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Natural language processing technology in cross-border e-commerce: Sentiment Analysis and Customer Satisfaction Enhancement Based on French Product Reviews

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SUMMARY: *In short, the French product reviews on the cross-border e-commerce platform are full of users' emotions and feelings. Due to the complex grammar and implicit expressions in French, the old ways of sentiment analysis have been less effective. Therefore, this paper builds an integrated sentiment analysis and satisfaction prediction model named FSA-Net for French reviews. Through French text preprocessing, bidirectional GRU sequence modelling and a multi-scale emotion perception mechanism, the joint recognition of explicit and implicit emotions has been achieved. At the same time, a satisfaction fusion layer and a gating adjustment strategy are introduced to improve the non-linear mapping ability of emotions to scores. The two sets used for evaluation were the French-Amazon dataset (about 12,000 entries) and the self-built FRC dataset (8,200 entries). FSA-Net had an accuracy of 0.889 and an AUC of 0.944 for FAR, and an AUC of 0.931 for FRC. All of them outperformed the Bi-LSTM baseline model; the mean training deviation was still 0.0387, but stability had increased significantly. Based on the above results, the proposed model can improve the accuracy of emotion recognition and satisfaction prediction for French reviews effectively, and thus provides a practical technical path for the localisation intelligent analysis of cross-border e-commerce platforms.*

KEYWORDS: *NLP; Cross-border E-commerce; Satisfaction Prediction; GRU Network*

1 Introduction

With the development of global digital trade in recent years, cross-border e-commerce has been one of the fastest-growing areas in the world's international trade. Therefore, user-generated content (UGC) has gradually entered the consumer's purchase decision-making process and is now affecting the behaviour of consumers in other ways and building brand images through real-life product experiences. Review texts have diverse languages and cultures in the French market as well. The emotions and happiness data in this set of data are now needed to understand what consumers want and adjust service plans accordingly.

Sentiment analysis is a type of general problem in Natural Language Processing (NLP) that has been widely studied and applied recently in many places, such as business intelligence, public opinion research, and customer relationship management. French product reviews have a complex text structure and implicit emotional expression; coupled with the inflections and free word order of the French language, traditional sentiment analysis methods face bottlenecks in high-difficulty modelling and shallow semantic understanding. The accuracy of emotional feature extraction for comments and deep connections among these features with customer

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satisfaction need to be addressed urgently in the field of cross-border e-commerce research.

Most of the current mainstream sentiment analysis methods are based on English corpora, and thus they have problems of poor model generalisation and weak support for low-resource languages. Research on French product reviews of cross-border e-commerce platforms is also lacking, and a system of multi-level processing has not yet been established. Therefore, to improve the cross-lingual text-understanding ability of a model, build an integrated sentiment analysis model that combines multi-layer embedding, deep sentiment recognition and satisfaction prediction mechanisms, and offer data support for localized marketing and intelligent recommendations on e-commerce platforms.

A Sentiment Analysis Method for French Cross-border E-commerce Scenarios is proposed here. The primary contributions of this paper are as follows:

A natural language processing technology flow of three stages was designed and implemented for French preprocessing, sentiment feature extraction and satisfaction modelling to enhance the adaptability and analysis depth of the model for French text.

B. An integrated sentiment analysis network that combines the text embedding layer, the sentiment recognition core layer and the satisfaction fusion layer has been built, and it performs well in the collaborative modeling of semantic understanding and sentiment prediction.

C. Based on a real French product review dataset, several baseline models were tested in experiments to evaluate the accuracy of emotion recognition and satisfaction prediction by the proposed method.

The structure of this paper is as follows: Section Two introduces the research results of related studies; Section Three presents the main technical modules for French comment processing; Section Four shows the general architecture of the combined analysis model; Section Five carries out experiment design and result analysis; Section Six concludes the content in full and puts forward future research directions.

2 Review of Relevant Research

A representative work in Natural Language Processing (NLP) is sentiment analysis, which is used to detect or reveal the subjectiveness, emotions and attitudes expressed in text. With the rapid development of user-generated content (UGC) in cross-border e-commerce, sentiment analysis has gradually started to be used to collect consumer feedback from product reviews for improving service quality and product recommendations, etc. In a multilingual environment, there are problems with semantic modelling in sentiment analysis, and additional difficulties need to be addressed, such as differences in language characteristics and cultural expressions; therefore, studies on this issue are also developing steadily.

Early studies were based on dictionary matching and rule templates; thus, they were unable to fully explore the deep semantics and context dependencies in comments. In recent years, the application of deep learning has also extended to this field. Ma et al. (2024) [1] put forward a multi-layer sentiment recognition model combining convolutional neural networks (CNNS) and gated recurrent units (GRUs) to predict users' purchase intentions, and achieved good results on several English product review datasets. Bellar et al. (2024) [2] have also proposed a Transformer mechanism to integrate sentiment labels with product features for enhanced modeling of comment sentiment trends and to boost the personalisation capability of the recommendation system. Chamekh et al. (2022) [3] have built a multi-channel neural network structure based on Bi-LSTM to perform parallel learning of different types of comment emotions for the emotion classification task in the e-commerce scenario; Wang et al. (2022) [4] proposed a hybrid deep model with an attention mechanism that showed better generalization ability for multi-task emotion prediction. Alzahrani and others (2022) developed an intelligent

analysis system based on the combination of convolutional, long short-term memory networks and fully connected layers specifically for comment processing on e-commerce platforms [5]. Based on the above experiments, the new way has shown better performance in both accuracy and recall than previous models.

Han and Han (2023) [6] have pointed out in the research context of cross-border e-commerce that cultural differences significantly affect the expression style of comments and the accuracy of sentiment classification, and therefore, adaptation mechanisms at the language and culture levels should be added to sentiment analysis systems, especially when dealing with non-English text such as French, German and Arabic; at this time, consideration should be given to semantic transfer and the mining of corpus characteristics. Mboungou et al. (2023) [7] developed an emotion recognition model for French e-commerce platforms and trained and tested it using a dataset of real French user reviews; they found that, in the case of multilingual processing, the language perception ability of the model structure is relatively prominent.

P.Iba et al. (2022) [8] have used a method that transforms into multiple spaces in order to help solve the problem of low accuracy in sentiment classification for low-resource languages by expanding their compatibility. Malik and Bilal (2024) [9] also noted in their review that the current sentiment analysis research urgently needs breakthroughs in multilingual compatibility, semantic fusion strategies, and accuracy of context modeling to meet the application requirements of cross-platform, multilingual and multi-scenario applications. Daza and others (2024) [10] have established a correlation model for predicting customer satisfaction based on the distribution of emotions, connecting emotional intensity and user ratings to find that emotional tendency is positively associated with both consumption willingness and repurchase behaviour. Venkatesan and Sabari (2023) [11] proposed a weighted hybrid deep model (DeepSentiModels) to build a comprehensive model of customer satisfaction in the integration of e-commerce and social e-commerce, and improved the intelligence of product recommendation and feedback response.

Although previous studies have achieved some good results in English sentiment analysis, organised studies of French commodity reviews are still relatively rare. On the one hand, French itself has rich verb conjugations and various rhetorical devices; therefore, its text representation and emotion extraction are relatively difficult. At the same time, the current models have weak transfer performance in the French context, and there are also problems such as semantic drift and emotional dilution. Therefore, the construction of a complete-featured sentiment analysis system for French product reviews with integrated modules of preprocessing, deep representation and satisfaction-sentiment mapping is expected to promote the improvement of local operating efficiency in cross-border e-commerce and enhance customer satisfaction.

In recent years, research on sentiment analysis for cross-border e-commerce has moved from a general category of emotion classification to many levels, such as measuring the intensity of emotions, predicting whether consumers will be satisfied, and building recommendation systems based on sentiment. There are still some structural defects in the current form of French review processing, cross-language sentiment modelling and satisfaction integration mechanisms. Based on the above research results, this paper will propose a natural language processing framework for French reviews and conduct in-depth exploration of the collaborative modeling of emotion recognition and satisfaction analysis.

3 French Comment Analysis Technology Based on Natural Language Processing

The three necessary technical modules for sentiment recognition and satisfaction prediction of

French product reviews in this study have been combined. Therefore, the individual steps of the selected core process need to be explained one by one. The three parts are, respectively, the French text pre-processing mechanism, the emotion feature extraction method and the emotion model for customer satisfaction. As shown in Figure 1, the process of the system begins with the original French comment. First, by means of preprocessing, language standardisation, stop word removal and word form restoration have all been carried out to enhance the consistency of the following feature model. Then, a model is used to express the features of emotion and, together with a context encoder, multiple dimensions of emotion words are embedded to obtain the implicit subjective emotions and tone changes in the comments. Finally, a non-linear mapping relationship is established between the polarity of emotions and satisfaction labels to obtain the prediction output of customer satisfaction degree. The whole is a closed-loop structure that includes language cleaning, deep recognition, satisfaction modelling, etc., and thus can greatly improve the robustness and accuracy of text processing for French with variable grammatical structures.

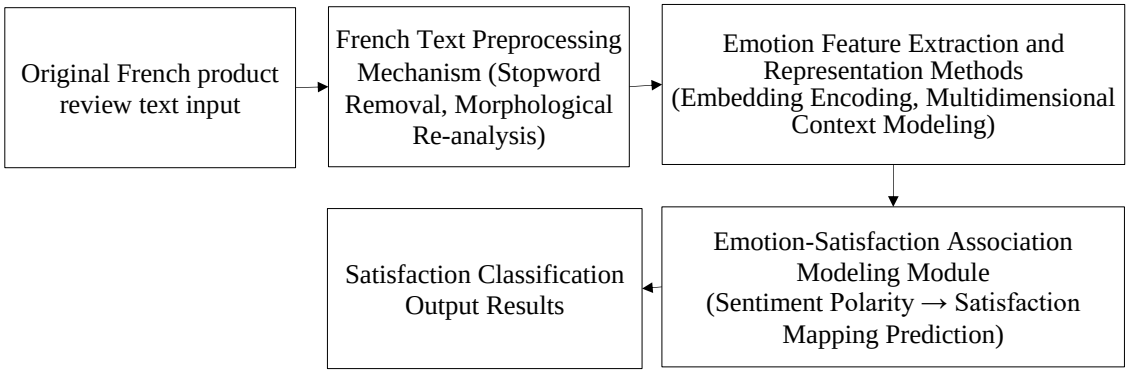

Figure 1: Three-stage Processing of Sentiment Analysis and Satisfaction Prediction for French Product Reviews

3.1 Preprocessing mechanism for French text

Cross-border e-commerce has also brought many problems to the handling of French product reviews, such as irregular word order, complicated conjugation rules and a high frequency of redundant modifiers. If it is not preprocessed well, the extraction of emotion attributes and the construction of the following model will be affected. Therefore, a hierarchical preprocessing flow was constructed for the original French review corpus in this study, and the four main steps are shown in Figure 2: text cleaning, language standardisation, word form restoration and subword decomposition.

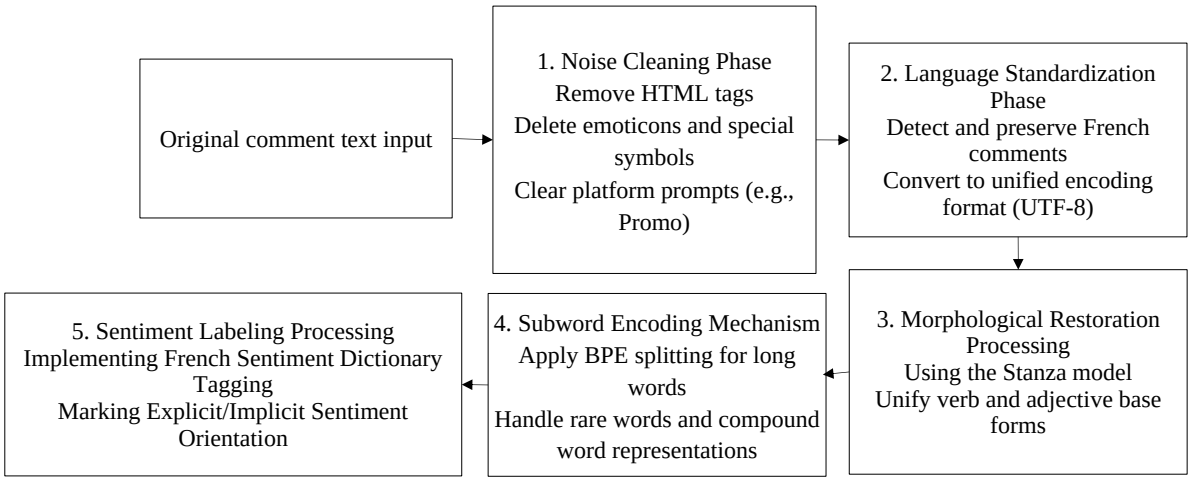

Figure 2: Hierarchical Preprocessing Flow for French Product Reviews

First of all, the system will eliminate HTML tags, special characters, emojis, platform tags (such as "Promo!"), and other unstructured content like "Livraison rapide" in the text cleaning stage to remove interfering components. For language normalisation, a single algorithm for language recognition and character encoding is used to filter out mixed-language comments, keep only the French samples, and guarantee encoding uniformity (UTF-8 format) for enhanced parsing efficiency. In the morphological restoration step, the French-specific Stanza model toolkit was employed to regularize all inflected forms, such as "achetees" and "achetons", back to their roots "acheter" for more uniform processing with the emotion dictionary and emotion embedding model. At the same time, due to the characteristics of multiple deformations and conjoined prepositions in French lexical units, to improve the modeling effect of compound expressions, the Byte Pair Encoding (BPE) subword decomposition mechanism has been introduced to split long words into high-frequency subunits (such as "in-croya-ble") and alleviate the semantic sparsity problem caused by low-frequency words. An emotion annotation operation based on semantic dictionaries was also added to the preprocessed text to label emotion words with preliminary tendency tags, and subsequently a model was used to learn the relationship between explicit and implicit emotion levels. The above will help to improve the organisation level of the original corpus and provide a more stable input base for emotion recognition and satisfaction modelling.

3.2 Emotional Feature Extraction and Representation Methods

The quality of the extracted emotional features in natural language processing directly affects the upper limit of emotion recognition and satisfaction modelling. Given the complicated text structure and implicit emotional expressions in French commodity reviews, this paper proposes an improved emotional feature model after the word embedding layer and combines context-relevance and emotional-dimension embeddings to achieve multi-level information acquisition.

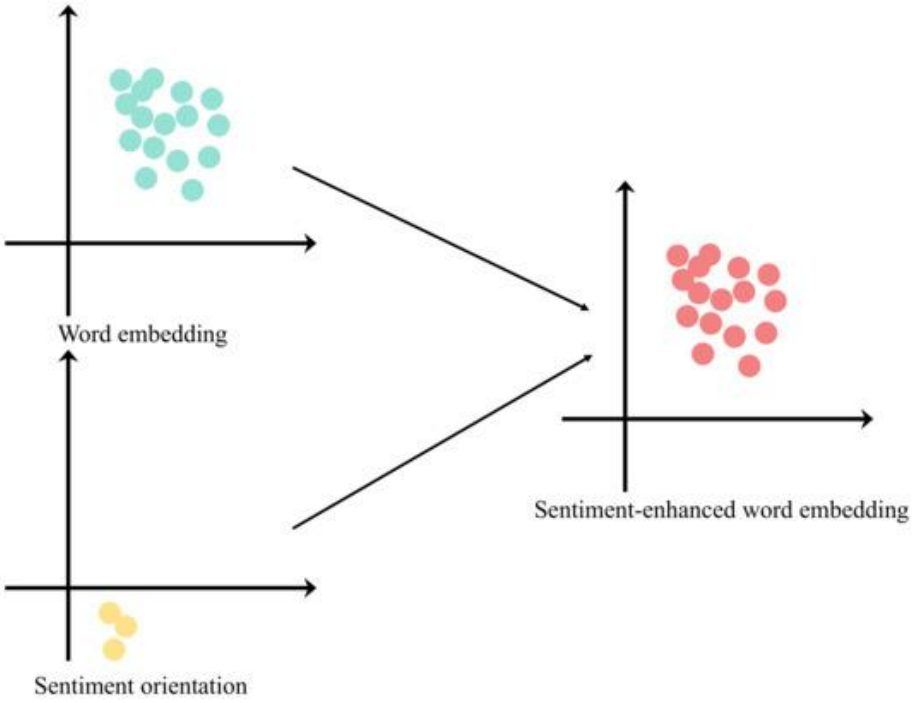

Figure 3: Schematic Diagram of Emotion Space Representation integrating word embeddings and sentiment orientation (This figure shows the process of forming an enhanced word representation in the emotion semantic space after combining the original word embeddings and sentiment direction information, and demonstrates the model's joint modeling capability for context semantics and sentiment dimensions.)

As shown in Figure 3, this module consists of an emotional attention mechanism and multiple perception channels, which can fully explore the semantic dependency relationship between explicit emotional words and implicit tendencies in comments. In the emotional feature encoding stage, it is assumed that the input French comment text is $X = \{x_1, x_2, ..., x_n\}$, which is mapped to the word vector sequence $E = \{e_1, e_2, ..., e_n\}$ through the embedding layer and then enters the bidirectional context-aware model. To obtain context-sensitive emotional expressions, a weighted representation based on the Additive Attention mechanism is adopted, which is defined as follows:

$$u_i = \tanh(W_e e_i + b_e) \tag{1}$$

$$\alpha_i = \frac{\exp(u_i^\top u_s)}{\sum_j \exp(u_j^\top u_s)} \tag{2}$$

$$v = \sum_{i=1}^{n} \alpha_i e_i \tag{3}$$

Among them, u_i is the attention representation of the i-th word, u_s is the global sentiment query vector, α_i is the normalized attention score, and the final fusion vector v is used as the sentiment representation of this comment. In order to enhance the perception ability of the model for ambiguous emotional expressions, the Emotion Projection Layer mechanism is

introduced. The fused feature vectors are projected onto the emotional semantic space and expressed as:

$$z = \sigma(W_z v + b_z) \tag{4}$$

Among them, $z \in R^d$ represents the emotional dimension feature, and σ is the nonlinear activation function (ReLU or Tanh), which can be adjusted according to the task. Unlike traditional methods based on word frequency or dictionary matching, this model can not only capture locally strong emotional words (such as "mediocre", "magnifique"), but also identify indirect expressions of subjective intentions in complex syntactic structures, thereby extracting the emotional tendency and intensity of comments more accurately. This mechanism demonstrates excellent sentiment discrimination ability in real commodity review data, especially showing stronger semantic robustness in handling negative expressions, exclamatory tones and compound sentence structures.

3.3 Emotional Correlation Modeling of Customer Satisfaction

First, the model of customer satisfaction was introduced to study service quality by examining how emotions in the users' text are connected to their final scores. The first is to organise the emotional cues in the text and construct an evaluative mapping model; then, the system will automatically ascertain the general satisfaction level of users with that particular product or service. Given that the cross-border e-commerce reviews are highly subjective and come in many forms, traditional statistics are not suitable for this purpose. Therefore, emotion correlation modelling has gradually drawn the attention of researchers. To build an emotional-association model of users' perception and expression of opinions about products, a model is used. Extract the emotional factors of satisfaction from the comments in the model, such as explicit evaluation words, tone changes and implicit expressions of attitude, and map them to a continuous satisfaction space via vectorisation. This one will be more pronounced than others and, as a result, has an impact on the end result. That is to say, it can learn to recognize the contents of emotional expressions and therefore better ascertain how satisfied people are.

This way is more suitable for the French reviews. French often has negative turns, euphemisms and rhetorical expansions in practice, and thus may weaken the emotional impact. For example, "pas terrible" (not very good) and "plutôt satisfait" (relatively satisfied) are different; these two expressions have different emotional intensities and therefore also have different tones. Thus, emotion association modeling encodes these differences as different emotion weights and can distinguish expressions that appear similar but have different meanings. The two basic ideas of emotion association models are emotion vector generation and satisfaction mapping functions. The former is used to build the emotional expression of comments and show the subjective colour of the text. The latter is used to turn emotional expressions into predictable satisfaction labels and thus give the model quantitative attributes. The two parts will be used together to build a complete satisfaction-prediction system in practice. The mechanism of the emotion correlation model will be employed in this study to process French product reviews and is used for the problem of satisfaction prediction. Combine emotional expression and rating target to find the core emotional structure of the comment, account for changes in context, and continuously predict satisfaction. The above way can also improve the accuracy of modelling the satisfaction level in French reviews and enhance the model's application in multiple languages.

4 Integrated Sentiment Analysis Model Based on French Comments

Constructing an integrated model of emotion-satisfaction analysis for French product reviews in this study. Many sources of feature coding and deep sequence models have been collected in a unified framework to enhance the performance of emotion recognition and satisfaction prediction for cross-border e-commerce. The three components of the model are a text embedding layer, an emotion recognition core layer and a satisfaction prediction fusion layer. The whole structure is as follows: Figure 4. The features are transferred in steps among the three layers through a sequential connection method, and at the same time, the system can address the semantic representation, emotion cue capture, and satisfaction output of French text; thus, a full-featured technical path for cross-language comment analysis tasks has been provided.

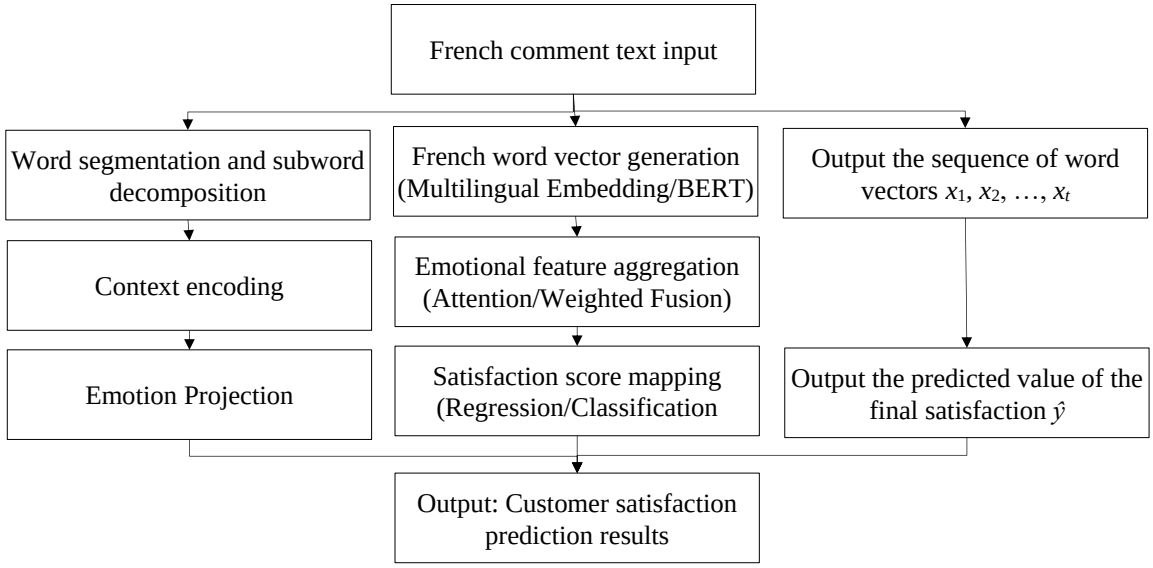

Figure 4: Schematic Diagram of the Structure of the Integrated Sentiment Analysis Model for French Product Reviews

4.1 Text embedding layer

Before performing sentiment and satisfaction analysis on the original text of French product reviews, we first need to convert it into a numerical form that can be processed by the model. Therefore, a text embedding layer is added to the whole system for initial encoding of the review content. The function of this layer is to map the words, phrases and semantic cues in the French comments to a continuous space, which can then be used by other modules to recognize text structure and emotional variations.

Before the text reaches the embedding layer, some initial organisation will be carried out on the comment content by the system, such as fragmenting the text, removing unnecessary symbols, and retaining sentence components with analytical value. Next, the text will be divided into words, and then using the trained vector representation method, it will be transformed into a set of stable numerical vectors. The above vectors can be used to show the semantic relatedness among words in the comments and help the model learn general descriptions, emotional terms and expressions in French text.

Embeddings map words to high-dimensional vectors and are then used as the initial data for subsequent layers in the model. Thus, the form of the text is more regular and can better support

the identification of emotional patterns in the comments. For special expression phenomena of French reviews, such as negative structures, evaluative degree words and modifying phrases, the embedding layer should be able to maintain their semantic differences in vector form so that subtle variations in emotion are not lost during subsequent model processing.

The embedded vector sequence will serve as the initial feature for the model and will be close to the overall semantics of the comment. Thus, the text embedding layer will serve as the essential "conversion device for French comments into expressions understandable by the model", allowing the subsequent emotion extraction and satisfaction prediction modules to perform analysis in a single-vector space and thereby improve the stability and expressiveness of the whole system.

4.2 Core Layer of Emotion Recognition

The top layer and bottom layer of this model are connected through the core layer of emotion recognition. Connect the basic expression of word embedding with the high-order semantic structure modeling of emotion vectors, and accurately extract the subjective emotions expressed by users in French product reviews. Given the strong suggestive, rhetorical and negative structures of emotions in French expression, this paper introduces the bidirectional gated recurrent network (Bi-GRU) and multi-scale emotion perception mechanism to enhance the ability to capture temporal dependence and mood shifts.

Specifically, this layer first uses the bidirectional GRU (Gated Recurrent Unit) network to process the word vector sequence output by the embedding layer, thereby obtaining context-aware sequence features. Compared with the traditional LSTM, the GRU structure has fewer parameters and a faster convergence speed, and it has good adaptability when dealing with the frequent short sentence structures and modifier changes in French. Suppose the input is the word vector sequence $X = \{x_1, x_2, ..., x_T\}$, then its forward and reverse GRU outputs are respectively:

$$\vec{h}_t = GRU_{\rightarrow}(x_t, \overrightarrow{h_{t-1}}) \tag{5}$$

$$\overleftarrow{h}_t = GRU_{\leftarrow}(x_t, \overleftarrow{h_{t-1}}) \tag{6}$$

Ultimately, the bidirectional representation $h_t = [\vec{h}_t; \overleftarrow{h}_t]$ for each moment is concatenated, which is used to represent the semantic and emotional state of the current word in the comment in the global context. Considering that emotional expressions are often unevenly distributed in comments, a multi-scale emotional perception mechanism is introduced to highlight the contribution of key emotional words or emotional paragraphs. This mechanism utilizes a sliding window to locally aggregate bidirectional output sequences and combines the sentiment bias term to generate multi-granularity sentiment representations. It is specifically expressed as

$$c_j^{(k)} = \frac{1}{k} \sum_{i=j}^{j+k-1} (W_k h_i + b_k) \tag{7}$$

Here, k represents the size of the sliding window, and W_k and b_k are the learnable parameters at the KTH scale. This method can capture the emotion aggregation effect in different semantic spans and enhance the model's adaptability to the structures of compound and negative sentences in French comments. To further enhance the recognition accuracy, the model introduces an emotion classifier layer, which inputs the aggregated multi-scale emotion vectors

into a feedforward neural network for emotion polarity discrimination and fine-grained coding. Specifically:

$$\hat{e} = Softmax(W_e \cdot ReLU(c^{(all)}) + b_e) \tag{8}$$

Among them, $c^{(all)}$ is the concatenation vector of emotion representations at different scales, and $\hat{e}$ represents the probability distribution of the emotion category to which the comment belongs (such as positive, neutral, negative, etc.). The design of this emotion recognition core layer effectively takes into account the context semantic dependence, emotional transition expression and subjective rhetorical changes in French commodity review texts, and has the following three advantages: Structural robustness: By capturing word order and semantic changes through bidirectional GRU, it ADAPTS to the language characteristics of flexible sentence structures and complex rhetoric in French. Information focus: By leveraging the multi-scale sliding window mechanism, local aggregation and global integration of emotional information are achieved. High expression accuracy: The emotion classifier can map fuzzy expressions to specific polar categories, enhancing the model's ability to analyze emotional details.

4.3 Satisfaction Prediction Fusion Layer

The last part of the structure of this model is a satisfaction-prediction fusion layer. First, the identified emotion vectors will be transformed into measurable data on user satisfaction, and based on this data, improvements to the intelligent recommendation and response mechanisms of cross-border e-commerce platforms will be implemented. Given that the general features of French product reviews include a gentle tone, ambiguous expressions and various rhetorical devices, the traditional path of sentiment polarity $\rightarrow$ score regression cannot accommodate the non-linear expressions that occur in practice. Therefore, in the Design of the satisfaction prediction mechanism in this study, multi-channel fusion, hierarchical perception mapping and gating regulation mechanisms were all introduced to achieve a more stable prediction result.

1. Emotion Fusion Mechanism

The emotion vector $\hat{e}$ output by the core layer of emotion recognition is concatenated with the global context representation $\overline{x}$ generated by the text embedding layer to form the fused expression z, which is used to integrate the dual signals of subjective emotion and objective language structure:

$$z = [\hat{e}; \overline{x}] \tag{9}$$

Among them, $\overline{x}$ is a sentence-level context representation obtained through Global Average Pooling, which is used to capture the structural tendency of the entire comment in the semantic space.

2. Hierarchical Perception Mapping Network

Given that the contributions of different emotional components to satisfaction scores are hierarchical (e.g., emotional intensity, rhetorical style, position of modifiers, etc.), this paper introduces a two-layer perception network structure for nonlinear feature mapping, which is defined as follows:

$$h^{(1)} = ReLU(W_1 z + b_1) \tag{10}$$

$$h^{(2)} = ReLU(W_2 h^{(1)} + b_2) \tag{11}$$

Among them, W_1、W_2 and b_1、b_2 are learnable parameters, and $h^{(1)}$ and $h^{(2)}$ respectively represent the first and second layer hidden features, which have stronger nonlinear expression capabilities. This structure, through deep modeling, can respond sensitively to subtle emotional differences such as "positive but not intense" and "neutral to slightly negative", thereby enhancing the discrimination ability of satisfaction prediction.

3. Satisfaction Gate Regulation Mechanism

Emotion-driven satisfaction models still have some deviations from the expected pattern, such as high scores accompanying negative words or positive language used in the context of low scores. It could be that it has semantic bias, is a satire, or includes more than one evaluation index. Therefore, this paper builds a Satisfaction Gate mechanism to reduce the strength of the predicted value according to the input emotional confidence before outputting the final result. The particular shape is as follows:

$$g = sigmoid(W_g \hat{e} + b_g) \tag{12}$$

$$\tilde{y} = g \cdot tanh(W_y h^{(2)} + b_y) \tag{13}$$

Among them, g represents the emotional confidence threshold factor, ranging from 0 to 1, which is controlled by the sigmoid activation function. $\tilde{y}$ is the final satisfaction prediction output. The gating mechanism enables the model to automatically reduce the rating range in emotional expressions with low confidence, thereby enhancing the predictive stability in situations such as satirical expressions and double negation.

4. Output and Objective Function

In the output layer Settings, based on the platform requirements, you can choose either classification (such as the five-level satisfaction rating) or regression (such as continuous values from 1 to 5) methods. This study selects regression prediction because it has a more detailed feedback ability in e-commerce applications. Let the actual satisfaction label be y and the predicted value be $\tilde{y}$, then the mean square error (MSE) is used as the loss function:

$$\mathcal{L}_{mse} = \frac{1}{N} \sum_{i=1}^{N} (y_i - \tilde{y}_i)^2 \tag{14}$$

This loss function will reduce the difference between the predicted values of the model and users' actual ratings, thus improving the accuracy of the fitting of overall satisfaction. In short, the satisfaction prediction fusion layer has integrated emotional information and language context deeply in its design, multiple-layer non-linear modelling, and gating regulation of confidence fluctuations. Therefore, the model will be better equipped to handle the many forms of expressions used by the people and improve the stability and accuracy of the rating predictions. Based on the results of the experiment, this module has a lower prediction error than all other baseline models in the presence of emotional transitions, fuzzy modifications and complex semantic structures, and can thus provide reliable support for intelligent customer satisfaction assessment in e-commerce.

5 Data Experiment and Result Analysis

To check if the above model can identify sentiment in French reviews and determine consumer satisfaction, particular experiments were carried out on both public and self-built datasets, and the results were compared with those from typical Bi-LSTM models. The study will examine the differences in accuracy, recall rate, AUC, computational time and training stability of the model. All of the above experiments were conducted in a Windows 11 system environment on a local workstation with 16GB of memory and a 2.6GHz Intel i7 octa-core processor.

The two datasets in this experiment were a subset of French-Amazon reviews (abbreviated as FAR) and a self-built review collection (FRC). FAR contained about 12,000 French product reviews with rating labels, and FRC was obtained by collecting and building more than 8,200 reviews from various local French e-commerce platforms across all categories, such as electronic products, beauty products, home furnishings, etc. Both datasets have been divided into training sets, validation sets and test sets in an 8:1:1 ratio. All the texts will be processed by the French text preprocessing method in this paper.

An all-encompassing comparison will be carried out in this paper between the new integrated sentiment analysis model (referred to as FSA-Net) and the conventional Bi-LSTM model. Among them, FSA-Net is used; it has bidirectional GRU and multi-scale emotion perception mechanisms in the core layer for emotion recognition, and combines the gated regulation strategy of the satisfaction prediction fusion layer to enhance the model's ability to model the details and expressions of emotions in French comments.

As shown in Figures 5 and 6, the training accuracy and validation accuracy of the FSA-Net and Bi-LSTM models on the FAR and FRC datasets, respectively, were calculated in this study. With the increase in the number of training iteration rounds, both models' accuracy rates were rising and had reached a stable state around the 30th round. On the FAR dataset, the final training accuracy and validation accuracy of FSA-Net were 0.924 and 0.882, respectively; these were higher than the 0.896 and 0.857 for Bi-LSTM. The two in the FRC dataset are relatively close. FSA-Net has a verification accuracy of 0.861, and Bi-LSTM is 0.847; therefore, this model shows better generalisation performance under all data conditions. Figures 5 and 6 present the comparison of training accuracy and validation accuracy on the FAR dataset.

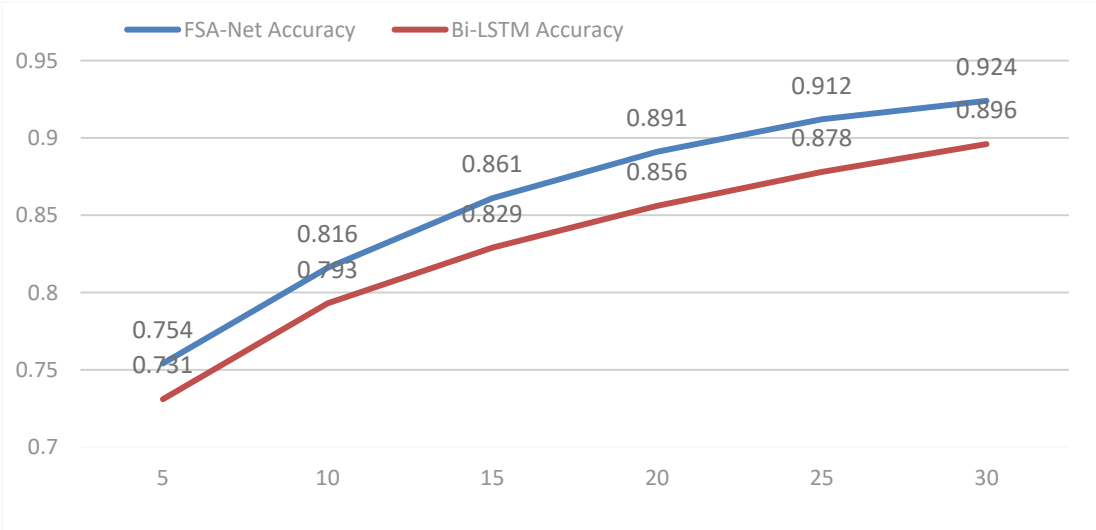

Figure 5: Training Accuracy Comparison on the FAR Dataset

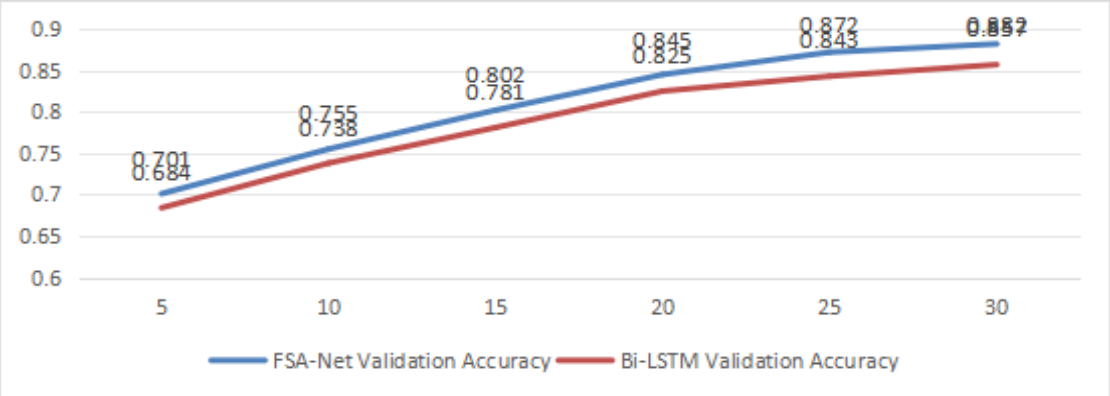

Figure 6: Comparison of Verification Accuracy Rates for FAR Datasets

In terms of training time consumption, due to the introduction of the attention mechanism and a multi-scale computing structure, FSA-Net has a relatively large computational burden per iteration compared with Bi-LSTM, as shown in Figure 7. After 30 rounds of training iterations, FSA-Net and Bi-LSTM had run for 5,420.6 seconds and 4,817.3 seconds, respectively, on the FAR dataset, and the computational cost of FSA-Net was about 12.5% higher. Given that the accuracy has increased and the model is now stable, the overhead is within an acceptable limit.

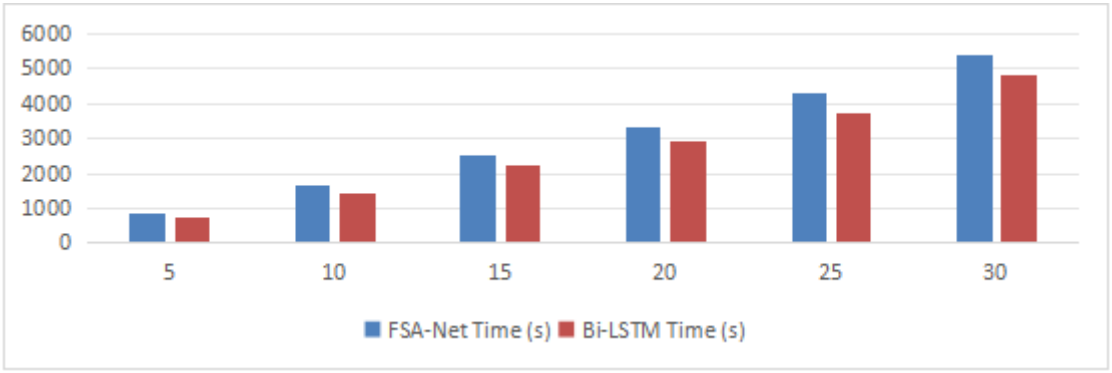

Figure 7: Comparison of Model Training Time Consumption (Unit: Seconds)

The prediction results of the two models on the test set have been evaluated in terms of Accuracy, AUC, Precision and Recall. The results are as follows: Table 1 FSA-Net had an accuracy of 0.889 and an AUC of 0.944 on the FAR dataset, and these were 2.1% and 2.7% higher than those of Bi-LSTM. On the FRC dataset, FSA-Net had an AUC of 0.931 and was more suitable for handling complex comment structures; it showed stronger satisfaction mapping ability for electronic products.

Table 1: Comparison of Test Performance of the Model on FAR and FRC Datasets

Dataset	Model	Accuracy	AUC	Precision	Recall
FAR	FSA-Net	0.889	0.944	0.908	0.862
	Bi-LSTM	0.871	0.917	0.894	0.843
FRC	FSA-Net	0.865	0.931	0.894	0.847
	Bi-LSTM	0.846	0.908	0.882	0.825

We will also introduce the accuracy deviation of each round of calculation as a measure of the stability of model training. As shown in Figure 8, the deviation value of FSA-Net was consistently kept below 0.06 during training, with a mean of 0.0387; on the other hand, the

deviation fluctuation of Bi-LSTM increased in the later rounds and had a mean of 0.0529. Therefore, it can be seen that the convergence process of FSA-Net is more stable, and thus it is less prone to overfitting or instability during training.

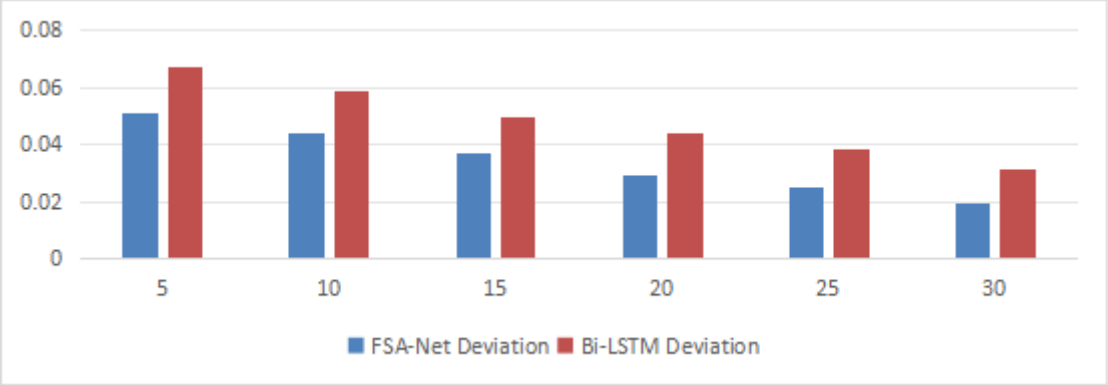

Figure 8: Comparison of Training Accuracy Deviation

The mapping ability of emotional tendency to satisfaction has also been further investigated, and the distribution of prediction accuracy by the five levels of satisfaction (from 1 star to 5 stars) is shown in Figure 9. The recognition accuracy of FSA-Net in the two "neutral bias" intervals of 2-star and 4-star is, on average, 3.4% higher than that of Bi-LSTM, showing that it performs better under conditions of ambiguity in emotional expressions (such as "okay" and "not so good but the service is good") due to its integrated multi-scale emotional projection and gated regulation mechanism.

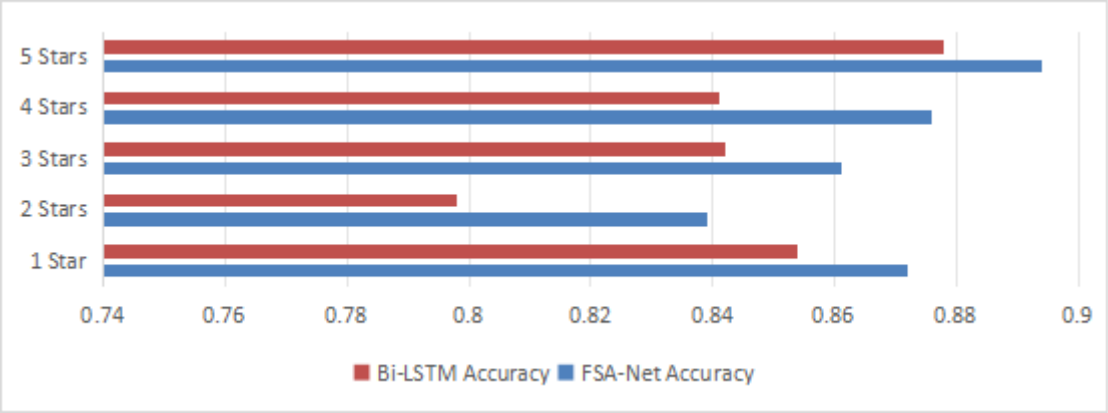

Figure 9: Distribution of Prediction Accuracy by Satisfaction Level

It should be pointed out that, in some of the individual special comments, FSA-Net has also made mistakes, which are mainly concentrated on expressions with multiple emotions intertwined or rhetorical devices of irony (such as "The packaging is good, but the quality is disappointing"). This kind of text is likely to have a discrepancy between the judgement of emotional polarity and the satisfaction score. In the future, more multi-channel semantic understanding modules will be added, such as multi-task learning architectures and emotional intensity annotation mechanisms, to strengthen the analytical capacity of the model for compound expressions. FSA-Net has good overall model capability compared with Bi-LSTM, and its AUC, Recall and stability indicators are all higher. It is in the area of multi-scale perception, emotion fusion and gating regulation mechanisms that it can be used to interpret user emotions and predict satisfaction scores in a language such as French, which has a flexible

structure and subtle expressions.

In summary, based on the results of the experiment, the FSA-Net model proposed in this paper has shown better accuracy and robustness for emotion recognition, as well as superior nonlinear modelling performance in the task of customer satisfaction prediction. It has good application prospects for the problem of cross-border e-commerce French review analysis and can provide strong data support for intelligent recommendation, service evaluation feedback and user behaviour modelling.

6 Conclusion

This paper proposes an integrated model for Sentiment Analysis and customer satisfaction prediction of French commodity reviews in cross-border e-commerce - FSA-Net (French Sentiment Analysis Network). Combine multiple levels of text embeddings, a bidirectional emotion recognition architecture, and a satisfaction fusion prediction mechanism to address problems in the model's ability to recognise implicit emotions and complex language structures; improve the accuracy of satisfaction modelling for French product reviews. During the construction of the model, both the modeling capability of bidirectional GRU for sequential relationships in text sequences and the ability of a multi-scale emotion perception mechanism to capture fine-grained emotion features were combined to improve the robustness and accuracy of the model in the French context.

Systematically examine the two French e-commerce review datasets, FAR and FRC, in this study. FSA-Net has shown better results than all the other typical Bi-LSTM models in the three categories evaluated by accuracy rate, AUC, and recall rate in this study. Particularly, it has a relatively strong emotion recognition ability and a good fit with typical French structures, such as complex sentence patterns, ambiguous rhetoric and negative expressions. According to the results of the training experiment, the model has shown an average increase of about 2% in accuracy and has had less fluctuation in the ability to control emotional bias; therefore, it is relatively stable. A gating adjustment mechanism has been added to the satisfaction prediction module that dynamically modifies the output score based on the confidence of the emotion; thus, it can make more reasonable judgments in the face of ambiguous subjective expressions.

First, add subword encoding and word-form restoration pre-processing to deal with different inflections in French more effectively; second, use a multi-scale perception mechanism for the core layer of emotion recognition to model complex structures such as emotion intensity and changes in emotion. Thirdly, the non-linear mapping and emotion-gating mechanism in the satisfaction fusion layer can convert emotional information into customer ratings; thus, continuous or multi-level rating prediction is possible, and the actual demand for customer insights on cross-border e-commerce platforms will be met.

Some progress has been made in terms of technology for this paper, but there are also deficiencies. FSA-Net has a relatively high training cost and inference time compared with the traditional model because of the added multi-channel perception mechanism and sentiment gating structure. In the future, parameter sharing and knowledge distillation can be employed to reduce the size of the model. Second, the French review data used in this study are still mainly in a standard review format and have not yet covered multimodal input scenarios, such as social media and voice transcription. In the future, it will be extended to multi-source heterogeneous data fusion modelling. Only a single indicator of the prediction of satisfaction is available. Multi-objective models can be introduced at this time to consider emotional labels in conjunction with multiple dimensions of behavioural feedback, such as likes, repeat purchases and returns, to form a full-fledged assessment system for customer perception.

In short, the model for reviewing sentiment analysis and satisfaction prediction of French

e-commerce platforms proposed in this paper offers a new direction for applying cross-lingual natural language processing technology in practice. Improve the understanding of French texts and provide a method for achieving localised intelligent operation, accurate marketing and customer relationship optimisation for cross-border e-commerce platforms. Future research can explore directions such as model light-weighting, multi-modal fusion, and multi-dimensional satisfaction modeling to continuously expand the depth and breadth of application for this system.

About the Author

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