An Intelligent Predictive Framework for Customer Satisfaction Analytics in E-Commerce

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Abstract:
Vietnam's fast-growing e-commerce market requires better tools to understand customer feedback. This study proposes a two-step framework combining deep learning (BERT, Bi-GRU) for sentiment analysis and machine learning (XGBoost) for predicting customer satisfaction. Using 10,021 reviews from major platforms (2015–2023), the models achieve over 70% sentiment accuracy and 80%+ satisfaction prediction accuracy, offering an effective way to enhance customer experience.

1. Introduction

E-commerce has rapidly grown in recent years, becoming a popular way to shop due to technological advancements. In Vietnam, this growth is especially strong in the cosmetic industry, which is expanding quickly with rising living standards. In such a competitive market, customer opinions play a key role in determining product and business success, making feedback analysis essential.

Online reviews on e-commerce platforms provide valuable insights for both businesses and customers. Sentiment analysis helps extract opinions from these reviews, enabling companies to understand preferences, improve products, and enhance customer experience. With advancements in machine learning and deep learning, analyzing large volumes of feedback has become more efficient and accurate.

However, analyzing Vietnamese customer feedback remains challenging due to language complexity and limited research focused on this market. This study addresses this gap by applying models like BERT and PhoBERT to analyze cosmetic product reviews and predict customer satisfaction. It explores sentiment patterns, evaluates a two-phase prediction approach, and aims to provide practical insights to help businesses better understand and manage customer feedback in Vietnam's cosmetic e-commerce sector.

2. Literature Review

2.1 Customer Satisfaction:

Customer satisfaction is a key concept in marketing, as it helps businesses design effective strategies and improve performance. It is generally defined as how customers feel when they compare their expectations with their actual experience. If the experience meets or exceeds expectations, customers feel satisfied; otherwise, they feel dissatisfied.

In e-commerce, customer satisfaction is especially important because it directly influences customer loyalty, brand reputation, and sales growth. Satisfied customers are more likely to return, recommend products, and contribute to business success.

Traditional methods like Net Promoter Score (NPS) are commonly used to measure satisfaction, but they often fail to capture detailed customer emotions and experiences. To overcome this, modern approaches use machine learning and deep learning techniques, which can analyze large volumes of customer reviews and uncover deeper insights. These methods enable businesses to better understand customer needs and improve overall satisfaction more effectively.

2.2 Sentiment Analysis:

Sentiment analysis, also known as opinion mining, focuses on understanding and evaluating people's

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opinions, emotions, and attitudes toward products, services, or events. It involves tasks like extracting opinions, analyzing sentiment, and identifying subjectivity in text.

In this study, sentiment analysis is categorized into three main approaches: dictionary-based methods, machine learning-based methods, and deep learning-based methods.

2.2.1 Dictionary-based methods:

Dictionary-based sentiment analysis determines the sentiment of text using predefined lexicons, where words are assigned scores ranging from negative to positive. It works by matching words in a text with entries in sentiment dictionaries to identify and quantify opinions. This approach is widely used in tasks like opinion mining, sentiment classification, social media monitoring, and customer feedback analysis.

Popular tools and lexicons such as NRC Emotion Lexicon, VADER, SentiWordNet, and AFINN make it easy to process large amounts of text efficiently. Although simple and effective, recent improvements focus on using domain-specific and context-aware dictionaries, which enhance accuracy and make the method more adaptable across different fields and languages.

2.2.2 Machine Learning- based Methods:

Sentiment analysis has been widely studied using traditional machine learning techniques. These methods rely on text processing approaches like TF-IDF and Bag-of-Words (BoW), along with algorithms such as SVM, Random Forest, and Naive Bayes. Before deep learning, they were the standard approach for sentiment classification.

Studies show that combining techniques like TF-IDF, Word2Vec, and models such as SVM can achieve good performance. Hybrid approaches, such as using VADER for sentiment scoring with SVM for classification, have also shown effective results even with imbalanced data. However, traditional machine learning models often struggle with complex language and context. As a result, deep learning models, especially neural networks like ANN, have gained popularity due to their ability to achieve higher accuracy and better handle complex sentiment patterns.

2.2.3 Deep Learning-based Methods:

Sentiment analysis has advanced significantly with the rise of deep learning. These models can effectively handle sentiment tasks at document, sentence, and aspect levels across multiple languages, including Vietnamese. Since sentiment data is sequential, models like RNNs and LSTMs are particularly useful for capturing context and improving performance. Research shows that deep learning models, such as LSTM-CNN and recursive autoencoders, outperform traditional machine learning approaches in analyzing complex text data. More recently, BERT-based models have further improved accuracy by providing strong feature extraction and contextual understanding. In the Vietnamese context, PhoBERT—a version of BERT tailored for the language—has shown promising results. However, most studies rely on limited standard datasets, highlighting the need for more diverse and domain-specific data to further enhance sentiment analysis performance.

2.3 sentiment Analysis:

Opinion analysis goes beyond simply counting reviews—it can also be used to measure customer satisfaction from multiple perspectives. For example, some studies use sentiment dictionaries to convert customer comments into numerical data and apply models like VIKOR to evaluate overall satisfaction. Others combine text mining (e.g., TF-IDF) with machine learning to analyze large-scale review data and predict satisfaction levels. In the Vietnamese context, research has applied TF-IDF and models such as Naive Bayes, SVM, Logistic Regression, and Neural Networks to predict customer satisfaction, achieving moderate to high accuracy. However, TF-IDF has limitations, such as ignoring word meanings and relationships.

While existing studies focus mainly on sentiment or topic analysis, there is still a clear need for more research on customer satisfaction in Vietnamese e-commerce—especially in fast-growing sectors like the cosmetic industry.

3. Methodology

3.1 Overview Model and Method

The overall research model follows a structured workflow with six main steps. First, data is collected from four e-commerce platforms: Tiki, Shopee, Hasaki, and Sendo. Next, the data is preprocessed using both manual and automated methods to ensure quality.

After preprocessing, the data is labeled and further prepared for training. It is then split using the hold-out method, with 80% used for training and 20% for testing. A deep learning model is built to predict emotions from customer comments, using advanced models like BERT and PhoBERT along with baseline models such as RNN, LSTM, and GRU to find the best-performing approach.

The outputs from the deep learning model are then used to develop a machine learning model that predicts overall customer satisfaction. Finally, the results are visualized, and practical solutions are proposed to improve the cosmetic e-commerce industr

Table II
Review matrix - machine learning based sentiment analysis.

ID	Study	Level	Domain	Language	Model / Approach
1	Kim et al.	Document Level	Multiple Domains	English	Multi-co-training (MCT) with TF-IDF, LDA, and Doc2Vec
2	Alsemaree et al. (2024)	Sentence Level	Social Media	English	SVM, Decision Tree, Random Forest, KNN; Ensemble model using TF-IDF and MRMR
3	Ramzy & Ibrahim (2024)	Sentence Level	Healthcare	English	ANN, SVM, KNN, Naive Bayes, Logistic Regression, Random Forest
4	Mee et al. (2021)	Document Level	Social Media	English	TF-IDF with Ordinary Least Squares (OLS) Regression
5	Agustina et al. (2024)	Sentence Level	Social Media	Indonesian	SVM with TF-IDF and Word2Vec
6	Siautama & Suhartono (2021)	Document Level	Hotel Reviews (TripAdvisor)	English	Extractive summarization using TF-IDF and Adjective-Noun Pairing
7	Isnan et al. (2023)	Document Level	Google Play Reviews	English	VADER for sentiment scoring + SVM for classification
8	Hidayat et al. (2022)	Document Level	Social Media	Indonesian	Doc2Vec, SVM, Logistic Regression
9	Borg & Boldt (2020)	Document Level	Telecom	Swedish	VADER for labeling + SVM for sentiment classification

3.2 Data Preparation:

As illustrated in Fig. 2, the data preparation process is divided into two main phases: data collection and data processing. Data collection involves gathering information using different techniques, while data processing includes four key steps—data filtering, data cleaning, data preparation, and data labeling.

3.2.1 Data Preparation

In this study, Python was utilized along with the Asyncio library to collect data from four e-commerce platforms: Sendo, Tiki, Shopee, and Hasaki, using appropriate APIs. The data retrieved from these APIs

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was subsequently processed and extracted for relevant research purposes using BeautifulSoup and JSON libraries, and then stored in a data repository. The collected dataset comprises two parts: Cosmetic industry product information data and previous product review data. With product review data, we research and focus on Vietnamese comments in this study. Data collection occurred between September 10th, 2015, and March 1st, 2023. Hasaki, Sendo, Shopee, and Tiki accounted for 34.92%, 9.72%, 33.39%, and 21.97% of the 13,844 products in the product dataset, respectively (see Table 3). The team collected 921,635 rows of

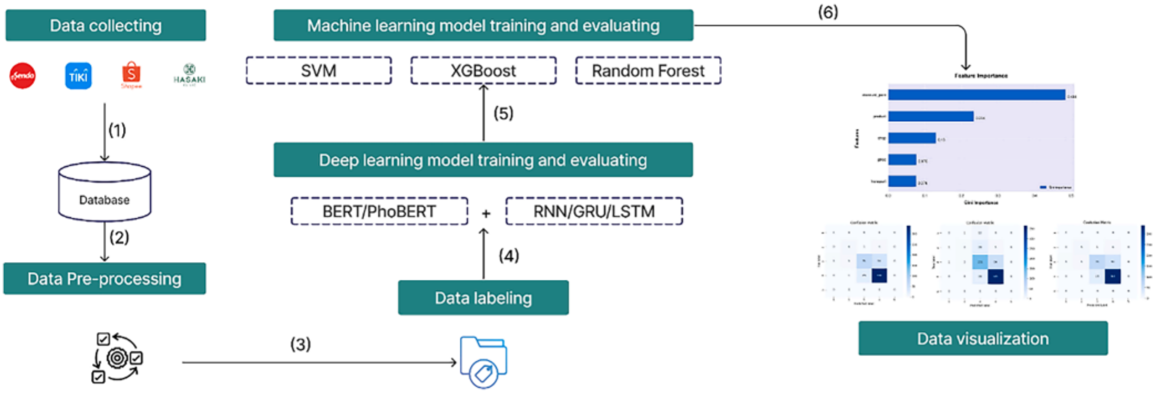

Fig 1. Proposed General Model and Methods

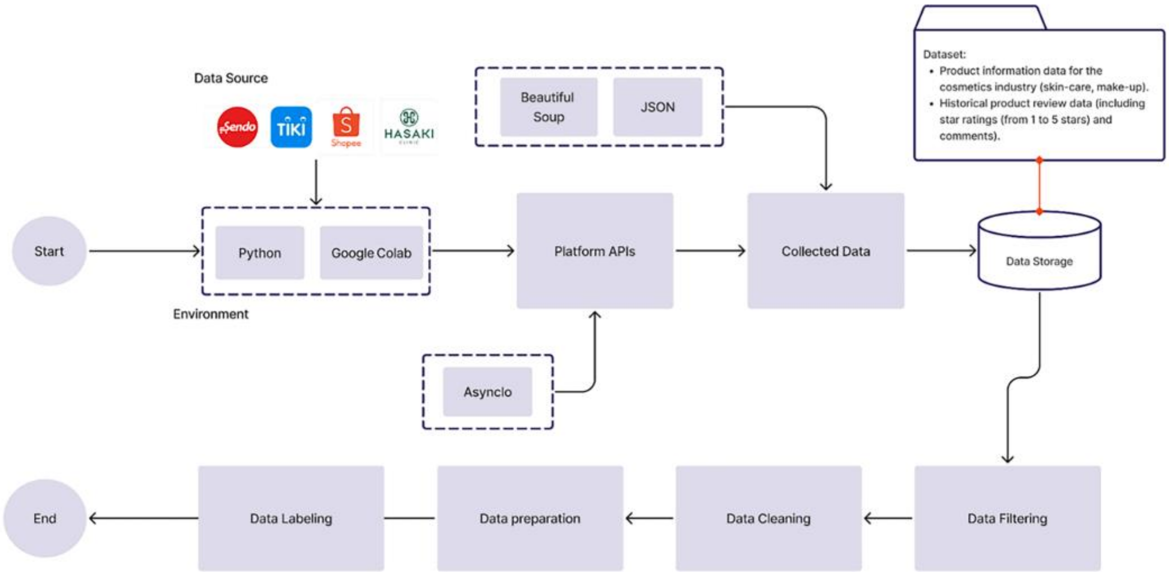

Fig. 2. Proposed data preparation flow

data for the comment dataset, with Hasaki, Sendo, Shopee, and Tiki accounting for 3.02%, 0.63%, 79.55%, and 16.8% of the data, respectively.

3.2.2 Data-Preprocessing Phase

3.2.2.1. Data filtering: Data filtering is an important step to improve the quality and consistency of the dataset. It includes correcting spelling errors, separating combined words, and expanding abbreviations (e.g., “kq” → “kết quả”). English terms are also standardized (e.g., “ok” → “okay”) to ensure clarity. After these steps, only relevant and meaningful data is retained, resulting in 10,021 comments used for training the deep learning models.

3.2.2.2 Data cleaning: Data cleaning improves the dataset by making the text more structured and consistent. Missing punctuation is added to enhance readability, and extra spaces are removed to maintain uniformity. Finally, word tokenization is applied, where sentences are split into meaningful units (e.g., “dịch vụ” → “dịch_vụ”). This helps the model better understand and process the text for analysis.

3.2.3 Data labelling Phase

This study applied the Latent Dirichlet Allocation (LDA) method to identify key topics in customer reviews. Using six topics (k = 6), the analysis grouped comments into meaningful categories based on frequently used keywords.

The results revealed five main useful groups:

Group 1: Product, price, and delivery (e.g., product quality, shipping).

Group 2: Packaging, store experience, and customer service.

Group 3: Skincare product quality.
Group 4: Makeup product quality.
Group 5: Customer emotions and overall experience (e.g., satisfaction or disappointment).
A sixth group contained vague or overlapping terms and was removed to improve clarity.

Based on these results, the data was manually classified into three main aspects: Product, Shop, and Transport. Each comment was also labeled by sentiment: positive (3), neutral (2), and negative (1). The reliability of labeling was measured using Cohen's Kappa coefficient to ensure consistency between annotators.

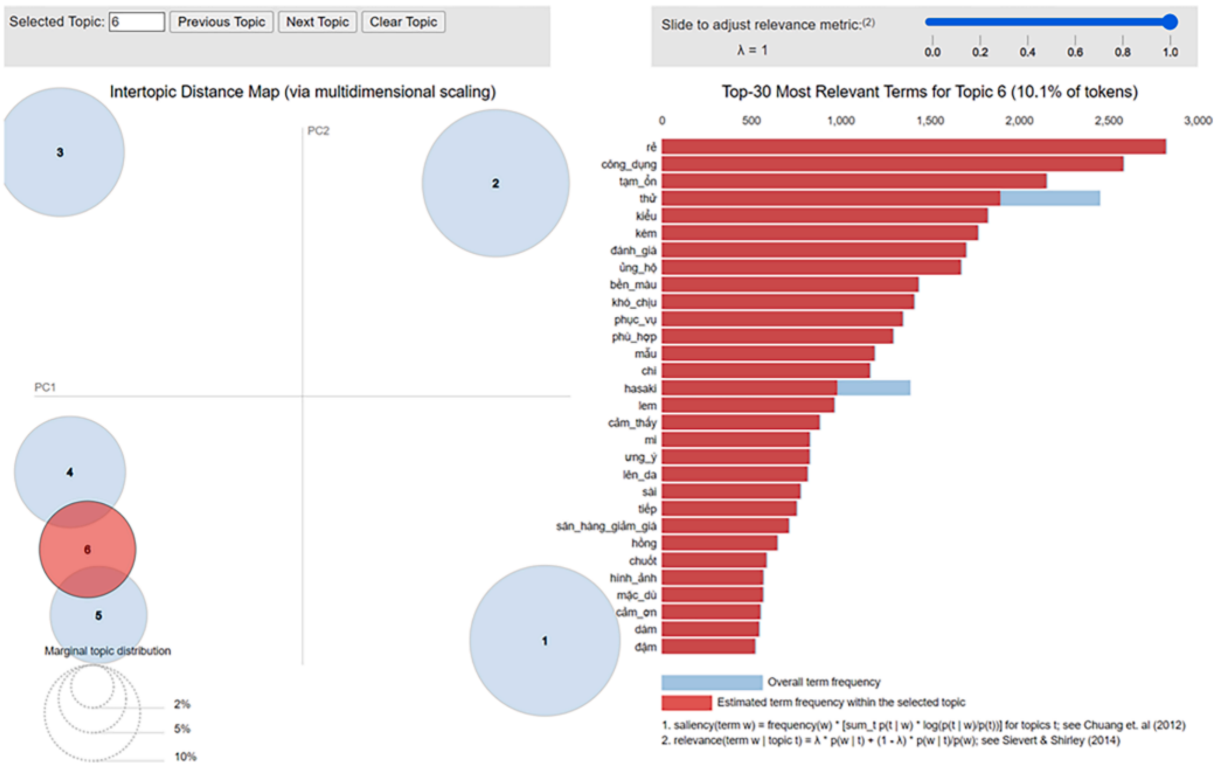

Fig. 3. LDA result on our dataset (k = 6)

Table II
Result of Topic Modelling Model

	Keywords									
Topic 1	sản phẩm	tốt	Giao hàng	chất lượng	hơi	giá	chất	ổn	tiền	kem
Topic 2	da	xài	ẩm	mịn	khô	nhẹ	mặt	mụn	dưỡng	dầu
Topic 3	hàng	đónggói	cửa hàng	giao	cẩn thận	hộp	Giao hàng	chắc chắn	Hài lòng	nắp
Topic 4	mùi	thơm	chai	tuyệt vời	hương	sạch	tẩy	đỏ	ảnh	kết cấu
Topic 5	son	đẹp	kẻ	môi	trôi	thất vọng	phấn	ưng	mắt	bút
Topic 6	rẻ	Công dụng	tạm ổn	thử	kiểu	kém	Đánh giá	ủng hộ	bền màu	Khó chịu

3.3 Sentiment analysis using deep learning

Previous research shows that while traditional machine learning methods (like SVM and Decision Trees) can handle sentiment classification, deep learning models—especially BERT and RNN-based approaches—achieve better performance, particularly in e-commerce data. Building on this, the study uses a hybrid deep learning approach combining BERT, PhoBERT, and RNN-based models (Bi-LSTM, Bi-GRU, Bi-RNN) to find the most effective model. BERT is chosen for its strong ability to understand context and handle language ambiguity, while PhoBERT is specifically designed for Vietnamese text.

The model works as follows:

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- Text is tokenized and padded to a fixed length.
- Pre-trained BERT/PhoBERT embeddings extract features from comments.
- These features pass through sequential models (LSTM, GRU, RNN) to capture context.
- Finally, a deep neural network (DNN) classifies sentiments across three aspects: Product, Shop, and Transport, with labels positive, neutral, and negative.

To ensure fair comparison, all models use the same architecture, with only the core models changing. Techniques like dropout, batch normalization, and regularization are applied to prevent overfitting and improve performance.

3.4 Predicting customer satisfaction using machine learning

Customer satisfaction in e-commerce is influenced by factors like pricing, discounts, and customer feedback. Studies show that price not only affects satisfaction directly but also plays a key role in building customer loyalty. In this study, machine learning models are used to predict customer satisfaction by combining two types of data: sentiment results generated from deep learning models (based on customer comments) and additional factors such as product price and discount rates. By integrating these inputs, the model provides a more accurate and comprehensive evaluation of customer satisfaction.

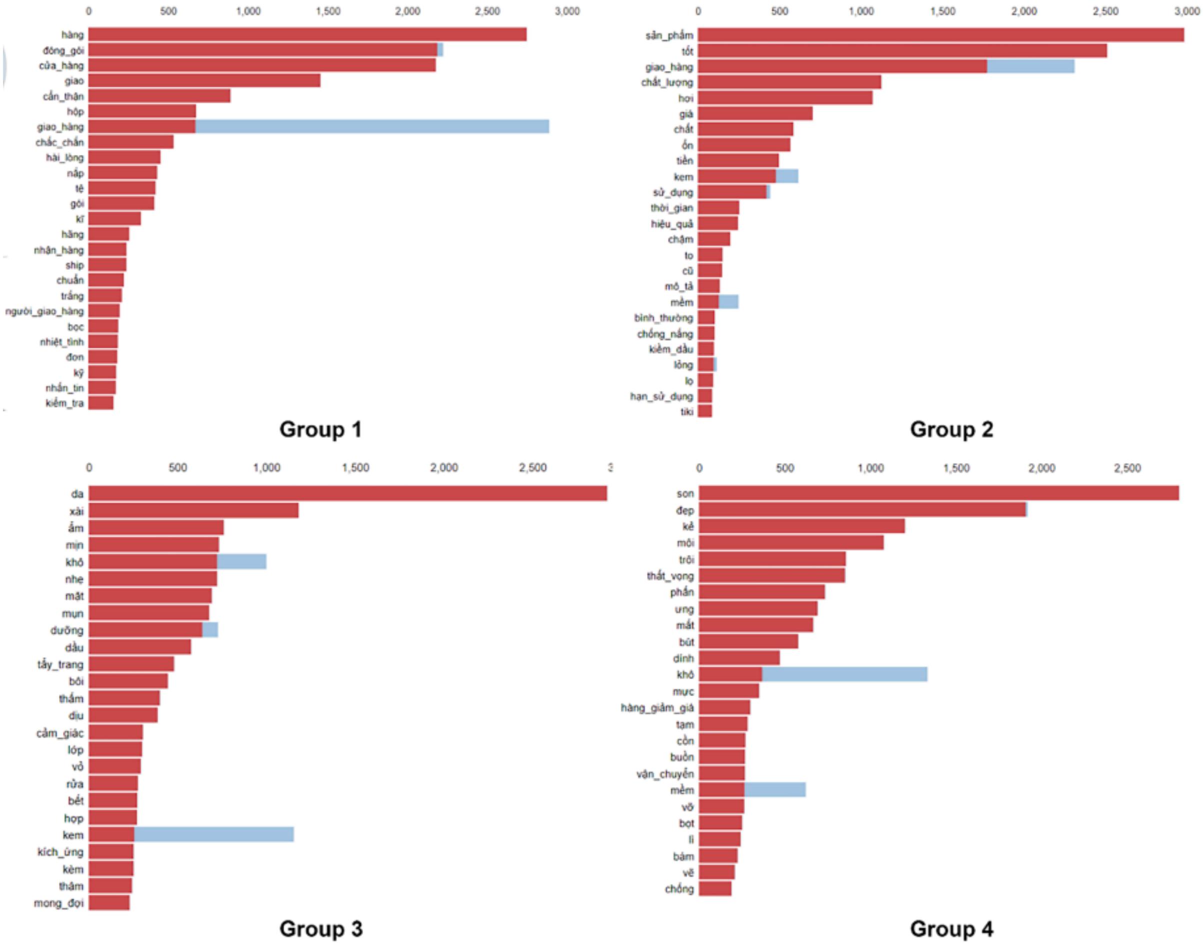

Fig. 4 Keyword groups analyzed in collected comments

3.5. Classification models evaluation metrics

3.5.1 Accuracy:

Accuracy is a simple and commonly used metric to evaluate classification models. It measures how many predictions are correct out of all predictions made.

$$k = \frac{Number\ of\ Correct\ Predictions}{Total\ Number\ of\ Predictions} \quad (2)$$

across all classes, weighted by how many samples each class has.

$$Weighted\ Precision = \frac{\sum_{i=1}^{n}(Precision_{\ i} \times Support_i)}{Total\ Support}$$

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3.5.3 Weighted Recall

Recall measures how many actual positive cases are correctly identified by the model.

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Weighted recall is computed as:

$$Weighted\ Recall = \frac{\sum_{i=1}^{n}(Recall_i \times Support_i)}{Total\ Support}$$

Where Recalli is the recall for class i, Supporti is the number of true instances of class i, and Total Support is the total number of instances.

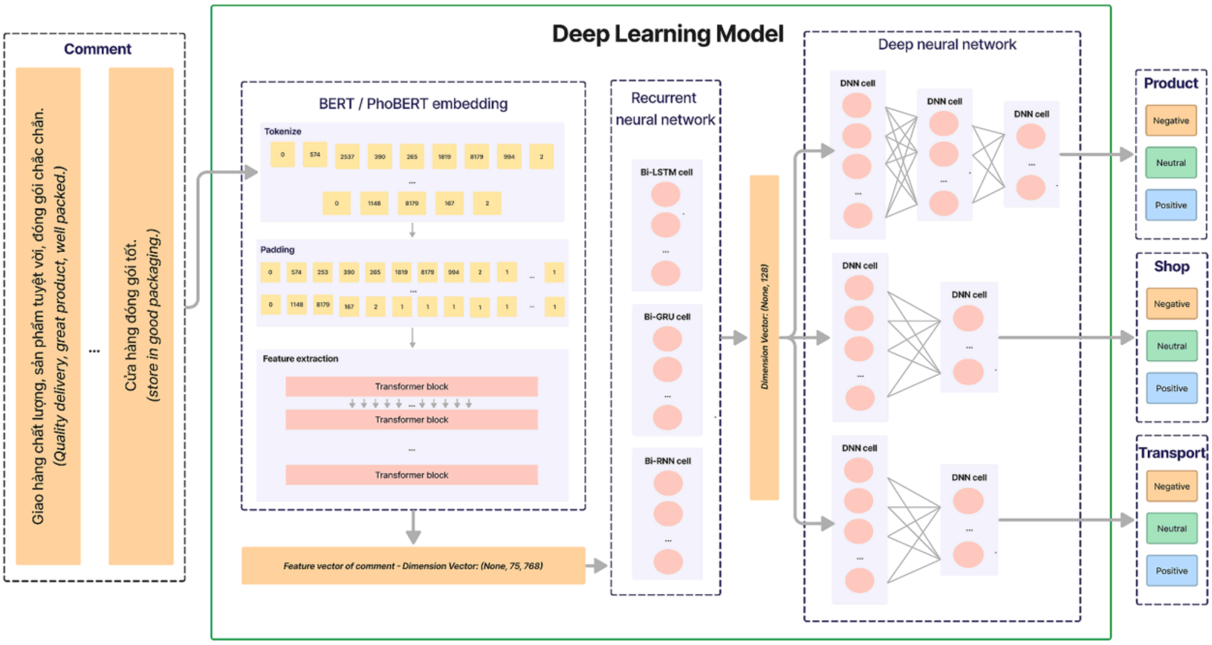

Fig. 5. Deep Learnings Model Architecture

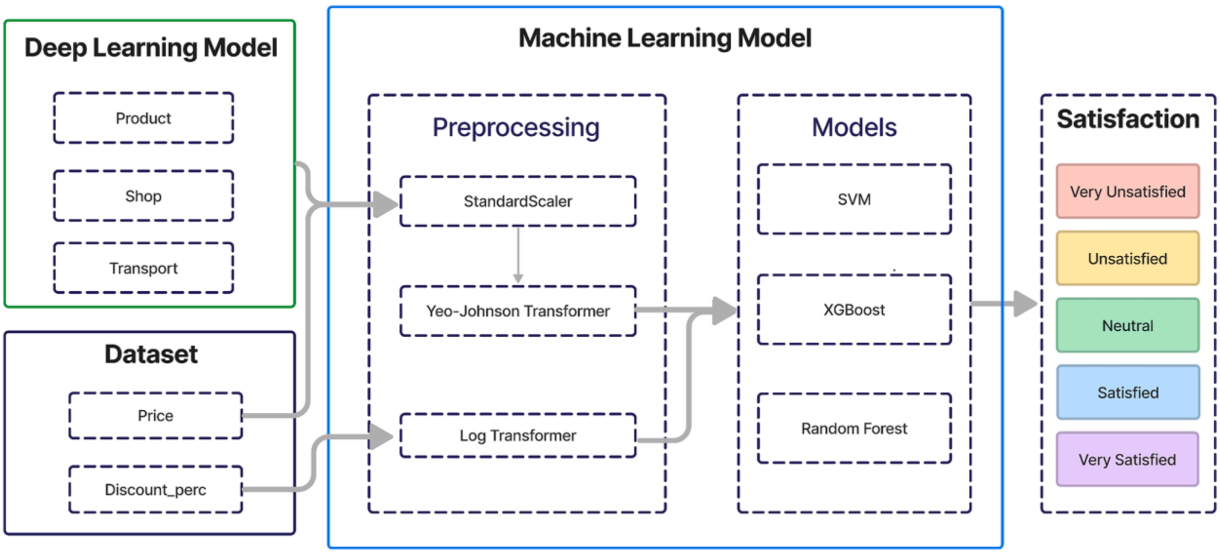

Fig. 6. Overall Process of Machine Learning Models

4. Results

4.1 Dataset

Initially, the agreement between annotators was low, indicating inconsistency in labeling. To address this, the research team refined the labeling guidelines and conducted a second round of labeling, which significantly improved reliability and data quality.

The analysis shows that neutral comments dominate across all categories—Product (33%), Shop (70.3%), and Transport (63.9%).

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Key insights from the dataset include:

- Short and abbreviated language: Most comments are brief and use shortcuts or abbreviations.
- Limited emotional expression: Many comments lack detailed opinions or strong sentiments.
- Product-focused feedback: Users mainly talk about products, with less emphasis on shop or delivery services.
- High linguistic diversity: Variations in language, symbols, and expressions make analysis more challenging.

These findings highlight the need for advanced models to better capture and interpret customer sentiments.

4.2 Result discussion on sentiment analysis with deep learning

4.2.1 Models Result:

To ensure reliable performance, the study used 5-fold cross-validation, and results showed consistent model behavior across the dataset. Among all models, BERT + Bi-GRU performed best in terms of accuracy (0.728) and recall (0.62), while PhoBERT + Bi-LSTM achieved the highest precision (0.673). Overall, BERT-based models outperformed PhoBERT-based ones, though F1-scores (0.56–0.63) indicate room for improvement.

The models performed best on neutral comments, mainly due to data imbalance. In contrast, performance on positive and negative labels—especially for *shop* and *transport* topics—was unstable and often low. This is likely because of fewer training samples in these categories.

Among all models, GRU-based architectures showed better performance than LSTM and RNN, likely due to their effectiveness in handling short text sequences. Overall, BERT + Bi-GRU was identified as the most stable and suitable model for prediction.

The results also highlight an important trade-off between precision and recall. While some models are more precise, they may miss many relevant cases (low recall), and vice versa. In this study, accuracy is used as the main metric for comparison, providing a clear baseline for evaluating and improving future models.

	Test 1			
Models	Precision	Recall	Accuracy	F1-Score
BERT + Bi-LSTM	0.673	0.617	0.721	0.620
BERT + Bi-GRU	0.660	***0.620***	***0.728***	***0.630***
BERT + Bi-RNN	0.647	0.607	0.719	0.600
PhoBERT + Bi-LSTM	0.673	0.560	0.710	0.563
PhoBERT + Bi-GRU	***0.677***	0.570	0.710	0.583
PhoBERT + Bi-RNN	0.660	0.570	0.707	0.580

	Test 2			
Models	Precision	Recall	Accuracy	F1-Score
BERT + Bi-LSTM	0.675	0.620	0.725	0.623
BERT + Bi-GRU	0.662	**0.622**	**0.730**	**0.632**
BERT + Bi-RNN	0.650	0.610	0.722	0.603
PhoBERT + Bi-LSTM	**0.680**	0.565	0.712	0.568
PhoBERT + Bi-GRU	0.665	0.573	0.713	0.586
PhoBERT + Bi-RNN	0.663	0.575	0.710	0.583

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Models		Product			Shop			Transport		
		Precision	Recall	F1-score	Precision	Recall	F1-score	Precision	Recall	F1-score
BERT +	Neg	0.60	0.54	0.57	0.60	0.60	0.60	0.58	0.42	0.49
Bi-LSTM	Neu	0.56	0.60	0.58	0.78	0.92	0.84	0.84	0.89	0.87
	Pos	0.70	0.72	0.71	0.70	0.12	0.21	0.71	0.72	0.71
BERT +	Neg	0.62	0.68	0.65	0.64	0.46	0.54	0.50	0.23	0.32
Bi-GRU	Neu	0.58	0.51	0.54	0.80	0.90	0.85	0.82	0.90	0.86
	Pos	0.73	0.75	0.74	0.58	0.40	0.47	0.69	0.72	0.71
BERT +	Neg	0.54	0.72	0.62	0.65	0.51	0.57	0.47	0.03	0.05
Bi-RNN	Neu	0.66	0.47	0.55	0.82	0.87	0.84	0.81	0.93	0.87
	Pos	0.73	0.72	0.73	0.54	0.50	0.52	0.62	0.72	0.66
PhoBERT + Bi-LSTM	Neg	0.60	0.63	0.62	0.63	0.42	0.51	0.74	0.10	0.18
	Neu	0.60	0.48	0.53	0.76	0.95	0.84	0.81	0.91	0.86
	Pos	0.67	0.75	0.71	0.67	0.08	0.14	0.61	0.72	0.66
PhoBERT + Bi-GRU	Neg	0.60	0.64	0.62	0.85	0.09	0.17	0.56	0.25	0.35
	Neu	0.56	0.54	0.55	0.76	0.94	0.84	0.81	0.91	0.86
	Pos	0.70	0.69	0.69	0.58	0.41	0.48	0.67	0.67	0.67
PhoBERT + Bi-RNN	Neg	0.57	0.68	0.62	0.71	0.37	0.49	0.52	0.18	0.27
	Neu	0.62	0.46	0.53	0.76	0.96	0.85	0.81	0.89	0.85
	Pos	0.66	0.71	0.68	0.67	0.19	0.29	0.61	0.68	0.64

4.3. Result discussion on predicting customer satisfaction using machine learning

The results show that XGBoost outperforms both SVM and Random Forest across all metrics, achieving the highest accuracy (81.45%), precision, recall, and F1-score (all around 0.81). SVM performs moderately well, better than Random Forest in most metrics, while Random Forest shows the lowest overall performance.

The models perform very well in identifying highly satisfied customers (label 5), but they often confuse moderate (label 4) and high satisfaction (label 5).

On the other hand, predicting lower satisfaction levels (labels 1–3) is more challenging, with frequent misclassifications. This is likely due to fewer examples and less clear distinctions between these classes in the dataset.

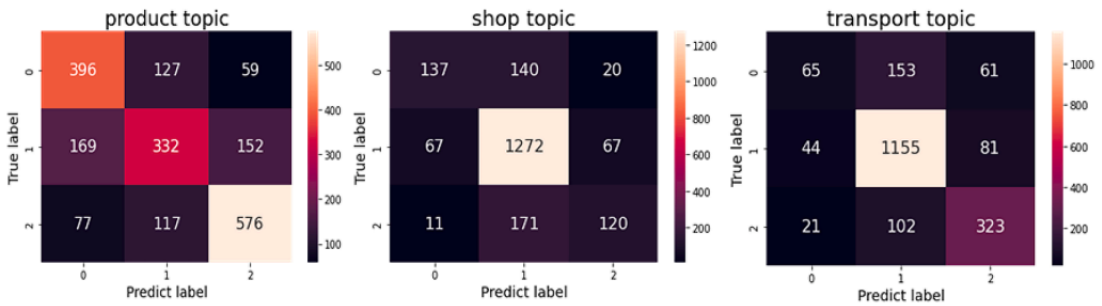

Fig. 9. Best model's confusion matrix.

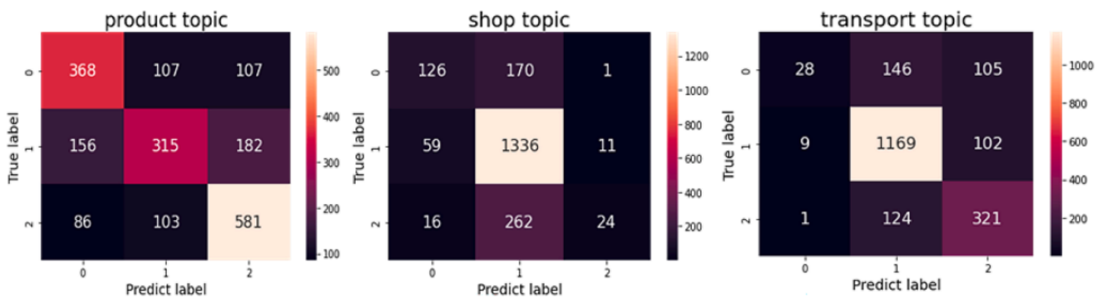

Fig Worst Models Confusion Matrix

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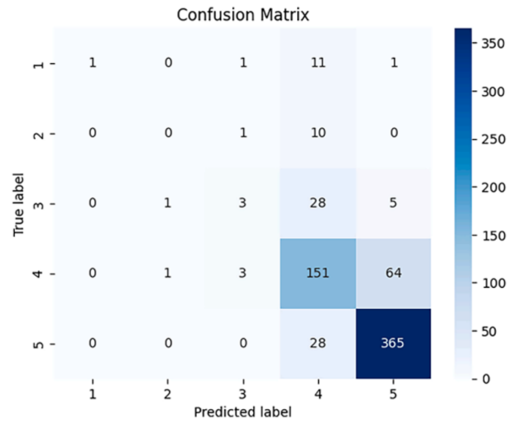

Fig Random Forest Confusion Matrix

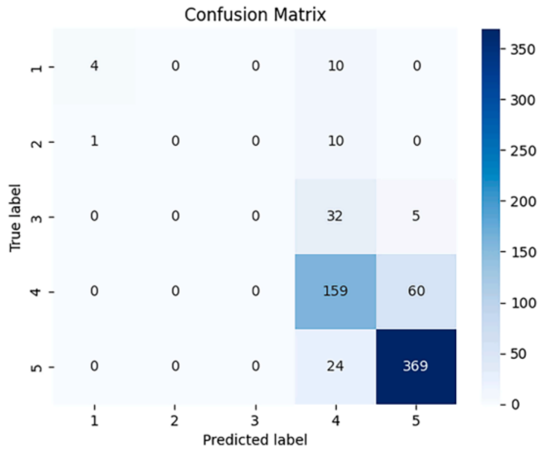

Fig. SVM`s Confusion Matrix

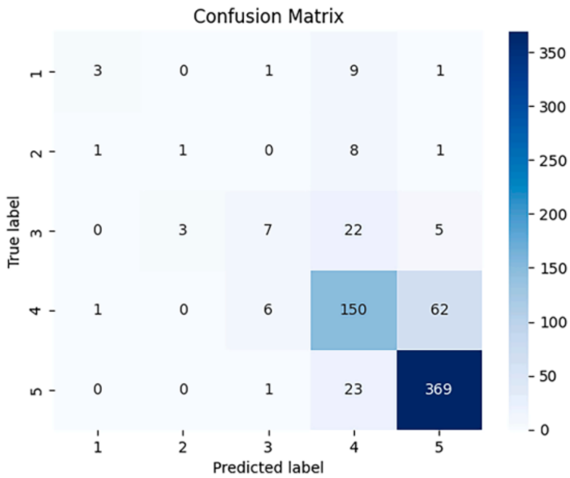

Fig XGBoost`s Confusion Matrix

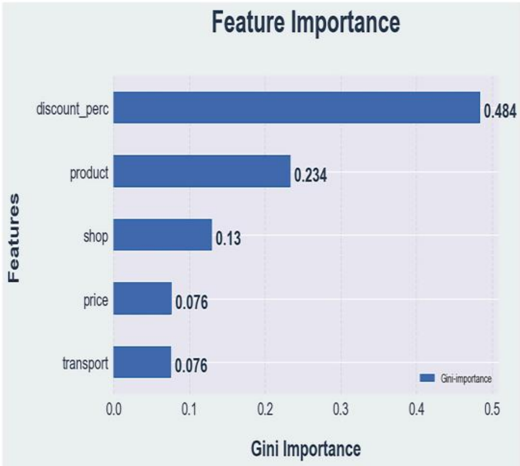

Fig. Random Forest features importance analysis

5. Discussion

This study advances sentiment analysis by applying modern deep learning models like BERT and PhoBERT to real-world e-commerce data, rather than relying only on standard datasets. The results show that these models face challenges when handling diverse and complex Vietnamese language in customer reviews, leading to some limitations in accuracy. To address this, the study introduces a new dataset tailored to the Vietnamese e-commerce context, which can support future research. It also combines sentiment analysis with additional factors like price and discounts to better predict customer satisfaction. The findings highlight that customer reviews play a crucial role in determining satisfaction, confirming that sentiment extracted from comments is a strong indicator of overall customer experience.

6. Conclusion

This study developed a predictive model for the Vietnamese cosmetics e-commerce sector, achieving over 70% accuracy. Among deep learning models, BERT + Bi-GRU showed the best overall performance, while PhoBERT + Bi-LSTM achieved higher precision but lower recall. For customer satisfaction prediction, XGBoost outperformed SVM and Random Forest across all metrics.

The research highlights the challenges of applying models like BERT and PhoBERT to complex, real-world Vietnamese data, but also demonstrates the effectiveness of combining sentiment analysis with price-related factors through a two-phase approach.

In practice, these insights can help businesses improve customer feedback analysis, optimize pricing and discount strategies, and enhance personalized recommendations, ultimately boosting customer satisfaction and engagement.

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