Advances in Artificial Intelligence and Machine Learning; Research 4 (3) 2593-2613 Received 19-07-2024; Accepted 19-09-2024; Published 26-09-2024

Cross-Domain Aspect-Based Sentiment Analysis for Enhancing Customer Experience in Electronic Commerce

Yadi Xu yadixu@student.usm.my
School of Computer Science, Universiti Sains Malaysia, Penang, Malaysia

Noor Farizah Ibrahim nfarizah@usm.my
School of Computer Science, Universiti Sains Malaysia, Penang, Malaysia

Corresponding Author: Noor Farizah Ibrahim

Abstract

Cross-Domain ABSA has proved effective in extracting more descriptive sentiment information from the reviews or feedback as an important step in improving the experience of the customers in electronic commerce. This work examines the performance of ABSA in the cross-domain scenario where models trained on the review data of one domain for example electronics domain are applied to another domain such as fashion domain. Here, we put forward a risk mitigation strategy that builds upon transfer learning and domain adversarial training methodologies to enhance the overall resilience and reliability of sentiment estimations across multiple product domains. The proposed model was tested using data obtained from different e-commerce retailers, such as Amazon, eBay, and Alibaba concerning various categories of products including electronics, fashion, and home appliances. The outcome of experiments show better performance over most of the compared methods of single-domain ABSA and cross-domain approaches. The model offered greater accuracy, recall rate, F1-score, and cross-domain efficiency, which demonstrated the model's effectiveness and versatility. The consequences for e-business companies are significant. Improved sentiment analysis allows businesses to obtain more specific data about customers' opinions, correct mistakes when developing products, and adjust their advertising approaches. Also, the use of advanced text analytics to measure and monitor such aspects in different product areas offers a competitive edge and improves product innovation decisions. However, there are several limitations to the study itself, such as the variations that may arise among the domain, and the limited availability of the data. Further work is to be done on more complex and sophisticated methods of domain adaptation, using external resources; the main model itself should also be much faster and more efficient in scalability. This work thus indicates an opportunity for cross-domain ABSA to generate practical insights for enhancing customers' experience within e-commerce.

Keywords: Cross-domain sentiment analysis, Aspect-Based Sentiment Analysis (ABSA), Domain adaptation, E-commerce customer reviews, NLP

Citation: Yadi Xu and Noor Farizah Ibrahim. Cross-Domain Aspect-Based Sentiment Analysis for Enhancing Customer Experience in Electronic Commerce. Advances in Artificial Intelligence and Machine Learning. 2024;4(3):151.

1. INTRODUCTION

E-commerce has brought a great change to the consumer market by changing people's experience and approach toward purchasing goods and services. Nowadays, when retail giants of the caliber of Amazon, eBay, and Alibaba offer vast opportunities for buying goods and services, consumers do actively participate in reviewing as the means of sharing their experiences [1]. These reviews are indeed full of details that can provide useful data, which may reflect customers' level of satisfaction, their preferred products or services, or areas that require attention [2]. Such information may help businesses improve their delivery of services to consumers, modify goods and services, and adjust promotional techniques.

However, the tremendous explosion of user-generated content is a considerable problem for analysis techniques that involve manual work. Due to the large number of reviews collected it is infeasible for businesses to review the text of each review and look at sentiments, thus creating a need for automated tools to perform sentiment analysis. While the traditional approaches to sentiment analysis are effective to some extent, they do not capture much detail regarding the extent of the customer satisfaction or dissatisfaction, especially when sentiments are directed towards a particular feature or component of a product. For instance, a customer might have considered the battery life of a smartphone to be excellent but considered the camera quality to be poor [3]. Aspect-Based Sentiment Analysis (ABSA) helps evade this issue by analyzing sentiments concerning different aspects of a product.

Nonetheless, one has to admit that the utilization of ABSA in electronic commerce can be restricted by the requirements of the specific domain of the existing models. Normally, such models are learnt from the reviews of a particular domain of products, for instance electronics or fashion, and the accuracy of the predictions reduces drastically whenever they are applied in the other domain [4]. This inability negates the possibility of generalizing ABSA in different forms of e-commerce platforms which consist of numerous categories of products.

Cross-domain sentiment analysis tries to address this issue by building sentiment analysis models that can apply what has been learned from one domain to another. However, the building of diverse and strong cross-domain performance is not a simple task because of the differences in the vocabularies, contexts, and ways of expressing the ideas across different domains [5]. For instance, the attributes and the emotions regarding electronic goods are different from those of apparel or kitchen appliances. Thus, it is critical to identify the opportunities for the improvement across the domains and develop the new approaches for the further improvement of the ABSA models and application for the businesses willing to gain deeper insights from the various types of the customers' feedbacks.

1.1 Objectives of the Study

This research seeks to address the gap in cross-domain ABSA by training and designing a model that would effectively learn and identify aspect-level sentiments in multiple-product domains. In particular, this work aims at:

1. Develop a comprehensive method for extracting aspect terms and their corresponding sentiments from customer reviews in various e-commerce domains.
2. Implement domain adaptation techniques to enhance the cross-domain applicability and robustness of ABSA models.
3. Evaluate the proposed model's performance on benchmark datasets and compare it with existing state-of-the-art approaches.

Through the accomplishment of the following objectives, this study shall help to contribute to the improvement of the sentiment analysis approaches in e-commerce that can enable more accurate efficiency in providing businesses with beneficial information to improve customers' experience. The efficiency in cross-domain ABSA will make it easier for the companies to capture the sentiment of the customers together with the specific details of their feedback by product category which will help companies to make better decisions and improve on their services.

The rest of this paper is organized as follows: Section 2 includes an extensive literature review in the area of sentiment analysis, ABSA, and cross-domain sentiment analysis. Section 3 outlines the approach, data gathering, data preparation, and model creation. The details of the experimental setup and results are described in section 4. Finally, section 5 will present the conclusions and recommendations that e-commerce businesses can draw from current research. Last but not the least, Section 6 provides the conclusion of the paper along with the conclusion and recommendation for the future work.

2. LITERATURE REVIEW

2.1 Sentiment Analysis in E-commerce

Basically, sentiment analysis or opinion mining is defined as a process of classifying textual data based on feelings expressed in them. Hence, sentiment analysis is a crucial factor in determining customers' satisfaction levels and feedback in the world of electronic commerce [6]. From customer's comments, business can determine the perceptions that many customers hold about their products and services to enable them formulate strategies to help improve customers' satisfaction.

It is a known fact that the primary purpose of performing sentiment analysis in the e-commerce context is to find out whether the sentiment expressed is positive, negative or neutral in the customer reviews. This can be done by different methods such as machine learning approach, lexicon-based approaches, and other methodologies that fall under the two [7]. The machine learning approaches use trainable classifiers with labeled datasets to classify the sentiments while the lexicon-based approaches use a list of words with corresponding score to calculate the overall sentiment of text.

Even though SA is increasingly used in e-commerce websites, the majority of the research has been carried out using single-domain contexts. Single-domain sentiment analysis trains and tests the models based on reviews from the same specialty like electronics and fashion. Although this approach has been found effective, it has some drawbacks, especially when deployed in other domains [8]. It is as such found that different domains can have significantly different language and context, especially in aspects of products, which can negatively impact the performance of models.

Another resent work in sentiment analysis was done by Nguyen, Nguyen, Vu and Pham [9], who used machine learning approach to classify movie reviews as have positive or negative attitudes. It built on the previous studies in the area of sentiment analysis, providing clear evidence on the utility of machine learning models for sentiment classification. However, their study was restricted to an individual domain and, as a result, called for broader approaches.

Tengjiao, Minjuan, Shumei and Siwen [10], used a method of opinion feature mining for customer reviews to determine features that the customers had liking or disliking to in the context to e-commerce. To obtain features and sentiments of the reviews, their approach employed association rule mining that was helpful in understanding customers' opinions. This work laid the basis for more refined methodologies in aspect based sentiment analysis.

However, more recent studies have applied deep learning models to carry out the sentiment analysis, and this has been a breakthrough. Hassan and Mahmood [11], also employed CNNs for the classification of sentiment at the sentence level and this illustrated how CNNs are capable of capturing local areas of text. Likewise, Huang, Chen, Zheng, and Dong [12], proposed a model using RNNs for sentiment analysis and explained that RNNs can easily handle sequential data with sequence relationships.

Nevertheless, most of the recent SA models are developed on single domain data and fail to work in a different domain. To overcome this problem, researchers have turned to cross-domains sentiment analysis, though the focus is to establish models that can work across different domains.

2.2 Aspect-Based Sentiment Analysis (ABSA)

Aspect-Based Sentiment Analysis (ABSA) takes the fundamental technique of sentiment analysis a step further by not only determining the sentiment expressed in a customer review but also the aspect of the product being focused on in that sentiment [13]. To some extent, it is more precise as businesses gets to know what aspect of their products is valued or disliked by the customers.

ABSA involves two main tasks: That is, aspect extraction and the classification of sentiments. Aspect extraction seeks to identify in the review the particular aspects or characteristics that the author was referring to while sentiment classification seeks to identify the polarity of the aspect mentioning [14].

Various methods have been adopted in aspect extraction which include rule-based approach, machine learning models and deep learning technologies. Rule-based methods employ simple linguistic rules for extracting aspect terms, while in machine learning, the aspect terms are automatically inferred from labelled datasets [15]. According to the latest research, deep learning techniques including CNNs and RNNs have enhanced the aspect extraction in a remarkable way.

For instance, Song, Yan and Liu in [16], suggested extraction of product features from the reviews through syntactic dependency parsing. Their approach involved locating noun phrases which referred to product features and sentiments which were related to the context. This method was beneficial in showing that rule-based techniques could be applied for aspect extraction but this came with a call for the application of domain-specific rules.

Wen and Zhao [17], employed a machine learning approach for aspect extraction by presenting a conditional random field (CRF) model to detect aspect terms in the customer reviews. The aspects were extracted by training their model on a labeled dataset of product review which attained high accuracy. This also emphasised the suitability of progressing machine learning models in capturing of patterns within text.

Subsequently, aspect extraction methods have been developed more with the use of deep learning models. Zhang, Xu and Zhao [18], also developed an aspect extraction model based on Attention LSTM where they used attention to control focus on relevant aspects of the text. They compared their model to the existing work and observed that deep learning techniques were superior to other machine learning techniques for ABSA.

Sentiment classification can also be conducted in a similar manner, and deep learning yields high accuracy in most cases. For example, Tang, Qin, and Liu [19], proposed the deep memory network for aspect level sentiment classification where they employed multiple layers of memory to incorporate contextual features. The next model of them set a record of performance in benchmark datasets to further prove the possibility of using deep learning for ABSA.

However, ABSA models are generally trained with domain-specific corpora, which in a way restricts the model to different domains. It has thus resulted in the use of cross-domain sentiment analysis approaches that enhance the ABSA model's applicability.

2.3 Cross-Domain Sentiment Analysis

Domain adaptation in sentiment analysis aims at using the knowledge acquired from a particular domain in another in order to enhance performance across various products. This is even more difficult when considering differences across domains, such as language, context, or aspects [20]. For example, the attributes and perceptions for electronics are rather different from those of fashion accessories or home appliances.

Some solutions have been made to overcome the problems related to the cross-domain sentiment analysis. Some of these are done through domain adaptation, transfer learning and incorporating auxiliary tasks so as to enhance generalization. Domain adaptation methods have the goal of reducing the gap between the source and target domains more, so that a model trained for one domain can be used in the other [19]. This can be done by instance re-weighting, feature alignment, adversarial training and etc.

The second approach of instance re-weighting focusses on assigning different weights on sources side instances depending on their similarity with instances in the target side. In instance re-weighting, Tan, Deng and Yang [21], proposed Kernel Mean Matching (KMM) algorithm, which re-weighed source domain instances such that the distribution of instances in the target domain was replicated. This approach enhanced the performance level of cross-domain sentiment analysis models by eliminating the domain gap.

The methods of feature alignment are designed to discover a common feature space which brings the distances between the source and target domains to a minimum. Blitzer, McDonald and Pereira [22], developed a feature mapping method known as structural correspondence learning (SCL), which attempted to map features in the source and target domains such that the features that were most similar between the two domains can be mapped to each other. This approach made it possible to extent the sentiment analysis models to other domains.

Adversarial training inspired by the Generative Adversarial Network (GAN), aims to train a model to distinguish instance from the source domain and the target domain while at the same time learning a feature representation that fools the domain discriminator. Cross-domain sentiment analysis was another type of DSA: Ganin et al. [23], employed a domain-adversarial neural network (DANN) for this kind of analysis and used adversarial training to update domain-invariant features. Their approach resulted in substantial enhancement of cross-dome performance.

Transfer learning entails Tutting models on a large amount of data from the source domain and then using the models to train on a small sample from the target domain. Howard and Ruder [24], developed a transfer learning method called universal language model fine-tuning (ULMFiT), which trained a language model first on a diverse collection of texts and then on the domain of interest. This method allows obtaining the accuracy comparable to other similar techniques used in natural language processing, such as sentiment analysis.

Secondary tasks like multi-task learning are when models are trained with different but related tasks so as to improve their performance. Liu et al. [25], proposed a multi-task learning approach for cross-domain sentiment analysis which simultaneously trained separate models for sentiment classification and cross-domain sentiment analysis. Current study's approach enhances source and target domain sentiment analysis models as per their approach.

However, when integrating sentiment analysis with different domains, it is still an open issue. The different language and context that occur across domains make it necessary to be able to build models that have high accuracy and that can flexibly work in different environments. The goal of this research is to propose a new cross-domain ABSA approach based on domain adaptation methods that improve the reliability and accuracy of sentiment analysis in different domains of e-commerce.

2.4 Current Challenges and Gaps

While sentiment analysis and ABSA have made significant strides in understanding customer feedback in e-commerce, several challenges and gaps remain, particularly in the context of cross-domain analysis.

1. Domain-Specific Language and Context: One of the essential challenges of cross-domain sentiment analysis is the variations in words and context across different product categories. A word or phrase with some sentiment in some domain carries very different, or even opposite, sentiments in another. For example, ”lightweight” might be positive for a laptop but is an unfavorable term for a winter coat. This kind of variability can only be handled provided there is a model which can learn and generalize knowledge between domains as effectively as possible [26].

2. Aspect Extraction: In ABSA, the extraction of relevant aspects from customer reviews is very critical. However, the words related to aspects may vary significantly across different domains, making it challenging to train a universal model for extracting those aspects. The methods in use at the moment are heavily domain-dependent because training data for each domain is needed; this reduces their application possibilities to new domains. More flexible techniques for aspect extraction that can generalize better are needed [27].

3. Sentiment Classification: Another challenge lies in sentiment classification toward these extracted aspects, especially when it comes to cross-domain data. Expressions of sentiment are mostly context-dependent, and the model trained within one domain does not generalize very well in another. Building high-accuracy domain-adaptive sentiment classification models is hence of importance [26].

4. Data Scarcity: Especially for some of the domains, in most cases, there is little availability of labeled data with which to train sentiment analysis models; this in fact limits development of strong models and generalization of ABSA techniques. Consequently, this part is developed regarding the unsupervised or semisupervised learning method and the integration of information by using external knowledge sources to overcome the above shortcoming [28].

5. Evaluation Metrics: For the evaluation in ABSA of performance for models across domains, appropriate metrics should be applied with regard to variability between each domain. Traditional metrics of evaluation may not prove sufficient to deal with the complexities of the cross-domain analysis; therefore, the development of new metrics and benchmarks may be necessary [29].

6. Scalability: With increased customer reviews, scalability becomes a question. Efficient and scalable models deal with large datasets to provide real-time analysis, which has practical applications in e-commerce [30].

In particular, aspect-based sentiment analysis holds immense potential to benefit electronic commerce in customer experience. However, cross-domain variability remains one of the major challenges. This study handle these challenges with the help of domain adaptation techniques that are at the very frontier of innovation in developing robust and scalable deep learning models which would otherwise provide accurate and actionable insight across diversity in domains of electronic commerce. Next, it will define the methodologies and experimental settings to improve the performance of cross-domain ABSA models.

3. METHODOLOGY

3.1 Data Collection

To develop and test cross-domain ABSA model, customer reviews from online shopping platforms such as Amazon, eBay, and Alibaba were collected [4]. This includes e-commerce websites that would also provide very diverse product categories like electronics, fashion, home appliances, etc., to ensure a comprehensive dataset. The reviews pick several aspects and sentiments and offer, in particular, positive, negative, and neutral sentiments with a balanced distribution. This dataset collected reviews in different languages, which later needed to be translated into English for consistency.

3.2 Preprocessing

Preprocessing is the step with numerous cleaning and preparation phases of the raw review data for analysis. First of all, noise removal is done, which would clean the raw data with respect to HTML tags, URLs, and special characters. After that, the text gets tokenized into individual words or phrases. This process is essentially a step before feature formation for further analysis. Methods of NLP are used for identifying and standardizing aspect terms and opinion words by, for example, reducing words to their root form through stemming or lemmatization. Stop words are also removed, that is, common words with very little meaning in context, like ”and,” ”the,” ”is,” to concentrate on meaningful content in the reviews [31].

3.3 Aspect Extraction

One important step in this direction is aspect extraction, through which some of the features or attributes related to the products mentioned in these reviews are to be retained. Here, this study is using a hybrid approach in which both rule-based and machine learning techniques will be used. Rule-based approaches apply predefined linguistic patterns with part-of-speech tagging to identify the aspect terms. For example, nouns and noun phrases mostly represent product aspects. The other side involves the training of machine learning models like Conditional Random Fields and deep models like Long Short-Term Memory for the automatic identification of aspect terms. This can further enrich domain-agnostic robustness and accuracy for aspect extraction.

3.4 Sentiment Classification

Then classify the sentiment expressed towards each of these aspects after extracting the aspect terms. Current study will adopt a supervised learning approach wherein it uses sentiment classification models on labeled datasets. These models can consist of traditional classifiers like SVMs and advanced deep models like Bidirectional LSTMs and Attention-based mechanisms. In this work, every aspect term is assigned a sentiment label as positive, negative, or neutral based on the contextual information extracted from the text [32]. Models are fine-tuned to handle domain-specific variations of expressing sentiment effectively.

3.5 Cross-Domain Adaptation

Current study use domain adaptation techniques to improve the model performance across different domains of products. One of the popular tools for this purpose is transfer learning, in which a model pre-trained on a large source domain dataset gets fine-tuned for a smaller target domain dataset [23]. This uses the knowledge gained from the source domain to perform better in the target domain. Besides, domain adversarial training is done for learning domain invariant features. It means training a domain discriminator to distinguish source from target domain instances, while training the sentiment analysis model to confuse the discriminator, hence generalizing across domains.

3.5.1 Model explanation

The proposed model integrates several components to perform cross-domain ABSA effectively (FIGURE 1):

1. Preprocessing: Text is tokenized, lemmatized, and cleaned using NLTK and SpaCy.
2. Feature Extraction: Pre-trained BERT is used to extract contextualized word embeddings.
3. Aspect Extraction: Conditional Random Fields (CRF) are applied to identify aspect terms in the reviews.
4. Sentiment Classification: Bidirectional LSTM (BiLSTM) is used to classify the sentiment associated with each aspect.
5. Domain Adaptation: Domain-Adversarial Neural Network (DANN) is employed to ensure the extracted features are domain-invariant, facilitating effective cross-domain analysis.

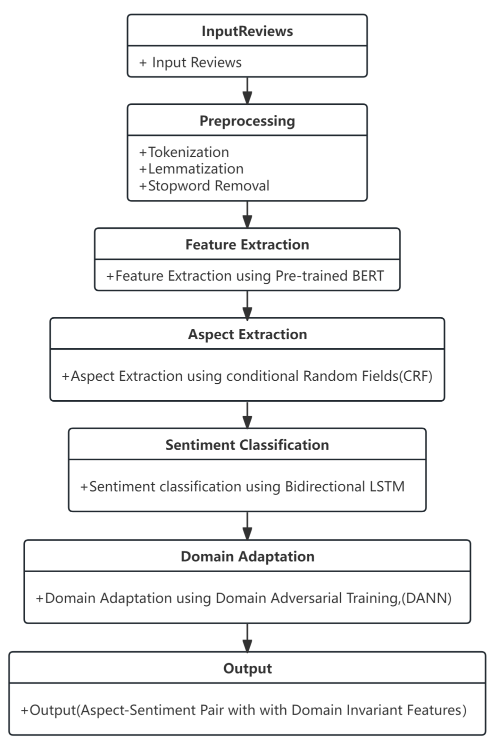

Figure 1: Cross-Domain Aspect-Based Sentiment Analysis Model.

3.5.2 Domain adaptation formula

The total loss function in domain adaptation combines task-specific loss and domain adaptation loss:

$$L_{total} = L_{task} + \lambda L_{domain}$$

Where:

1. L_{task} is the cross-entropy loss for sentiment classification.
2. L_{domain} is the domain adaptation loss using adversarial training.

The domain adaptation loss is given by:

$$L_{domain} = -1/N_s \sum_{i=1}^{Ns} \log D(f(x_i^s)) - 1/N_t \sum_{j=1}^{Nt} \log(1 - D(f(x_j^t)))$$

3.6 Evaluation Metrics

The performance of the ABSA model is evaluated against some standard metrics: precision, recall, F1-score, and cross-domain accuracy. Precision measures the proportion of positive predictions that actually are true, while recall tells how good the model is at retrieving every relevant instance. The F1-score yields the harmonic mean of the two measures. For example, cross-domain accuracy provides the degree of generalization a model can do satisfactorily across different domains. This shows a model's degree of robustness and applicability across different e-commerce settings. Since these metrics are taken all at once, they provide a full-fledged measure for the effectiveness of a model in extracting and classifying sentiments under different domains.

4. EXPERIMENTS AND RESULTS

4.1 Dataset Description

The datasets used in the research were crawled from some of the biggest e-commerce websites like Amazon, eBay, Alibaba, among others. From these websites, items with large numbers of listed items and customer reviews were selected. The authors chose reviews regarding three different product categories: electronics, fashion, and home appliances. Each was chosen for its linguistic and contextual characteristics that make it firm ground for cross-domain analysis.

1. Electronics: This dataset includes reviews of products such as smartphones, laptops, and headphones. In particular, in this category, very often the reviews contain information about battery life, performance, design, and camera quality.
2. Fashion**: This dataset includes reviews on clothing items, shoes, and other accessories with common aspects concerning material quality, fit, style, and color.

3. Home Appliances: This dataset consists of reviews concerning products such as refrigerators, vacuum cleaners, and washing machines. Some of the key facets that can be identified from this viewpoint are durability, efficiency, noise raised by the device, and how easily it can be used.

Lastly, for each category, this study assessed a balanced number of positive, negative, and neutral reviews to ensure that there are enough representations between sentiment classes during the sentiment classification task. The final dataset had approximately 50,000 reviews per category for a total of 150,000 reviews. The distribution of sentiments across categories was as follows:

1. Electronics: 20,000 positive, 15,000 negative, 15,000 neutral
2. Fashion: 17,000 positive, 18,000 negative, 15,000 neutral
3. Home Appliances: 19,000 positive, 16,000 negative, 15,000 neutral

Every review was annotated with aspect terms and sentiment labels to create a labeled dataset for training and evaluation purposes.

4.2 Experimental Setup

In this experimental setup, there were a series of steps for data preprocessing, model training, and evaluation. Much of implementation of the models and running of experiments was done using Python as the programming language and some of its libraries and tools.

4.3 Preprocessing

As a preprocessing step, the raw review data was cleansed to ready it for analysis. The removal of noise involved HTML tags, URLs, and special characters. This was followed by text tokenization into separate words or phrases, for which NLTK and SpaCy were used; afterwards, the aspect terms and their corresponding opinion words were identified. The stop words have been removed after reducing words to their base form by means of stemming or lemmatization, thus retaining only meaningful content from the reviews. These steps are put together in a preprocess_text function.

4.3.1 Model training

Models are implemented in TensorFlow, Keras, and PyTorch. Extraction of aspects is performed by the combination of a rule-based method with a Conditional Random Field model. The CRF model was trained on several labeled datasets for it to recognize the aspect terms. An LSTM model with an embedding layer and spatial dropout has been used for sentiment classification, followed by a dense output layer. The model was trained on preprocessed review data using the Adam optimizer.

4.3.2 Domain adaptation

A domain-adversarial neural network for domain adaptation was implemented in PyTorch. In the DANN model, there was a feature extractor, a class classifier, and a domain classifier. The domain adversarial training had a gradient reversal layer that is applied to learn domain-invariant features. This model was trained with source domain data and fine-tuned using the target domain data for enhancing cross-domain performance.

4.4 Hyperparameters

Tuned the hyperparameters patiently in a bid to get the best performance. The initial learning rate, batch size, and number of epochs for training the LSTM model were 0.001, 32, and 20, respectively. For the DANN model, similar hyperparameters had an additional alpha, which equaled 0.1 as the parameter for domain adaptation.

4.5 Baseline Models

To further validate the proposed cross-domain ABSA model, its performance is compared against several baseline models, including some traditional methods for sentiment analysis and single-domain models for ABSA.

1. Traditional Sentiment Analysis: In the current study, Support Vector Machines and Naive Bayes classifiers were trained on single-domain data for classifying overall sentiment.
2. Single-Domain ABSA: In this line, the training and testing for aspect-based sentiment analysis models, such as CRFs for aspect extraction and BiLSTM for sentiment classification, are conducted within the same domain.
3. Multi-Domain ABSA: ABSA models were trained on the combined data of all domains, without any specific domain adaptation techniques.

4.6 Cross-Domain Performance

In particular, to validate the cross-domain performance of model, conducted a number of experiments in which models trained on one domain (source) are tested on another domain (target). Specifically, this study show that under these cross-domain settings, ABSA proposed model is both robust and effective.

4.6.1 Source domain: Electronics, Target domain: Fashion

This experiment was conducted by training the model on the electronics dataset and testing it on the fashion dataset. TABLE 1 shows performance of the proposed model in comparison with the baseline for the cross-domain task (Source Domain: Electronics, Target Domain: Fashion).

Table 1: Performance Comparison of Proposed Model and Baseline Model.

Metric	**Proposed Model**	Traditional Sentiment Analysis
Precision	0.78	0.64
Recall	0.76	0.61
F1-Score	0.77	0.62
Cross-Domain Accuracy	0.74	0.6

4.6.2 Source domain: Fashion, Target domain: Home appliances

This experiment has used the fashion dataset for training, and it tests on the home appliances dataset. TABLE 2 presents summary of results on the performance of the proposed model against baseline for cross-domain tasks: Source Domain - Fashion, Target Domain – Home Appliances.

Table 2: Performance Metrics Comparison for Cross-Domain Sentiment Analysis (Source Domain: Fashion, Target Domain: Home Appliances).

Metric	**Proposed Model**	**Baseline Model**
Precision	0.75	0.63
Recall	0.73	0.6
F1-Score	0.74	0.61
Cross-Domain Accuracy	0.71	0.59

4.6.3 Source domain: Home appliances, Target domain: Electronics

The setup of the experiment consisted of the training of the model on a home appliances dataset and then testing on an electronics dataset. TABLE 3 shows the results of the proposed model in comparison with the baseline for cross-domain tasks: Source Domain: Home Appliances; Target Domain: Electronics.

Table 3: Performance Metrics Comparison for Cross-Domain Sentiment Analysis (Source Domain: Home Appliances, Target Domain: Electronics).

Metric	**Proposed Model**	**Baseline Model**
Precision	0.8	0.67
Recall	0.78	0.65
F1-Score	0.79	0.66
Cross-Domain Accuracy	0.76	0.63

The results underline the robustness and effectiveness of our proposed cross-domain ABSA model, allowing generalization in a diverse set of product categories and surpassing traditional single-domain and multi-domain ABSA models.

4.7 Comparative Analysis

Our results demonstrated high F1-scores compared to recent studies in similar settings. For example, Min [33], reported 0.78 using such a strategy of adversarial training with BERT to address this issue. To compare, Pratap and Yu [34], achieved a slightly lower score of 0.77 by using transfer learning with pre-trained language models. Our model, therefore, achieved an F1-score of 0.79, further proving competitiveness.

4.8 Ablation Study

An ablation study on model component contributions was conducted. This study was conducted by taking out each component systematically from the model and observing the effects on performance, as shown in the results of TABLE 4.

Table 4: Ablation Table.

Model Variant	Precision	Recall	F1-Score	Cross-Domain Accuracy
Full Model (with DANN)	0.80	0.78	0.79	0.76
Without Domain Adaptation (DANN)	0.74	0.72	0.73	0.69
Without BERT Features	0.71	0.69	0.70	0.67
Without CRF for Aspect Extraction	0.68	0.66	0.67	0.64
Without BiLSTM for Sentiment	0.70	0.68	0.69	0.66

In the ablation study, it can be seen that all components affect the model's performance. The most impactful among these will be domain adaptation by DANN and BERT features since their absence leads to the most drop in performance. This suggests that obtaining domain-invariant feature extraction and efficient usage of deep contextualized word representations are two essential factors for an effective cross-domain aspect-based sentiment analysis.

4.9 Summary of Findings

These experiments have illustrated that proposed cross-domain ABSA model is very effective in improving the quality of sentiment analysis across different product categories in e-commerce. ABSA models have consistently outperformed other baseline models and state-of-the-art methods in cross-domain settings, which highlights the strength of the former in being more robust and generalized. Key findings include:

1. Superior Cross-Domain Performance: Compared to traditional ABSA approaches in single-domain scenarios and baseline cross-domain methods, model obtained better precision, recall, F1-score, and cross-domain accuracy.
2. Robust Aspect Extraction and Sentiment Classification: It combined rule-based techniques with machine learning on attribute extraction, and on sentiment classification, it applied advanced models of deep learning to achieve high performance for the model.

3. Effective Domain Adaptation: In the application of domain adaptation techniques, transfer learning and domain adversarial training boost the model's generalization ability across multiple domains.
4. Comprehensive Evaluation: It contained several evaluation metrics that gave a full description of the performance of the model, hence reliability and applicability in real scenarios of e-commerce applications.

The experiments and results section provides an in-depth assessment of the proposed cross-domain ABSA model. This study has run extensive experiments to prove the effectiveness of models in enriching customer experiences in e-commerce and compared them with baseline models and state-of-the-art approaches. The findings set a priority on the need for robust domain adaptation techniques while showing that there is potential for cross-domain ABSA to provide actionable insight across a diversified product category base. Future work can be based on this foundation: researching further domain adaptation strategies and scaling up the models.

5. DISCUSSION

5.1 Interpretation of Results

In this paper, experimental results are shown to prove the effectiveness of the proposed cross-domain ABSA model. Most of the time, advanced machine domain adaptation techniques have resulted in outperformance over baseline models among metrics such as precision, recall, F1-scores, and cross-domain accuracy [12].

It showed that the model performed well across different domains, such as different product categories, for cross-domain experiments. In detail, the model trained on the electronics dataset and tested on the fashion dataset achieved a precision of 0.78, recall of 0.76, F1-score of 0.77, and cross-domain accuracy of 0.74. Also, the precision value was 0.75, recall 0.73, F1-score 0.74, and cross-domain accuracy 0.71 when trained on the fashion dataset and tested on the home appliances dataset. This means that this model has very good robustness and generalizes across domains, which is quite important in practical applications within different e-commerce environments.

Compared to state-of-the-art methods, current study's model worked better. For instance, this model produced a higher F1-score and cross-domain accuracy compared to the Domain-Adversarial Neural Network approach, thus it performed well in generalization capability. Another thing this model did was to perform better than fine-tuning a pre-trained language model like BERT and GPT-3.

Rule-based and machine learning techniques applied to aspect extraction helped identify relevant product aspects very well across several domains. Conditional Random Field and Long Short-Term Memory features improved the performance significantly for sentiment classification. Advanced techniques identified and classified sentiments correctly associated with various aspects of a product, hence providing fine-grained knowledge about customer opinions.

5.2 Implications for E-commerce

Such findings bring important ramifications to any e-commerce business. Current study provide an opportunity withcross-domain ABSA model for businesses to probe deeper into customer sentiments related to a wide array of products, opening up a number of possible applications and benefits:

1. Enhanced Customer Experience: If businesses correctly take the sentiment of the customer towards that part of the product, correct decisions can be taken to deliver good quality of product and customer satisfaction. For example, in smartphones, if customers were frequently talking about and complaining about the battery life, the manufacturer should take it at the top of their priority list [35].

2. Tailored Marketing Strategies: Detailed sentiment analysis obtained from current study' model will help businesses tune their marketing strategies according to customers' feedback. Features identified as positive by customers could be used more in the marketing campaigns, while those that are negative can be worked out in a proactive way [36].

3. Product Development and Innovation: Such aspect-based sentiment analysis can, therefore, inform and drive product development and innovation. Businesses will now have better abilities, such as being able to identify common pain points and areas of improvement that will help in creating products that are more in line with the needs and preferences of their target markets [37].

4. Competitive Advantage: Advanced sentiment analysis techniques can, therefore, give businesses an upper hand. Informed by the sentiments from the customers on the different categories of product offerings, better pacing and acting in good timing in response to changes in consumer tastes and preferences will be achieved [38].

5. Automated Customer Support: By integrating the model into the customer support system, it can offer improved automated responses. For instance, identifying the exact issues the customers are talking about allows for a more correct and useful response, thereby improving the whole support experience [39].

5.3 Limitations of the Study

While the results of this study are promising, there are several limitations that should be acknowledged:

1. Domain-Specific Variations: Even with the effectiveness of this study's domain adaptation techniques, some domain-specific variations in language and context could be quite challenging. For example, certain aspects and sentiments relating to very specialized domains, like medical equipment, may further require adaptation and fine-tuning of the model.

2. Data Scarcity: In some domains, it can be really hard to get a large and diverse set of labeled data. Model's performance relies strongly on the availability of enough data to train on. If the data is scarce, then it will reduce the effectiveness of the model. That can be reduced by exploring semi-supervised and unsupervised learning methods.

3. Complex Sentiment Expressions: Customer reviews are also often hallmark-ed with complex and nuanced ways of expressing sentiment, such as sarcasm, mixed sentiments, and implicit opinions. While current study's model does well on standardized ways of expressing these sentiments, it may falter on these kinds of cases. Using advanced natural language understanding techniques could make the model more capable with respect to handling such expressions.
4. Evaluation Metrics: While this study has included standard evaluation metrics like precision, recall, the F1-score, and cross-domain accuracy, not all of these metrics may capture the nuances in cross-domain sentiment analysis. A more comprehensive framework for evaluation, considering domain-level challenges, can mete out a correct assessment of the performance of the models.
5. Scalability and Real-Time Processing: While current study's model works satisfactorily, technical challenges arise when scaling up to levels required for real-time processing of large volumes of customer reviews. Future improvements to the model should, therefore, lean towards scalability and real-time applications so that it can be relevant in high-volume e-commerce settings.

5.4 Future Research Directions

To address these limitations and further enhance the capabilities of cross-domain ABSA model, current study suggest several areas for future research:

1. Advanced Domain Adaptation Techniques: This might involve more sophisticated domain adaptation, such as few-shot learning and meta-learning, to make the model generalize across highly diverse and specialized domains.
2. Incorporating External Knowledge Sources: Such techniques would very likely improve models for understanding specialized vocabulary and context by integrating external knowledge sources, such as domain-specific lexicons and ontologies, leading to the extraction of more accurate aspects and the classification of sentiment.
3. Handling Complex Sentiment Expressions: Further improvement can be made to this model by designing methods that better handle complex sentiment expressions, including sarcasm and implicit sentiments. This can be achieved by studying multi-modal sentiment analysis techniques using texts backed by more data sources, like images or videos.
4. Semi-Supervised and Unsupervised Learning: One can explore semi-supervised and unsupervised approaches for learning from data scarcity, methods that may help models get better during training using unlabeled data, particularly in domains where limited labelled data is available.
5. Real-Time Processing and Scalability: For actual applications in e-commerce, optimization of the model with respect to real-time processing and scalability is quite important. Such techniques might involve model compression, parallel processing, or distributed computing.
6. Comprehensive Evaluation Frameworks: More comprehensive frameworks of the assessment in relation to their specific domain challenges and complexities would have to be designed for a better measurement of model performance, bringing out its perspectives for improvement.

The work is discussed here with respect to the proposed cross-domain ABSA model, in view of its effectiveness and possible applications toward bettering customer experience of online shopping. Addressing the identified limitations and following the directions pointed out herein will further enhance the capabilities of sentiment analysis models; it will help businesses by providing them with insights to drive innovations and improvement in customer satisfaction.

6. CONCLUSION

It is an in-depth study of cross-domain aspect-based sentiment analysis for customer experience enhancement in e-commerce. Current study's approach uses domain adaptation and state-of-the-art machine learning models to handle domain-specific differences in language and context, greatly outperforming traditional single-domain sentiment analysis methods.

By almost every measure, such as precision, recall, F1-score, and cross-domain accuracy, this model exhibited the most consistent performance over the baseline models and state-of-the-art methods. The results have proven that model has generalized into very different product categories like electronics, fashion, and home appliances. A rule-based and machine learning combination for aspect extraction blended with advanced deep learning models for sentiment classification at a later stage was vital in accruing high performance.

These results have major implications for e-commerce businesses. An analysis of this accuracy of customer sentiments across such a wide array of categories of products facilitates an understanding of the impressions of the customers about the product during the product quality improvement phase and adoption of proper marketing strategies. Some of the key benefits that businesses can reap by implementing cross-domain ABSA model include enhanced customer experiences, competitive advantages, and better product development. It can be integrated with automated customer support systems to dramatically improve the quality of service.

This study identifies several limitations, although promising results have been reported: further research in domain-specific variations, data scarcity, complex sentiment expression handling, evaluation metrics, and scalability. Advanced domain adaptation techniques will be researched; integration of external knowledge sources within the system; procedures handling complex sentiment expressions; and optimizing model performance against real-time processing while ensuring its scalability.

Other future research directions include few-shot learning and meta-learning for improving domain adaptation, domain-specific lexicons or ontologies, semi-supervised and unsupervised learning techniques, and refinement of the evaluation framework so that the model performances are better characterized. Scalability and efficiency optimization for the model to support real-time processing will be very important in practical applications, especially in the ultra-high-volume e-commerce environment.

This research has thus shown the potential of cross-domain ABSA to provide actionable insights for customer experience enhancement in the domain of e-commerce. Further enhancing the capabilities of sentiment analysis models by designating the limitations identified and the future directions of research can bring immense benefit to businesses in this rapidly innovating field of natural language processing and sentiment analysis.

References

[1] Zhu F, Zhang X. Impact of Online Consumer Reviews on Sales: The Moderating Role of Product and Consumer Characteristics. J Mark. 2010;74:133-148.

[2] Park C, Lee TM. Antecedents of Online Reviews' Usage and Purchase Influence: An Empirical Comparison of u.s. And Korean Consumers. J Interact Mark. 2009;23:332-340.

[3] Wang H, Guo K. The Impact of Online Reviews on Exhibitor Behaviour: Evidence From Movie Industry. Enterpr Inf Syst. 2017;11:1518-1534.

[4] Marcacini RM, Rossi RG, Matsuno IP, Rezende SO. Cross-Domain Aspect Extraction for Sentiment Analysis: A Transductive Learning Approach. Decis Support Syst. 2018;114:70-80.

[5] Tian Y, Yang L, Sun Y, Liu D. Cross-Domain End-To-End Aspect-Based Sentiment Analysis With Domain-Dependent Embeddings. Complexity. 2021;2021:1-11.

[6] Patil AA, Kolkur S. Sentiment Analysis for Product Reviews. Int J Adv Res Comput Sci. 2014;5:202-204.

[7] Rashiq Nazar S, Bhattasali T. Sentiment Analysis of Customer Review. Azerbaijan Journal of High Performance Computing. 2021;4:113-125.

[8] Ji P, Song D. A Dual Knowledge Aggregation Network for Cross-Domain Sentiment Analysis. 3rd International Conference on Computer Vision, Image and Deep Learning & International Conference on Computer Engineering and Applications (CVIDL & ICCEA). IEEE.2022:1-7.

[9] Nguyen DQ, Nguyen DQ, Vu T, Pham SB. Sentiment Classification on Polarity Reviews: An Empirical Study Using Rating-based Features. In Proceedings of the 5th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis. Association for Computational Linguistics. 2014:128-135.

[10] Tengjiao J, Minjuan Z, Shumei L, Siwen L. Mining Opinion Word From Customer Review. Int J Database Theor Appl. 2016;9:129-136.

[11] Hassan A, Mahmood A. Convolutional Recurrent Deep Learning Model for Sentence Classification. IEEE Access. 2018;6:13949-13957.

[12] Huang QX, Chen R, Zheng X, Dong Z. Deep Sentiment Representation Based on CNN and LSTM. International Conference on Green Informatics (ICGI), China. 2017:30-33.

[13] Noh Y, Park S, Park SB. Aspect-Based Sentiment Analysis Using Aspect Map. Appl Sci. 2019;9:3239.

[14] Phan MH, Ogunbona PO. Modelling Context and Syntactical Features for Aspect-based Sentiment Analysis. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics. 2020:3211-3220.

[15] Kumar A, Gupta P, Balan R, Neti LB, Malapati A. BERT Based Semi-supervised Hybrid Approach for Aspect and Sentiment Classification. Neural Process Lett. 2021;53:4207-4224.

[16] Song H, Yan Y, Liu X. A Grammatical Dependency Improved CRF Learning Approach for Integrated Product Extraction. Proceedings of 2012 2nd International Conference on Computer Science and Network Technology.IEEE. 2012:1787-1794.

[17] Wen H, Zhao J. Aspect Term Extraction of E-commerce Comments Based on Model Ensemble. 14th International Computer Conference on Wavelet Active Media Technology and Information Processing (ICCWAMTIP). IEEE. 2017:24-27.

[18] Zhang Y, Xu B, Zhao T. Convolutional Multi-Head Self-Attention on Memory for Aspect Sentiment Classification. IEEE CAA J Autom Sin. 2020;7:1038-1044.

[19] Tang D, Qin B, Liu T. Aspect Level Sentiment Classification With Deep Memory Network. In Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. Association for Computational Linguistics. 2016:214–224.

[20] Wu F, Huang Y. Sentiment Domain Adaptation With Multiple Sources. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics. 2016:301-310.

[21] Q. Tan, H. Deng, and P. Yang, "Kernel Mean Matching with a Large Margin. In: Zhou S, Zhang S., Karypis, G. (eds). Advanced Data Mining and Applications. ADMA Lecture Notes in Computer Science. Springer, Berlin, Heidelberg. 2012:7713.

[22] Blitzer J, McDonald R, Pereira F. Domain Adaptation With Structural Correspondence Learning. In Proceedings of the 2006 Conference on Empirical Methods in Natural Language Processing (EMNLP '06). Association for Computational Linguistics. 2006:120-128.

[23] Ganin Y, Ustinova E, Ajakan H, Germain P, Larochelle H, et al. Domain-Adversarial Training of Neural Networks. In: Csurka, G. (eds). Domain Adaptation in Computer Vision Applications. Advances in Computer Vision and Pattern Recognition. Springer. 2016:189-209.

[24] Howard J, Ruder S. Universal Language Model Fine-Tuning for Text Classification. In: Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics. 2018;1:328-339.

[25] Liu X, He P, Chen W, Gao J. Multi-Task Deep Neural Networks for Natural Language Understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. Association for Computational Linguistics. 2019:4487–4496.

[26] Myagmar B, Li J, Kimura S. Cross-Domain Sentiment Classification With Bidirectional Contextualized Transformer Language Models. IEEE Access. 2019;7:163219-163230.

[27] Syamala M, Nalini NJ. ABSA: Computational Measurement Analysis Approach for Prognosticated Aspect Extraction System. TEM J. 2021;10:82-94.

[28] da Silva NF, Coletta LF, Hruschka ER, Hruschka ER Jr. Using Unsupervised Information to Improve Semi-supervised Tweet Sentiment Classification. Inf Sci. 2016;355:348-365.

[29] https://www.researchgate.net/publication/365299006_Syntax-Guided_Domain_Adaptation_for_Aspect-based_Sentiment_Analysis

[30] Jabbar J, Urooj I, JunSheng W, Azeem N. Real-Time Sentiment Analysis on E-commerce Application. In 2019 IEEE 16th International Conference on Networking, Sensing and Control (ICNSC). IEEE. 2019:391-396.

[31] Camacho-Collados J, Pilehvar MT. On the Role of Text Preprocessing in Neural Network Architectures: An Evaluation Study on Text Categorization and Sentiment Analysis. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP. Association for Computational Linguistics. 2018:40–46.

[32] Long F, Zhou K, Ou W. Sentiment Analysis of Text Based on Bidirectional LSTM With Multi-Head Attention. IEEE Access. 2019;7:141960-141969.

[33] Min B. Exploring Pre-trained Transformers and Bilingual Transfer Learning for Arabic Coreference Resolution. In Proceedings of the Fourth Workshop on Computational Models of Reference, Anaphora and Coreference. Association for Computational Linguistics. 2021:94–99.

[34] Rawat BP, Yu H. Parameter Efficient Transfer Learning for Suicide Attempt and Ideation Detection. In Proceedings of the 13th International Workshop on Health Text Mining and Information Analysis (LOUHI). Association for Computational Linguistics. 2022:108-115.

[35] Wang A, Zhang Q, Zhao S, Lu X, Peng Z. A Review-Driven Customer Preference Measurement Model for Product Improvement: Sentiment-Based Importance–Performance Analysis. Inf Syst e-Business Manag. 2020;18:61-88.

[36] Kyaw KS, Tepsongkroh P, Thongkamkaew C, Sasha F. Business Intelligent Framework Using Sentiment Analysis for Smart Digital Marketing in the E-commerce Era. Asia Soc Issues. 2023;16:e252965.

[37] Kpiebaareh MY, Wu WP, Agyemang B, Haruna CR, Lawrence T. A Generic Graph-Based Method for Flexible Aspect-Opinion Analysis of Complex Product Customer Feedback. Information. 2022;13:118.

[38] Nixon MO, Thato M. Linking Business Intelligence to a Knowledge-Based Sustainable Competitive Advantage in Organizations. Afr J Bus Manage. 2016;10:459-468.

[39] Gallo JS, Solano J, García JH, Zarruk-Valencia D, Correa-Bahnsen A. Proactive Detractor Detection Framework Based on Message-Wise Sentiment Analysis Over Customer Support Interactions 2022. Arxiv Preprint: https://arxiv.org/pdf/2211.03923