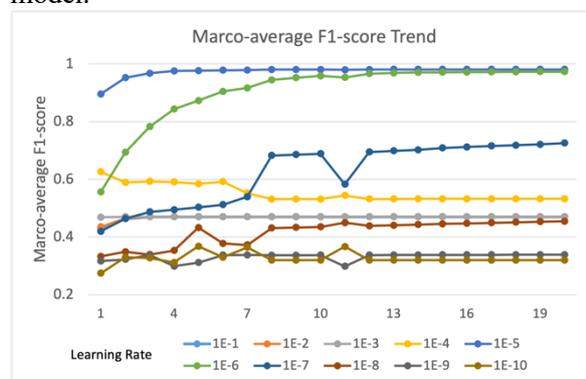


Figure 2. Marco-Average F1-Score Trend

4.3 LLM Result Analysis

When the temperature parameter was adjusted to 0.2, it showed better predictiveness; decisions were

more focused and consistent. This change greatly improved the performance and achieved the highest Macro-average F1-score of 0.49 on our validation set, indicating a significant improvement in classification accuracy.

However, these results are still low compared to the others, like BERT, SVM, and XGBoost, demonstrating that LLM is limited in recognizing and classifying donation intents only based on internal knowledge and thinking. Leveraging other techniques such as fine-tuning, multi-task learning, or including external knowledge bases can help the model better classify nuanced and cortical donation intentions.

4.4 SVM Result Analysis

We discovered that the impact of the kernel function on the data set varied greatly when training SVM models using various methods. When using TF-IDF technology for SVM model training, the cost was 10, Kernel was linear, and the best Macro-average F1-score was 0.8731 on the validation set. Figure 3. shows the parameter trend, where the linear kernel acts steadily, and the F1-score rapidly peaks and stabilizes as the cost value rises. On the other hand, the best Macro-average F1-score of 0.4959 was obtained on the validation set when employing Word2Vec technology for SVM model training, with cost set to 10 and Kernel to poly. The performance was relatively low, particularly with the sigmoid and linear kernels, which failed to improve the results significantly.

These findings demonstrate the linear kernel of TF-IDF is more suitable for high-dimensional data with sparse features in text classification, effect-

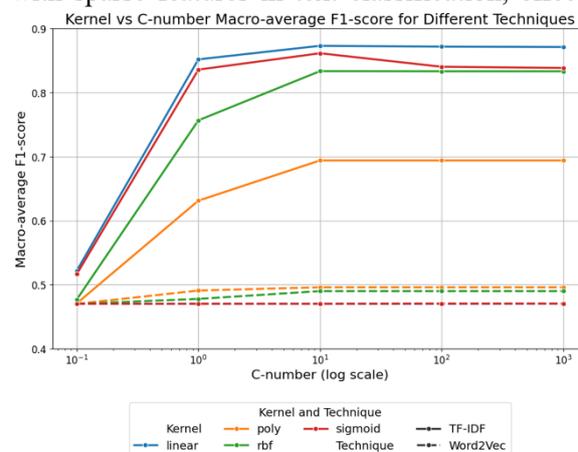


Figure 3. Kernel vs. C-number Macro-average F1-score for Different Techniques

tively capturing key semantic features. In comparison, while Word2Vec has the advantage of semantic connection in low-dimensional vector spaces,

its performance is not as good as expected in specific applications, such as multi-category classification.

4.5 XGBoost Result Analysis

During the training of the XGBoost model, when the learning rate was set to 1e-1, maximum depth to 5, and the number of estimators to 300, the best Macro-average F1-score of 0.8408 was achieved on the validation set, as shown in Figure 4. Figure 5 shows that as the learning rate increased, the model performance showed an upward trend but slightly declined after the learning rate reached 0.05. Furthermore, there was a clear interaction between tree depth and learning rate. For instance, at a learning rate of 0.1 and a tree depth of 5, the model reaches the highest F1-score of 0.8408, while at a tree depth of 9, a lower learning rate of 0.01 results in a lower F1-score of 0.82294. As the number of trees increased, model performance became more stable, but excessive depth could lead to overfitting. XGBoost demonstrates strong performance stability in multi-class classification tasks, particularly when handling large datasets and sparse features. Therefore, adjusting the learning rate, tree depth, and the number of trees according to the dataset's characteristics to improve model accuracy and stability across different applications must be carefully balanced to avoid unnecessary computational burden and over-fitting.

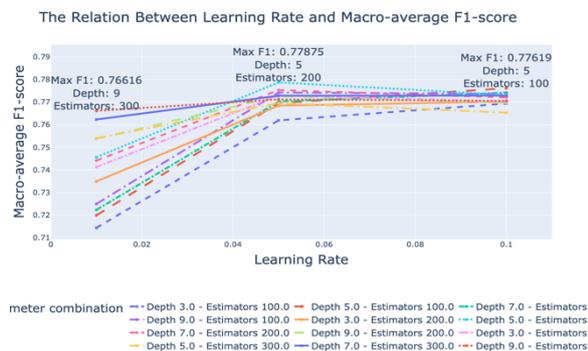


Figure 4. Learning Rate: 1e-1 Macro-average F1-score vs Max_Depth for Different N_Estimators

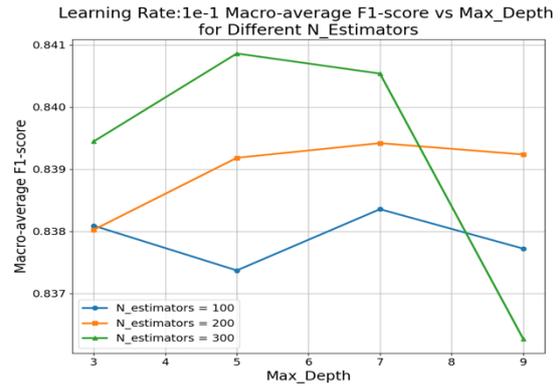


Figure 5. The Relation Between Learning Rate and Macro-average F1-score

4.6 Voting Classifier Result Analysis

The VotingClassifier designed in this section combined the optimal parameter configurations of SVM and XGBoost, using a 'soft' voting strategy to achieve better final classification results. The model achieved a Macro-average F1-score of 0.7945 on the test set, surpassing the performance of the standalone XGBoost, but slightly lower than the F1-score of 0.7965 on the validation set. This shows that although VotingClassifier combines the advantages of both algorithms, its overall performance may still be limited when encountering inconsistencies in handling certain class samples, particularly with edge cases. Theoretically, the integration method can improve the model's generalization ability, but in practical applications, it still requires careful planning and modification to produce better outcomes.

4.7 Misclassification Summary

Table 4 highlights which categories were most affected by model misclassifications. It was found that messages in the "Support and Encouragement" category mostly expressed support and encouragement for recipients, but these emotions are easily related to the "Gratitude" or "Hope" categories. Misclassifications in the "Empathy" category mainly occurred in messages containing abstract or strong emotions, highlighting the limitations of the current models in processing delicate emotions and deep empathy. This study also found that in the "Personal Information" category, the choice of word segmentation tools impacts the model's determination of personal information. For example, the model failed to correctly identify key information

in addresses or names, such as the complete address or name in '***Receipt,' leading to unexpected segmentation results and affecting classification accuracy.

Category Labels	Misclassification
Support Again	11
Environmental Protection	5
Personal Information	29
Taxation	9
Giveaways	12
Gratitude	9
Encouragement and Expectations	55
Care and Blessings	43
Hope	15
Empathy	56
Total	244

Table 4. Statistics of Models' Misclassifications

5 Conclusions

In conclusion, through detailed analysis and improvement, this study aims to introduce deeper emotion recognition techniques or strengthen the semantic understanding ability of the model in future applications, helping the model to more effectively process texts involving complex emotions and abstract concepts, thereby improving overall classification performance.

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