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Multi Domain Specific Sentiment Analysis for A Strategic Customer Queries and Feedback, from both Direct and Latent Sentiment by Semantic Associations: Survey

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Abstract

In the era of persistent digital platforms, sentiment analysis has become a vital tool for extracting valuable insights from customer feedback and social media data. While traditional sentiment analysis methods perform effectively within single domains, their applicability diminishes when extended across multiple, heterogeneous domains due to variations in vocabulary, contextual nuances, and sentiment expressions. This survey systematically reviews very recent advancements in multi-domain sentiment analysis, highlighting state-of-the-art techniques, including deep learning models, transformer-based frameworks, and semantic enrichment strategies. It critically examines existing challenges such as domain adaptation, subtle emotional cues, and the integration of multimodal information. Additionally, the survey identifies research gaps, emphasizing the necessity for adaptable, semantically aware, and scalable models capable of capturing both explicit and implicit sentiments across diverse sectors. By consolidating current methodologies and outlining future directions, this survey aims to guide researchers and practitioners towards developing more robust, context-aware, and domain-agnostic sentiment analysis systems that are essential for strategic decision-making in customer-centric applications.

Key words: Multi domain, NLP, ML, DL, Sentimental analysis

1. INTRODUCTION

Consumers often face a time-intensive challenge when searching online for reliable product reviews across multiple platforms [1]. To understand both the strengths and limitations of a product, individuals typically sift through several review sources. This fragmented process can be overwhelming and inefficient. A consolidated, criterion-specific summary of customer reviews would significantly simplify the decision-making process. Streamlining access to structured feedback not only aids consumer judgment but also enhances industry-wide awareness about product quality [2].

A review analytics system that rapidly distills user feedback would be instrumental in improving services and customer satisfaction. Therefore, there is a growing demand for sophisticated methods capable of extracting key phrases and evaluating sentiment polarity, facilitating a more effective connection between businesses and their customer base. Sentiment analysis has become a crucial tool across sectors, offering valuable insights for addressing a variety of business challenges [3].

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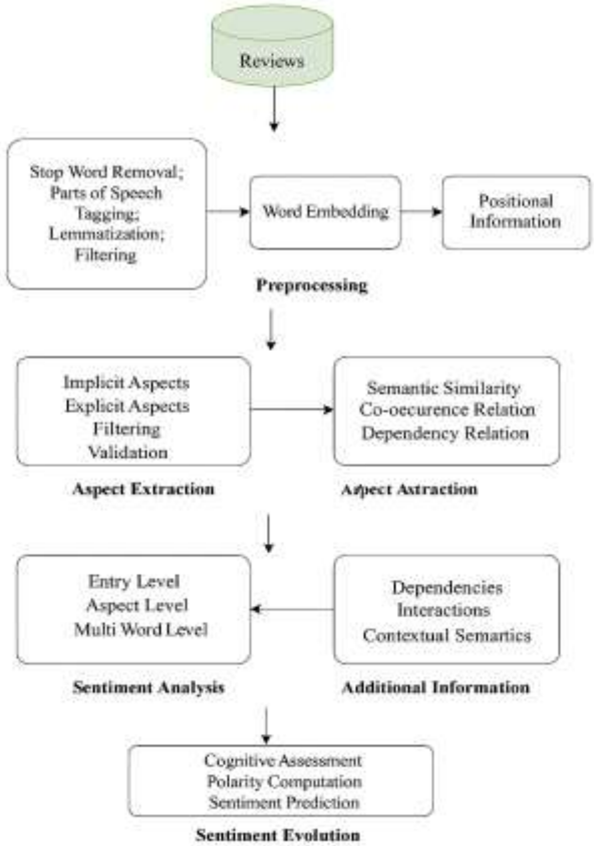

Figure 1: Traditional phases in aspect - based sentiment analysis.

Its applications span domains such as market intelligence, consumer behavior analysis, and product evaluation. In sectors like e-commerce, technology, and service industries, sentiment analysis proves particularly useful.

Although online platforms such as Amazon and Flipkart have incorporated some features of sentiment reflection into their systems, these methods often fall short. Their reliance on a limited set of user-generated evaluations within a specific industry weakens their comprehensiveness [4]. This issue is exacerbated by the "cold start" problem where insufficient data due to a small user base or limited reviews undermines the reliability of information retrieval [5]. The granularity of sentiment expressed in shorter text formats is particularly sensitive to these volume-related discrepancies, thus influencing the robustness of aspect-based sentiment analysis (ABSA).

Over time, ABSA has undergone substantial methodological evolution. It has adapted to address increasingly nuanced issues involving multiple dimensions of sentiment [6]. Researchers have utilized a broad spectrum of machine learning approaches, particularly in the area of deep learning, to develop sophisticated models that capture the complex nature of sentiment tied to various product features.

This research proposes a unified framework designed to collect and analyze reviews from prominent e-commerce platforms—namely Amazon, Flipkart, and Snapdeal. The system identifies relevant product attributes, aligns them with descriptive adjectives, and ensures syntactic consistency throughout the text analysis process [5].

ABSA is typically implemented in three core stages: aspect extraction, sentiment classification, and sentiment evolution tracking. The first stage focuses on identifying elements such as explicit and implicit aspects, target entities, and associated opinion expressions. The second phase involves determining the sentiment polarity corresponding to each identified aspect or entity, while also modeling the semantic and syntactic relationships between them. This allows for a more precise classification of sentiments, which may be expressed in granular forms such as positive, negative, or neutral. Finally, the third phase monitors changes in sentiment over time, acknowledging that evolving opinions are frequently shaped by social dynamics and individual user experiences [7].

2. LITERATURE SURVEY

According to previous studies, sentiment analysis (SA) is typically structured into

10.48047/jocaaa.2025.34.07.14

three hierarchical levels: document-level, sentence-level (subjective or objective), and aspect-level classification. These levels help determine whether the expressed sentiment is positive, negative, or neutral. Among them, Aspect-Based Sentiment Analysis (ABSA) provides a more refined approach, as it focuses directly on the sentiment associated with particular aspects rather than relying solely on syntactic or linguistic structure. This targeted approach contributes to a deeper and more context-aware understanding of the sentiment analysis problem.

The concept of an "aspect" is not restricted to mere evaluation; it involves broader cognitive dimensions such as opinions, viewpoints, interpretative lenses, thematic elements, or even social consequences linked to a particular entity. As a result, ABSA becomes a powerful tool to capture and analyze public sentiment trends across multiple domains and time frames [8].

Numerous strategies have been employed for the aspect extraction (AE) component, ranging from parsing and named entity recognition to bag-of-words approaches and semantic feature extraction. In addition, domain-specific methods such as word clustering have been explored [8]. Some models also concentrate on identifying nouns that reflect the sentiment of a given viewpoint. The use of word vectors**,** which transform words into fixed-dimensional numerical representations, has proven highly effective in handling multi-class classification challenges [9]. The adoption of word vectors has expanded the applicability of sentiment analysis considerably. In this study, combining word vectors with K-Means clustering resulted in the most accurate outcomes.

Over time, both traditional feature-engineered models and modern deep learning-based architectures have been proposed for ABSA [10,11]. More recently, researchers have leveraged pre-trained language models, such as BERT, through fine-tuning techniques to obtain superior performance on benchmark datasets [12]. While these models represent a significant advancement, many still primarily rely on text-based inputs, disregarding additional modalities such as images—particularly those involving human facial expressions or contextual cues.

Given the increasing prevalence of multimodal content in online reviews and social platforms, incorporating visual features has become essential for enhancing ABSA performance. This realization has driven recent efforts to include image-based cues, complementing textual analysis to improve sentiment polarity predictions for target aspects [13].

The review analysis process for ABSA can be categorized into two essential phases: aspect extraction and multi-domain scraping [14]. Older methods primarily focused on single-domain review extraction from individual websites, which limited the scope and richness of retrieved data. Multi-domain scraping, while more inclusive, faces challenges in identifying and parsing complex product information using basic HTML parsers [15,16]. Automation tools like Selenium are increasingly employed to manage navigation, perform intelligent browsing tasks, and use unique product identifiers to retrieve hard-to-locate reviews efficiently.

To further improve review understanding, Recurrent Neural Networks (RNNs) are utilized to handle the sequential nature and contextual dependencies of language,

10.48047/jocaaa.2025.34.07.14

offering a potential enhancement to models where static feature extraction may be inadequate [17]. Additionally, a trustworthiness scoring mechanism filters out reviews that fall below a specified credibility threshold. This ensures that only high-confidence reviews are retained for analysis.

Customers are thus encouraged to prioritize reviews with the highest trust scores to form more accurate judgments. This selective filtering significantly improves the reliability of insights into product performance and user satisfaction by excluding less credible feedback [18].

BERT-based models have demonstrated remarkable effectiveness across a broad range of natural language processing (NLP) tasks, including sentiment analysis. A standard approach involves employing a pre-trained language model and adapting it to the target task through fine-tuning. However, such fine-tuning necessitates annotated data, which may be insufficient or unavailable in specialized domains such as healthcare or finance. Despite the widespread adoption of BERT, limited attention has been given to understanding how its performance varies across datasets derived from multiple domains and sources, raising questions about the generalizability of these models in sentiment analysis tasks. Furthermore, for languages like Italian, existing evaluations predominantly focus on binary sentiment categories (positive and negative), omitting the neutral class, which plays a crucial role in distinguishing non-committal or ambiguous opinions.

An English multi-domain sentiment dataset was introduced by Mamta et al. [Mamta et al., 2020], comprising tweets collected using specific keywords related to socially significant topics. However, the assessment of models in this study excluded BERT-based architectures, and performance outcomes for individual domains were not reported. A more comprehensive BERT-based evaluation was conducted by Du et al. [Du et al., 2020] using Amazon product reviews spanning over twenty categories. Nonetheless, the variety in content was limited, as all the data fell under the broader domain of consumer products.

Two other efforts to compile multi-source, multi-domain sentiment corpora include those by Dai et al. [Dai et al., 2020] and Khan et al. [Khan et al., 2019], who merged various existing datasets for use in testing traditional, non-BERT sentiment models. Although their corpora differ in scope and size, both are centered exclusively on movie and product reviews sourced from platforms such as Amazon and IMDb. In contrast, Abid et al. [Abid et al., 2020] improved corpus diversity by integrating datasets from multiple domains, including tweets from Sentiment Strength Twitter [Thelwall et al., 2012] and Stanford Twitter Sentiment Corpus [Go et al., 2017], as well as reviews from IMDb [Maas et al., 2011].

Within the Italian context, two prominent publicly accessible BERT-based models are **AlBERTo** [Polignano et al., 2019] and **FEEL-IT** [Bianchi et al., 2021]. AlBERTo is a BERT-derived model trained exclusively on Italian tweets using the masked language modeling objective. For sentiment analysis, it was fine-tuned on the SENTIPOLC2016 dataset [Barbieri et al., 2016] using two separate classifiers: one each for identifying positive and negative sentiments. On the other hand, FEEL-IT is built upon UmBERTo2, which is based on the RoBERTa architecture and pre-trained on the Common Crawl Italian dataset. FEEL-IT focuses on classifying four emotional categories (excluding neutral),

10.48047/jocaaa.2025.34.07.14

having been fine-tuned on a namesake dataset of annotated tweets. Since the neutral category was omitted during FEEL-IT's training, direct comparison between the two models remains problematic. To date, neither FEEL-IT nor AlBERTo has been explicitly evaluated on data containing neutral sentiment examples.

In the financial domain, sentiment annotation poses significant challenges due to the highly specific and technical nature of the language used in financial reporting. This necessitates a careful design of annotation guidelines that take into account the domain's unique vocabulary and interpretative cues. Unfortunately, few comprehensive studies address this issue. One notable exception is the **Financial Phrase Bank** developed by Malo et al. [Malo et al., 2014], which offers an openly available, well-documented corpus comprising sentences extracted from financial news about Finnish companies. The annotation process was guided by an investor-centric perspective and involved only domain experts to ensure sentiment labels reflected real-world investment viewpoints. A similar approach was adopted by Takala et al. [Takala et al., 2014]. Nonetheless, the reliance on financial experts presents a major bottleneck for large-scale annotation efforts, as recruiting such professionals via crowd sourcing platforms is often cost-prohibitive and constrained by limited availability.

Sno	Name of the author	Year	Methodology	Key Findings	Limitations
1	Hu Xu et al.	2020	**DomBERT**: Domain-oriented BERT fine-tuned on both in-domain and related corpora for aspect-based sentiment analysis.	Enhanced performance in low-resource domains by integrating domain-specific semantics into BERT.	Requires domain-specific corpora; may not generalize well to completely unseen domains.
2	Deepanway Ghosal et al.	2020	**KinGDOM**: Utilizes ConceptNet-based graph convolutional autoencoder for domain adaptation in sentiment analysis.	Improved cross-domain sentiment classification by incorporating commonsense knowledge.	Relies on external knowledge bases; performance may degrade if such resources are unavailable or incomplete.
3	Mamta et al.	**2020**	Developed a multi-domain tweet sentiment corpus; implemented deep learning baselines.	Provided a valuable resource for sentiment analysis across diverse domains; established baseline performances.	Focused solely on tweets; may not be directly applicable to other text forms or domains.
4	Neha Singh & Umesh Chandra Jaiswal	**2023**	Surveyed cross-domain sentiment analysis techniques and challenges.	Offered a comprehensive overview of existing methods and highlighted persistent challenges in domain adaptation.	Lacks empirical validation; primarily a theoretical survey.
5	Bipin Kumar Rai et al.	**2023**	Employed sentiment mining to assess data authenticity in multi-domain opinion mining.	Enhanced understanding of data reliability across domains using sentiment analysis.	Specific methodologies and datasets used are not detailed; applicability may vary.
6	Chunyi Yue & Ang Li	**2025**	Proposed a Dynamic Domain Information Modulation Algorithm for multi-domain sentiment analysis.	Achieved superior performance across 16 domains by dynamically adjusting domain information during training.	Computational complexity increases with the number of domains; may face convergence issues.
7	Benjamin White & Anastasia Shimorina	**2025**	Developed an aspect-based sentiment analysis system using large language models for multi-domain, multilingual settings.	Demonstrated that a combined multi-domain model can match specialized single-domain models while reducing operational complexity.	Challenges remain in handling non-extractive predictions and evaluating various failure modes.

10.48047/jocaaa.2025.34.07.14

3. PROBLEM STATEMENT

Despite significant progress in sentiment analysis, existing approaches struggle to generalize across multiple domains while capturing both explicit (direct) and implicit (latent) sentiments embedded in customer queries and feedback. Traditional models are predominantly domain-dependent, making them less effective in dynamic, cross-domain environments like e-commerce, healthcare, finance, and public services. Furthermore, most models rely heavily on superficial lexical features, failing to capture nuanced sentiments expressed through sarcasm, ambiguity, idiomatic expressions, or context-specific semantics. This leads to misinterpretation of user intent and sentiment polarity, which in turn adversely impacts strategic business decisions, customer experience, and service delivery.

To address this gap, there is a pressing need for a robust, scalable, and semantically enriched sentiment analysis framework capable of adapting across domains and extracting both direct and latent emotional signals. This research proposes the design of a multi-domain specific sentiment analysis system empowered by deep semantic associations, domain ontologies, and transformer-based language models. By integrating cross-domain knowledge graphs, contextual embeddings, and latent sentiment mining techniques, the proposed framework aims to accurately decode nuanced customer sentiment, enhance interpretability, and provide actionable insights for strategic decision-making in customer-centric services.

4. RESEARCH GAP

While extensive research has been conducted in the field of sentiment analysis, most existing models are tailored to single-domain applications and are unable to generalize effectively across multiple domains with diverse vocabularies, contextual nuances, and sentiment expressions. These models often depend on large amounts of domain-specific labeled data, which is not always available or feasible to obtain for every sector. Moreover, they primarily focus on extracting overt sentiments and tend to overlook subtle emotional cues, sarcasm, or latent sentiments that are contextually implied rather than explicitly stated. The absence of mechanisms to capture such indirect signals severely limits their effectiveness in accurately understanding customer intent and emotional tone, especially in strategic applications where precision is critical.

Furthermore, there is a lack of comprehensive frameworks that seamlessly integrate domain adaptation, semantic enrichment, and latent sentiment detection into a unified model. Current methods often treat these components in isolation, leading to fragmented solutions that fail to deliver holistic sentiment insights. Despite the advancement of deep learning and transformer-based models like BERT, their performance in multi-domain scenarios is constrained by the absence of domain-sensitive semantic alignment and real-time adaptability. This creates a significant research gap in developing a domain-agnostic, semantically aware sentiment analysis system capable of understanding both direct and indirect sentiments across heterogeneous customer feedback streams.

5. OBJECTIVES

1. To collect Text Labeling and Dataset Preparation Using VADER Lexicon
2. To Develop an NLP-based Baseline Model for Result Exploration
3. To Implement of Advanced and Novel Models for Enhanced Latent Sentiment Detection
4. To Design and Deployment of a Custom Production-Grade Model for Real-Time Applications:

10.48047/jocaaa.2025.34.07.14

6. PROPOSED METHODOLOGY OF THE WORK

To address the limitations of existing sentiment analysis systems in multi-domain and latent sentiment contexts, the proposed research methodology adopts a multi-layered, hybrid approach integrating semantic knowledge, deep learning, and domain adaptation techniques. The core objective is to develop a comprehensive sentiment analysis framework that can extract both direct (explicit) and latent (implicit) sentiments from customer queries across diverse domains such as healthcare, retail, finance, and education.

The methodology encompasses multiple phases: dataset preparation from heterogeneous domains, preprocessing and semantic annotation, feature extraction using contextual embeddings (e.g., BERT or RoBERTa), and a novel sentiment classification architecture augmented with domain ontologies and knowledge graphs. Additionally, latent sentiment cues are captured through attention mechanisms and semantic association networks. The system is further enhanced with a cross-domain adaptation module to ensure robust performance and generalization. Evaluation is conducted using benchmark datasets and performance metrics such as accuracy, F1-score, precision, recall, and domain transferability. This multi-pronged methodological strategy ensures interpretability, scalability, and strategic applicability of sentiment insights for real-world decision-making.

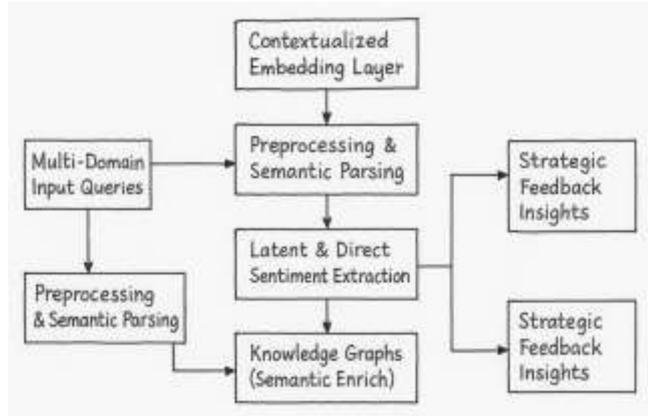

Figure 2: Block diagram of flow of research Methodology

Step 1: Multi-Domain Dataset Collection

- Gather structured and unstructured feedback from multiple domains (e.g., e-commerce, finance, healthcare, etc.).
- Include both labeled and unlabeled datasets for training and testing domain generalization.

Step 2: Preprocessing & Semantic Parsing

- Text normalization, stop word removal, lemmatization, and domain-specific keyword annotation.
- Apply POS tagging and dependency parsing to preserve grammatical structure.

Step 3: Contextual Embedding Layer

- Use transformer-based models (BERT, RoBERTa) to generate high-dimensional contextual embeddings.
- Fine-tune embeddings using domain-specific corpora to preserve semantic context.

Step 4: Semantic Enrichment via Knowledge Graphs

- Construct or integrate domain-specific knowledge graphs (e.g., DBpedia, ConceptNet).
- Map extracted terms to entities and relationships to identify hidden sentiment patterns.

10.48047/jocaaa.2025.34.07.14

Step 5: Latent Sentiment Detection

- Use self-attention mechanisms and semantic similarity measures to identify indirect sentiments.
- Detect sarcasm, implication, or emotional drift through latent association mining.

Step 6: Sentiment Classification

- Combine direct sentiment scores (from BERT classifiers) and latent sentiment scores (from semantic association model).
- Use multi-task learning or ensemble classifiers (e.g., BiLSTM + Attention + Graph Neural Networks).

Step 7: Domain Adaptation Module

- Apply transfer learning techniques such as domain adversarial training or MAML (Model-Agnostic Meta-Learning).
- Adapt models for cross-domain sentiment inference without needing complete retraining.

Step 8: Sentiment Fusion and Strategic Interpretation

- Fuse results from direct and latent sentiment detection modules.
- Provide strategic insights based on dominant sentiment trends, customer intent, and critical feedback points.

Step 9: Evaluation Metrics

- Evaluate with Accuracy, Precision, Recall, F1-Score, Domain Transfer Accuracy, and Interpretability Index.
- Benchmark against state-of-the-art models across different domains.

7. Conclusion

This survey mainly highlights the significant progress made in the field of multi-domain sentiment analysis, emphasizing the development of advanced models capable of understanding nuanced and implicit sentiments across diverse sectors. Despite notable advancements, several challenges remain, including effective domain adaptation, capturing latent emotions, and incorporating multimodal data. Current approaches often struggle with generalization, scalability, and handling subtle contextual cues such as sarcasm and ambiguity. Future research should focus on creating unified frameworks that seamlessly integrate semantic knowledge, transfer learning, and domain-specific features, ensuring robust and scalable sentiment analysis systems. Addressing these research gaps will be instrumental in moderate the accuracy and applicability of sentiment analysis, ultimately enabling more insightful and strategic decision-making in various customer-centric and social applications.

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