Improving Sales Forecasting Models by Integrating Customers' Feedbacks: A Case Study of Fashion Products

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Abstract

In this paper, we investigate the task of predicting sales in the fashion companies – a very fascinating sector by utilizing advanced machine learning models incorporated with rich features. This can help businesses predict the sales by using data from past transactions and other factors. To this end, we propose a method to improve the performance of sale forecasting models by enriching the models with the information of customers' online feedbacks (i.e., consumers' ratings and comments). This method involves leveraging both historical sales data and direct customer feedback to create predictive models that offer a comprehensive understanding of market dynamics. To facilitate the experiments, we also introduce a newly-built dataset about fashion products on a large e-commerce platform in Vietnam. We conducted extensive experiments on this dataset using three robust regression models which are Linear Regression, Decision Tree, and Random Forest. To classify customers' reviews, we exploit the innovative pre-trained language model, namely Bidirectional Encoder Representation from Transformer (BERT). Experimental results on this dataset showed that integrating this kind of information indeed boosts the sale forecasting models' accuracy significantly by all conventional evaluation metrics such as MAE and RMSE scores. Specifically, the proposed sale forecasting models integrated with customers' feedbacks significantly decreased the error rates of RMSE scores by 12%, 23.3%, and 17,8% using Linear Regression, Decision Tree, and Random Forest respectively.

Keywords: Sale forecasting, sentiment analysis, time series analysis, machine learning, fashion products, e-commerce analytics

1. INTRODUCTION

Sales forecasting is the process of estimating future revenue by predicting the amount of product or services a company will sell in the future. Accurate sales predictions provide companies with the insights needed to make informed decisions, optimize their operations, stay competitive in a dynamic market environment, improve their economic benefits and reduce losses [1]. By using a combination of historical data, advanced modeling techniques, and domain knowledge, businesses can significantly improve their ability to anticipate and plan for future sales trends. To our knowledge, lots of work on sale prediction have been done using different machine learning techniques [3-7] [11-15] such as CNN, linear regression, decision tree, random forest, ARIMA and so on. Most of this work focus on using historical data of previous sales to make prediction. However, according to many research, one of the primary factors which influences consumers' purchasing decisions is customers' feedbacks. Online reviews have a significant influence on product sales. They may reduce or increase their uncertainty about the product by providing customers with rich information about the users' experience with products. Unfortunately, this sentiment information has not been properly investigated to accurately predict sales of companies, especially for low-resourced language like Vietnamese. Nowadays, online reviews have become more popular with the development of information technologies. A number of large Vietnamese e-commerce companies such as Shopee[1], Lazada[2] or Sendo[3] have established online review systems on their websites to encourage consumers to post product reviews in order to receive some awards. This leads to a change in customers' behavior patterns and affects

[1] https://shopee.vn/
[2] https://www.lazada.vn/
[3] https://www.sendo.vn/

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consumer purchasing decisions. These reviews often reveal personal emotions such as *positive*, *negative* attitudes towards products and potential consumers can browse them to inform their purchase decisions. *Positive* reviews can indicate customer satisfaction, while negative reviews can highlight areas for improvement [11-14] [19] [21]. This information is an important indicator which suggests higher or lower potential for future sales. Accordingly, sentiment analysis techniques have been used to measure the sentiments conveyed through the content of online reviews. This sentiment analysis helps businesses understand customer perceptions, which can influence sales predictions. In this study, we investigate how these specific sentiment information or general customers feedbacks (including both sentiments of reviews and ratings of customers on each product item) can be used to leverage the accuracy of sale forecasting models. To achieve this goal, we propose a new method to enrich the conventional regression model with rich information from customers' feedbacks to forecast product sales. Natural language processing techniques are exploited to analyze the sentiment of customer reviews. Specifically, to detect sentiments in customers' reviews, we incorporate the innovative pre-trained BERT language model [23] to compute the sentiment of the reviews. Then, these sentiments are incorporated to improve the accuracy of the traditional sale forecasting models. In addition, in this study, a real-world fashion dataset on a Vietnamese platform for this task is also developed to facilitate performing comparison experiments. We conduct extensive experiments on this dataset and find out that that integrating this kind of information indeed boosts the sale forecasting models' accuracy significantly by all conventional evaluation metrics such as MAE and RMSE scores. Specifically, the newly-proposed models decreased the error rates of RMSE scores by 12%, 23.3%, and 17,8% using Linear Regression, Decision Tree, and Random Forest respectively. To the best of our knowledge, this is also the first work done for Vietnamese and in the fashion domain.

The remainder of this paper is structured as follows. Section 2 provides a literature review on sale forecasting models, whereas Section 3 describes the research framework, including sentiment analysis models, and forecasting models integrated with the customers' feedbacks. Section 4 then provides the data collection and annotation process, the evaluation metrics. In this section, experimental results of sentiment analysis models and the sales forecasting models are also presented and compared to some strong standard baseline models. Section 5 concludes the paper and suggests some future research directions.

2. RELATED WORK

The application of machine learning techniques to sales prediction has revolutionized the way businesses anticipate and plan for future actions. This field leverages historical data, market trends, and various features to create predictive models that estimate future sales performance. Machine learning algorithms, such as regression, time series analysis, and neural networks, analyze patterns and relationships within historical sales data and external factors (e.g., economic indicators, marketing campaigns, seasonal trends). By learning from past sales behaviors, these models can forecast future sales with a reasonable degree of accuracy.

Due to the exponential increase of the vast volume of data used in e-commerce transactions [2], the industry has significant hurdles in identifying an accurate data mining technique and successful prediction strategy [3]. Numerous problems arise while analyzing sales data, and the key sales functions include determining the product attribute, setting the price, realizing net sales, and introducing new products. Hence, in previous studies, the Expectation Maximization (EM) algorithm and many prediction techniques are covered in [4], [5] and [6]. According to [5], sales forecasting in e-commerce has been accomplished using the convolution neural network (CNN) method. Based on their respective studies, [6] and [7] have both decided to use the neural network technique. Some research exploited ARIMA models for building better prediction models [7, 8]. Based on the study [10], both the random forest and gradient boosting models performed admirably in terms of successfully fitting the data into the models. However, because it has lower error accuracy compared to gradient boosting, random forest is the best model for regression models.

We have witnessed that many machine learning methods have been applied to predict sales such as regression models, time-series models. However, challenges exist in this domain. Accurate sales predictions demand more external factors that influence sales unpredictably. Specifically, customers' feedback has a profound impact on sales prediction by providing valuable insights into consumer sentiments, preferences, and behaviors. Customer feedbacks can be analyzed using sentiment analysis techniques, which determine the emotional tone expressed in the text. Positive sentiments in feedbacks often indicate satisfaction with a product or service, suggesting higher potential for future sales. Negative sentiments might highlight areas that need improvement or correction, helping businesses mitigate issues that could otherwise negatively impact sales. Therefore, incorporating customer feedback into sales prediction models can enhance the accuracy and relevance of predictions. By understanding customer sentiments, businesses can make informed decisions that lead to better products, more targeted marketing, and increased sales potential.

So far, most research has focused on the domains such as restaurant or electronic devices [9], [11-14]. This will assist the e-commerce platform, as well as these industries in tracking and analyzing sales so that better financial decisions can be made. To our knowledge, there is no research focusing on the fashion domain due to data shortage, especially for poorly-resourced language such as Vietnamese. Therefore, in this paper, we focus on this fashion domain and introduce a new dataset for sale forecasting in the Vietnamese fashion domain. To verify the effectiveness of the proposed method, we also conduct extensive experiments to see how customers' feedbacks can help to enhance the prediction model. To our knowledge, this is also the first work done for sale forecasting in Vietnamese companies which incorporating with customers' feedbacks.

3. A PROPOSED MODEL TO IMPROVE SALES FORECASTING ACCURACY BY USING CUSTOMERS' FEEDBACKS

In this section, we present the architecture for integrating customers' feedback to the conventional sale forecasting models. Then, we describe each component in more details.

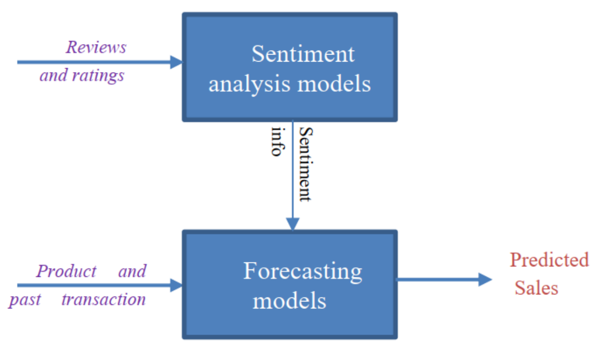

Fig. 1. A framework for integrating customers' feedback into forecasting models

Figure 1 shows the overall architecture which includes two main components. The first component is the sentiment analysis models which will help to recognize the sentiment of each customers' review. This information will be fed into the second component – sale forecasting models to help generating the final sale prediction.

To integrate the customers' feedbacks, we generate several new columns for each record. Specifically, three new columns are appended which correspond to three labels known as "*Negative", "Neutral", "Positive*". The value in each column is the rate of comments belonging to each label divided by the total number of comments. This rate value is integrated as an independent variable in the conventional sale prediction models using machine learning. Besides the sentiment information, we also employ customers' rating information (from 1 to 5 stars) to enrich the model. Specifically, we appended one more column with the value is the average rating of customers for each product item. Then, the training set and testing set is taken from this merged data frame diving by date. Quantity sales for 300 items we crawled from the Shopee platform. The training set would take data from date is smaller than or equals to a specific pre-defined date. The testing set is taken from all date after that pre-defined date.

Sales Forecasting Models

The process of modeling entails choosing the algorithms that will be used for the project's research. We will employ three distinct methods for this study: linear regression [26], decision trees [25], and random forests [24]. The algorithms were chosen because they are frequently used in prediction analysis and yielded the great performance.

The goal of linear regression, a machine learning technique, is to predict the value of one variable based on the value of another variable. Dimensionality reduction techniques, regularization, and cross-validation are used to manage overfitting rather effectively. The sale prediction is evaluated based on some indicator features $x_i\{i = 1 \dots n\}$.

DTs are classic algorithms, which are organized in a tree-like structure in which each internal node represents a 'test' on an attribute. The core algorithm for building DT called ID3 which employs a top-down, greedy search through the space of possible branches with no backtracking. The main challenge while building the tree is to decide on which attribute to split the data at a certain step in order to have the 'best' split. To do this, we use the concept of information gain (IG), which measures the difference between the entropy before and after a decision. In regression setting, the ID3 algorithm uses standard deviation reduction as a replacement of IG to construct a DT. A decision support tool that handles both numerical and categorical data uses a tree-like model of decisions and their potential consequences, including chance event outcomes, resource costs, and utility. As a result, it performs well even when its assumptions are slightly violated by the true model from which the data were generated.

In this paper, we also exploit an ensemble method, namely Random Forest. Given a sample of data, multiple bootstrapped subsamples are drawn out. Then, a DT is built on each of the bootstrapped subsamples. After the tree has been formed, an algorithm is used to aggregate over the trees to form the most efficient predictor.

Sentiment Analysis Models

The goal of sentiment analysis is to categorize the reviews as having a positive, negative, or neutral sentiment. This work has been explored extensively for high-resourced languages such as English. Unfortunately, not much work has been done for Vietnamese [27]. Motivated from the achievement of innovative pre-trained models on many NLP tasks, namely BERT (Bidirectional Encoder Representations from Transformers). In this paper, we also investigate this powerful approach that leverages BERT's contextual understanding of language to accurately determine the sentiment expressed in a piece of text. BERT is a pre-trained transformer model that has demonstrated remarkable performance in various natural language processing tasks, including sentiment analysis. For Vietnamese, PhoBERT [25] is the first publicly available large-scale monolingual language models with Vietnamese pre-training using RoBERTa architecture. PhoBERT achieves new state-of-the-art performances on four downstream Vietnamese NLP tasks of Part-of-speech tagging, Dependency parsing, Named-entity recognition, and Natural language inference, outperforming prior monolingual and multilingual techniques. The results of the experiments demonstrate that PhoBERT consistently outperforms the most recent best pre-trained multilingual model XLM-R (Conneau et al., 2020) and advances the state-of-the-art in a number of NLP tasks that are unique to Vietnamese.

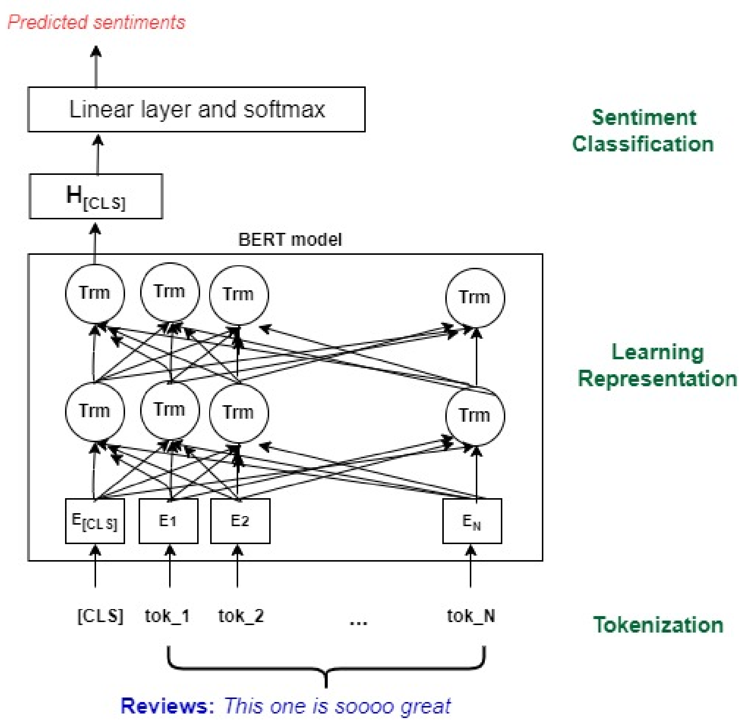

Figure 2 - Overall architecture to detect sentiments in customers' reviews.

In this study, this pre-trained PhoBERT is used to classify customers' review for each item into one of three possible labels "*Negative", "Neutral", "Positive*". The data used to train and test the model are the raw data we crawled from Shopee combined with VLSP 2016[4] dataset. Figure 2 shows the architecture of applying PhoBERT in sentiment analysis. It includes three main phases as follows:

- **Tokenization**: Split the input text into individual tokens (words or subwords) using BERT's tokenizer. There is one Special Tokens: [CLS] (start token) and [SEP] (end token) to mark the beginning and end of the text.
- **Learning Representation**: Choose a pre-trained BERT model variant (such as PhoBERT-base or PhoBERT-large) to learn the vector representation for the whole reviews. The final output $\mathbf{H}_{[CLS]}$ will capture the contextual representation for the input review.
- **Detecting sentiments**: In order to detect the sentiments of reviews, we add a classification layer on top of BERT's output. This layer will be trained to predict sentiment labels (positive, negative, neutral) based on the contextualized embeddings from BERT. This layer uses a labeled sentiment dataset for fine-tuning. This dataset should include text examples along with their corresponding sentiment labels.

[4] https://vlsp.org.vn/vlsp2016/eval/sa

During training, input the tokenized and preprocessed text into the BERT model. The model calculates the loss between the predicted sentiment probabilities and the actual sentiment labels. Backpropagate the loss to update the model's weights using gradient descent. After fine-tuning, the model can be used for sentiment analysis on new text to obtain the predicted sentiment probabilities for each class (positive, negative, neutral). The sentiment class with the highest probability is considered the predicted sentiment of the input text. You can set a threshold for the predicted probabilities to classify the sentiment into different levels of confidence.

We recognized that the VLSP 2016 dataset having customers' review about technological field is suitable for comments in Shopee platform. In PhoBERT experiment, training dataset is to adjust model to learn by sample while testing dataset is output that we are desired to solve in exact context in testing dataset as same as in training dataset. In testing dataset, we are expected to have the best sample to evaluate new sample. PhoBERT model would analyze sentences in sample, and then it classifies into sentiment categories. The output is when putting new sentence into new model, result of PhoBERT model would predict new sentence is *positive, negative*, or *neutral*.

4. EXPERIMENTS

In this section, we first describe the process of building the dataset to conduct experiments. Then, experimental results on sentiment analysis models and sale forecasting models are presented.

4.1. Building Datasets

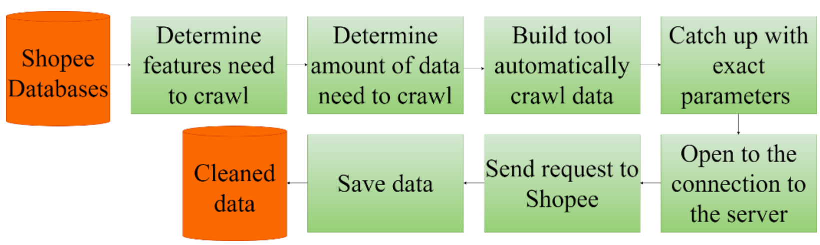

Fig. 3. Data collection process

We collect and build the data based on the Shopee platform[5] - one of the largest e-commerce platforms in Vietnam. Figure 3 shows the corpus annotation process which consists of 7 main steps as follows:

Step 1. Determining the products and their features need crawling on Shopee. After investigating, we decided to crawl the necessary information which consists of Item Names, Daily Quantity Sales, Prices, Ratings, and customer reviews related to the items.
Step 2. Determining amount of data need to crawl: We collect all features determined in many days recently
Step 3. Building tool automatically crawl data day by day.
Step 4. Catching up with exact parameters returning features in Shopee API
Step 5. Open to the connection to the server
Step 6. Send request to Shopee to collect and process data
Step 7. Save data in csv files or save in databases if having large volume of data and clean features in dataset if necessary: Price and Customer reviews

Table 1. shows some statistics about this dataset. There are 3,000 historical data collected by using the tool we built. This process performed manipulations in gathering practical data updated day by day, resulting better results in

[5]shopee.vn

testing data rather than manual method which is impossible to crawl large volume of up-to-date customer reviews and quantity sales as much as possible. We also manually annotated sentiment labels for 5,646 comments collected. Each comment will be manually classified as *positive, negative* or *neutral* labels.

Table 1. Some statistics on crawled data

Attributes	**Crawl methods**	**Number of data crawled**
Item Names	Automatically crawl using tool	300 items
Daily Quantity Sales	Automatically crawl using tool built	10 rows of quantity sales for each item (10*300 records)
Prices	Manually crawl information showed in Shopee website	300 ranges of prices
Ratings	Manually crawl information showed in Shopee website	300 ratings
Reviews	Manually crawl information showed in Shopee website	5,646 comments
Quantity sold in Vietnam and global	Manually crawl information showed in Shopee website	300 general quantity sales for 300 items

4.2. Evaluation metrics

For the sentiment analysis models, we evaluate the performance of the model by using precision, recall, the F1 score as commonly used in many other classification problems as follows:

$$F_1 score = \frac{2 * precision * recall}{precision + recall}$$

$$precision = \frac{TP}{TP + FP}$$

$$recall = \frac{TP}{TP + FN}$$

where TP (True Positive) is the number of samples of class *i* that are correctly identified. FP (False Positive) is the number of samples that are mistakenly identified as not belonging to class *i*. FN (False Negative) is the number of samples belonging to class *i* that are not identified.

Then, the final precision, recall, and F1 score when considering these classes is the micro average over the data.

For the sale forecasting models, there are four error metrics that are commonly used for evaluating and reporting the performance of a regression model which are: *Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE)* and *R2*. We used the scikit-learn Python machine learning library to do this. It can be interpreted that the lower values indicating better predictive accuracy.

4.3. Experimental results of sentiment analysis models

Table 2. Results of the three models on sentiment analysis

	precision	recall	F1-score
LSTMs	82.16	81.99	82.05
CNNs	82.75	80.05	80.48
PhoBERT	88.13	88.47	**88.26**

We combine two sources of data including sample data from 2016 VLSP, and Shopee' comments data collected in the previous step. From VLSP, we got 10,351 reviews on hotels and restaurant domains which are also labeled as *positive, negative* and *neutral* labels. This new combined dataset is divided into training set and testing set with a ratio of 8:2. Table 2 shows the experimental results using the proposed PhoBERT architecture (as mentioned in Section 3) and two strong robust baseline models which are LSTMs and CNNs. From these results, we can see that PhoBERT model yielded the best performance with more than 88% in the F1 score.

We also measured the performance on each label as shown in **Table 3.** It can be seen that, the *negative* and *positive* labels got very high performance (more than 90% in the F1 score). Unfortunately, the *neutral* label got quite low results. The reason may be caused by the high ambiguity of the label with the other two labels.

Table 3. Results of PhoBERT model on each label (%)

	precision	recall	F1-score
Negative	90.00	92.81	91.39
Neutral	66.61	59.19	62.68
Positive	92.26	92.86	92.56
Average	88.13	88.47	88.26

These results are exploited to calculate the rate of comments belonging to each sentiment label (i.e. *positive, negative* and *neutral)* for each item. This rate equals to the number of reviews of each sentiment label divided by the total number of reviews for each item.

4.4. Experimental results of the forecasting models

In this section, we present the experimental results with and without integrating customers' feedbacks. There are two main kinds of feedbacks investigated. The first one is ratings of products. The second one is the sentiments of customers' reviews which were detected via the sentiment analysis models. These outputs were generated by using the best PhoBERT architecture as shown in the previous sub-section 4.1.

The experimental results are shown in **Table 4.** We can see that the linear regression model got the RMSE score of 12.60. RandomForestRegressor and DecisionTreeRegressor, meanwhile, produced comparable outcomes. RandomForestRegression has a slightly higher R2 score and RMSE score than DecisionTreeRegressor (0.48 and 0.46 for R2 score, 13.08 and 13.26 for RMSE, respectively).

Table 4. Experimental results of sales prediction models with/without integrating customers' feedbacks on four evaluation metrics

	R2	MSE	MAE	RMSE
LinearRegression	0.52	158.89	6.97	12.60
+ *sentiments*	0.34	124.68	6.42	11.16
+*sentiments*+*ratings*	0.33	122.88	6.37	11.09
DecisionTreeRegressor	0.46	175.72	7.15	13.26
+ *sentiments*	0.44	104.91	6.34	10.24
+*sentiments*+*ratings*	0.44	103.42	6.28	10.17
RandomForestRegressor	0.48	171.13	7.02	13.08
+ *sentiments*	0.36	119.27	6.50	10.92
+*sentiments*+*ratings*	0.37	115.51	6.36	10.75

The results also showed that integrating customers' rating as one more feature for each row of data, evaluation metrics would slightly diminish to 11.09 for RMSE measure, which decreased to 0.94% for combining Linear Regression and Sentiment analysis, Rating. Meanwhile, RandomForestRegressor model has better evaluation metrics, which is for 10.74 RMSE. Other measures perform evaluation of integrated sales forecasting model are 0.37, 115.51, 6.36 for R2, MSE, MAE, respectively, for integrating both customers' review, and customers' rating, compared to 0.34, 124.68, 6.42 for same figures for linear regression model combination of customers' feedbacks and customers' ratings.

When combining the result of PhoBERT sentiment analysis and customers' rating in Linear Regression, we can conclude that performance of result for quantity sales is better with RMSE decreases to approximately 1.6. In detail, it diminishes error by 1.6*100/12.60, equals to 11.98% compared to Linear regressor model is not integrated with result of sentiment analysis model and customers' rating. Meanwhile, compared to Random Forest regressor, integrating sentiment analysis feature and customers' rating makes RMSE score decrease to 2.33, meaning error rate goes down by 17.81% with the same model without having this combination. Decision Tree regressor model has comparative evaluation metrics with Random Forest regressor; however, the least error performed by RMSE, 10.17 makes Decision Tree regressor is the best regression model when integrating two features known as sentiments and rating. The error rate is gone down to 23.30%. We also see that since R2 score of Decision Tree regressor with combination of sentiments and ratings is slightly higher than same figures for Random Forest Regressor, 0.44, 0.37, respectively, resulting in Decision Tree regressor model fits better than the other. As a result, although Linear Regression is the best model without combination, this model performed the worst evaluation metrics with any combination. Meanwhile, Decision Tree regressor is the best model when having combined sentiments and rating with 103.42 and 6.28 for MSE and MAE scores, respectively.

These results confirm that incorporating sentiment analysis and customers' feedbacks into sale forecasting models, we can capture the emotional component in order to complement traditional quantitative method alone. It leads to more accurate prediction of future sales trends.

5. CONCLUSION

This paper presented a work on sales forecasting for Vietnamese e-commerce companies. Instead of the traditional approach which mostly exploited the historical sale data only, we proposed a new method to enhance the accuracy of predicting sales in the fashion industry by enriching the models with the customers' feedbacks information. In addition, we also contributed a dataset about sentiment analysis and sale forecasting in this field basing on the Shopee platform. We conducted extensive experiments to show that integrating this kind of information indeed boosts the sale forecasting models' accuracy in all evaluation metrics. Experimental results on three robust machine learning models showed the potential of combining machine learning with human insight. Specifically, the proposed sale forecasting models integrated with customers' feedbacks significantly decreased the error rates of RMSE scores by 12%, 23.3%, and 17,8% using Linear Regression, Decision Tree, and Random Forest respectively.

In future work, we would extend this research to other product types and other platform in order to make sure that sentiment analysis is one of paramount factors contributing to efficiency of sales prediction. Moreover, it is essential to figure out common pattern of unique shops in one category to predict daily sales more accurately when integrating more features so that recently trendy models or deep learning models are taken advantage as much as possible. Many techniques which are not applied in this problem such as parallel-oriented sentiment analysis focusing on the extent of importance of each word, Bass or Norton model for sales forecasting need being conducted. After this research, we would be able to draw a conclusion that the more quantity sales and updated customer' reviews in exact context with daily quantity sold for each item have lots of variation day by day, the more accurate results we would attain.

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