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A Review on Sentiment Classification of Amazon Product Review Dataset using NLP Techniques

Ashish Mathur[1], Dr. Pharindara Kumar Sharma[2]
[1]Research Scholar, [2]Associate Professor, [1,2]Dept of Computer Science and Engineering, SRCEM College Banmore, Morena, M.P. India

Abstract: With an emphasis on its applicability to research into consumer behaviour and online shopping, this review paper examines recent developments and methods for sentiment categorisation. With the proliferation of online marketplaces comes an increased need for user-generated material, particularly product reviews, and the realisation that thorough sentiment analysis aids buyers in making informed purchases. The study delves into a number of To classify sentiments using natural language processing techniques, one can use either traditional or deep learning models, such as Support Vector Machines (SVMs), Decision Trees, Naive Bayes, or Convolutional Neural Networks (CNNs) or Long Short-Term Memory networks (LSTMs). One of the most important feature extraction procedures in "translating textual input into suitable forms for sentiment analysis" is word embeddings. Other approaches include Bag of Words (BoW), and Term Frequency-Inverse Document Frequency (TF-IDF). Tokenising, stemming, and stop word elimination are preprocessing techniques included in the review as well. These are essential for improving the input data quality and the model's performance. This study highlights some of the major challenges and restrictions of sentiment classification, such as the following: sarcasm detection; negation handling; and training set internal biases. I would like to emphasise the importance of explainable artificial intelligence in enhancing confidence in sentiment analysis applications, especially in significant corporate settings. Using contextualised word embeddings, multimodal sentiment analysis, and the development of domain-specific models matching industry-specific demands are some of the future breakthroughs in natural language processing (NLP) that the paper discusses. Learning systems must be constantly adapting to reflect client opinions and language growth. Focussing on its importance in enhancing consumer experiences and directing strategic business decisions in the dynamic digital market, this review aims to provide a comprehensive view of sentiment classification's current state and future prospects.

Keywords: Sentiment Classification, Natural Language Processing, E-commerce, Machine Learning, Consumer Behavior

I. INTRODUCTION

Natural language processing (NLP), the act of ascertaining, from a text, whether positive, negative, or neutral sentiment, depends much on sentiment analysis—also known as opinion mining. Customer reviews have become a major tool for both consumers and companies as e-commerce sites proliferate. Given this context, Amazon—one of the biggest online markets—offers an amazing array of product reviews capturing several consumer points of view. By means of analysis of these assessments, one can better understand consumer happiness, product performance, and brand reputation, thereby impacting marketing decisions and company policies. Since textual data is unstructured and thoughts can be expressed in numerous ways, sentiment categorisation of Amazon product evaluations is a difficult but required chore. Processing raw text input is one aspect of complexity; another is spotting linguistic nuances that could compromise the accuracy of sentiment classification models: sarcasm, irony, and context dependence. Sentiment analysis relies heavily on logistic regression, support vector machines, the Naive Bayes classifier, and other conventional machine learning approaches to visualise text using Bag of Words (BoW) and Term Frequency-Inverse Document Frequency (TF-IDF). Emerging from deep learning in recent times are models that are more complex. Machines like BERT, RNNs, and LSTMs fall into this category, as do CNNs and transformer-based models. These models are able to capture contextual information and improve classification accuracy [1]–[3]. This paper attempts to assess the several NLP techniques used for sentiment categorisation of the Through contrasting traditional machine learning methods with more modern deep learning algorithms, we can analyse the Amazon product review dataset. Noted here are the field's major challenges, promising areas for growth, and promising new prospects. by means of analysis of the strengths and constraints of numerous methodologies, therefore offering a full knowledge of the current situation of sentiment categorisation in e-commerce. The results will provide perceptive study on how to efficiently apply NLP methods to extract significant sentiment from vast review datasets, thereby assisting academics as well as businesses [4]–[6].

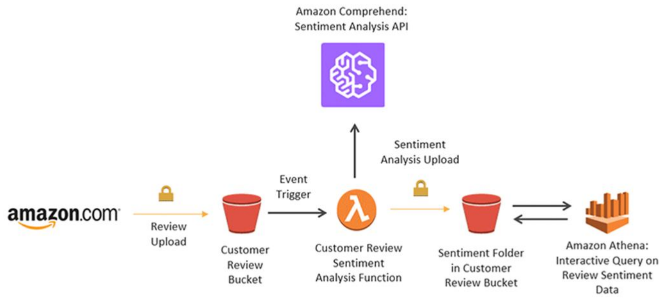

Figure 1 Sentiment Classification of Amazon Product [7]

In e-commerce, sentiment classification is essential since it helps companies to grasp consumer attitudes and feelings on a large scale, therefore guiding rational decision-making and raising customer happiness. Consumer reviews are a great kind of feedback in the very competitive e-commerce market since they reveal knowledge about general consumer experience, product quality, and service efficiency. Separating these emotions into good, negative, or neutral categories helps companies assess customer responses and change their plans rapidly. Should a given product consistently get bad reviews, for example, businesses can find the underlying problems—related to delivery delays, product features, or post-sale services—and try to raise customer satisfaction. Moreover, sentiment categorisation proposes products depending on past sentiments indicated in reviews, therefore enabling e-commerce enterprises to tailor the user experience. This focused strategy raises the possibility of turning potential consumers into real ones, so promoting increased loyalty and purchases [8]–[10]. More generally, sentiment classification helps companies to manage their brands by letting them track public opinion in real-time and react quickly to unfavourable emotions before they become more major reputation issues. Furthermore, it helps identify bogus reviews as some emotional patterns in them differ from those in real user comments, therefore preserving the integrity of the website. By exposing unmet consumer desires or desired changes in current products, sentiment analysis also aids in the production of innovative ideas. Analysing a lot of customer reviews helps companies to see changing preferences and trends, thereby guiding their activities to satisfy customer needs. Sentiment classification gives consumers value and streamlines the process of product choice by pooling their sentiment score. All things considered, sentiment classification is a must-have tool for e-commerce since it helps businesses to use consumer comments to sustain a competitive advantage, improve product offers, and protect customer experience while concurrently arming consumers with better buying knowledge [11], [12].

II. RELATED WORK

Xu et al. 2024 demonstrates exceptional performance in several sectors where achievement is paramount. Supply chains, logistics, financial markets, and technology legitimacy evaluations are just a few of the many areas that might benefit from sentiment research, which can help with public opinion, actionable data, and better decision predictions. Our study adds to the expanding data corpus by presenting a new multi-view deep learning approach to sentiment analysis that incorporates non-textual elements such as emojis. For the sentiment classification model, the suggested method considers both the textual and emoji viewpoints on emotional data, appreciating the value of both viewpoints in sentiment analysis. When compared with baseline classifiers, emoji features significantly improve sentiment analysis, which in turn improves the proposed model's accuracy, F1-score, and runtime. And to help high-stakes companies understand what influences customer sentiment, this study uses LIME for explainable sentiment analysis to shed light on the model's decision-making process. Companies can get an advantage in the ever-changing digital marketplace by using this study's innovative analytics tool to extract vital emotional information from eWOM. It also adds to our knowledge of social media frameworks for multi-view text classification. Also, these results have significant implications for social media surveillance and digital communication policymaking. If lawmakers realised the value of emojis for conveying feeling, they could improve public sentiment analysis and address public issues through tailored legislative actions [13].

Aakash et al. 2024 The volume of created data has been expanding at a rapid pace in recent years, with examples including online debates, product reviews, and social media posts. Businesses are increasingly relying on sentiment analysis to get insights into customer sentiment, inform decision-making, and enhance products and services. Building a sentiment analysis system using item URLs as review data sources is the goal of this project.

It uses web scraping techniques to gather this data. Data tokenisation and stop word deletion are two examples of the many natural language processing (NLP) methods used in data preparation. Within the support vector classifier, sentiment analysis makes use of a number of machine learning methods, including Naive Bayes, Logistic Regression, Random Forest, KNN, and deep learning models such as LSTM and GRU. You may measure the models' performance with measures like recall, accuracy, and precision. Across all experiments, the LSTM and GRU models consistently identified sequential connections quite well. Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) models routinely outperform other models, proving their superior accuracy-recall balance, with F-1 ratings of 90% and 91%, respectively. On the other hand, K-Nearest Neighbour (KNN) shows a clear trade-off: it has a lightning-fast training time of 0.01 seconds, but it takes 102.34 seconds to generate a prediction, which results in a lower F-1 score of 47%.

Both Logistic Regression (84% efficiency) and Support Vector Machine (SVM) (85% competitiveness) have somewhat slow training and prediction timeframes. While both Naive Bayes and Random Forest are very accurate, their F-1 ratings couldn't be more different: 71% and 80%, respectively. Because of this, it is critical to consider processing efficiency and performance when deciding on the optimal method. This article provides fresh and helpful criticism of some of the sentiment analysis approaches that have been the focus of heated controversy. The findings might help us learn more about sentiment analysis approaches and pick the right one for URL-based sentiment analysis [14].

Syed et al. 2024 For better comprehension, evaluation, and action based on consumer feedback, categorisation systems are vital. We need to automate these procedures since the amount of review data from sources like social media, review websites, and e-commerce platforms is growing at an exponential rate. Recently, deep transfer learning has decided to take on a plethora of difficult Natural Language Processing (NLP) challenges in an attempt to reduce the demands of laborious training and the necessity for enormous labelled datasets.

This study introduces pre-trained language model (PLM) frameworks for sentiment analysis (SA) and abstractive summarisation (ABS) of airline evaluations. Domain adaptation and final task learning are the two main phases of fine-tuning that abstractive summarising models normally go through. Many research' experimental results demonstrate a robust relationship between review rating and sentiment valence. We constructed the sentiment categorisation system using the BERT (Bidirectional Encoder Representations from Transformers) architecture as its foundation. To determine the tone of the review, we looked at the rating value. We performed a comprehensive examination of our models by applying multiple measures. Our data shows that the models are competitive across the board when it comes to the evaluation categories [15].

Jim et al. 2024 reading between the lines to identify sentiments or emotions. Classifying ideas as positive, neutral, or negative is possible through word and phrase analysis. Sentiment analysis is significant because it enables businesses to comprehend consumer sentiment, make informed decisions, and enhance their products by intelligently analysing large amounts of text data. Foreseeing the possible growth of sentiment analysis requires knowledge of its methodologies, applications, current condition, and problems. Therefore, we began by conducting a comprehensive examination of the many domains of use for sentiment analysis in this large-scale survey, taking into account all of the existing knowledge.

For this reason, we sought out popular pre-processing methods, datasets, and evaluation criteria to strengthen our grasp. Furthermore, the advantages and disadvantages of various machine learning, deep learning, pre-trained, and large language model approaches were covered in relation to sentiment analysis. Following that, we thoroughly examined the most recent state-of-the-art articles' policies and experimental findings.

Finally, we outlined the numerous challenges of sentiment analysis and provided some research directions for the future of the discipline. In this comprehensive study, we will go over all the important aspects of sentiment analysis, including its models, applications, results analysis, challenges, and research goals [16].

Sultana et al. 2023 offered online; the practice of purchasing goods and services on the Internet is rapidly expanding. Nowadays, some online shops even allow customers to leave reviews after they've bought something. This helps to improve the buying experience for clients.

The quantity of reviewers is enormous. This results in a dramatic increase in the amount of reviews a product gets. Due to the large number of submissions, manual analysis of customer comments takes time. So, sentiment analysis is useful for collecting, evaluating, and extracting product views from discussion websites. The purpose of this research is to analyse product reviews using an Advanced Naive Bayesian Algorithm to determine if the reviews are favourable or negative [17].

Table no. 1 Literature summary

Author/year	Methods	Findings	Research gap	Parameters
Rao/2021 [18]	Methods involve data preprocessing, feature extraction, and sentiment classification algorithms.	Findings show effective sentiment classification with high accuracy using algorithms.	Limited handling of sarcasm and context challenges in sentiment analysis.	The model achieved high accuracy in classifying Amazon reviews.
Sultana/2021 [1]	Methods use supervised machine learning models to classify Amazon reviews.	Support Vector Machine and Random Forest achieved the highest accuracy rates.	Limited focus on sarcasm and nuanced expressions in reviews.	Machine learning models successfully classify reviews with significant accuracy improvements.
Ali/2021 [19]	Methods involve supervised learning to classify sentiment in Amazon reviews.	Traditional machine learning techniques effectively classify Amazon product review sentiments.	Insufficient exploration of contextual nuances and sarcasm in sentiment analysis.	Results indicate high accuracy for sentiment classification using traditional techniques.
Shah/2021 [20]	Methods compare word2vec-CNN and FastText-CNN for sentiment classification.	Word2vec-CNN model outperforms FastText-CNN in sentiment classification accuracy.	Limited research on model interpretability and context in sentiment analysis.	Results show significant accuracy improvements using word2vec-CNN model.
Hawlader/2021 [21]	Methods compare classifiers and preprocessing techniques for sentiment analysis accuracy.	MLP classifier using Bag of Words yields highest accuracy results.	Need for improved sentiment analysis techniques for nuanced language understanding.	MLP classifier achieved 92% accuracy, outperforming other methods significantly.

III. NATURAL LANGUAGE PROCESSING TECHNIQUES FOR SENTIMENT CLASSIFICATION

A. Text Representation Techniques

To enable sentiment analysis based on word occurrence, Bag of Words (BoW) interprets text as a group of words, focussing on word frequency rather than syntax and order. The TF-IDF method improves classification performance by giving more weight to less common and informative terms, and by weighting word frequencies according to their importance, it increases BoW. Word2Vec, GloVe, and FastText are word embeddings that help models understand tone and context by transforming words into dense vector representations that capture semantic meanings and links. When applied collectively, these techniques improve sentiment classification accuracy across a wide range of domains.

B. Feature Extraction

NGrammes provide context that individual words might overlook since they form consecutive sequences of "n" objects from the text. Common phrases, for instance, can be caught by bi-grams and tri-grams, therefore enhancing emotional indication as opposed to looking at single words by themselves. Furthermore, lexicon of emotions.By building adjacent sequences of "n" objects from the text, n-grams offer context that individual words could ignore. Bi-grams and tri-grams let one document common phrases, therefore providing more accurate emotion indicator than just looking at individual words. Sentiment lexicons also have pre-defined dictionaries including words matched with their corresponding sentiment ratings.

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These lexicons serve to identify sentiment by pointing out particular words in the text, therefore enabling models to quantify sentiment relying on predefined emotional values by means of specific phrases. N-grams and sentiment lexicons taken together improve the way complex emotions in textual material are perceived. NS comprises pre-defined dictionaries of words coupled with sentiment scores. These lexicons enable models to quantify sentiment by identifying specific terms in the text, therefore helping to classify sentiment based on established emotional values. Taken combined, sentiment lexicons and N-grams help to better understand difficult emotions in textual material [22], [23].

C. Machine Learning Approaches

When it comes to sentiment categorisation, supervised learning approaches like Naive Bayes, Decision Trees, Supported Vector Machines (SVM), Logistic Regression, and Random Forests are among the most popular. These techniques use labelled training data to generate predictions on unseen data, which improves the accuracy of emotion classification. Deep learning methods sift through massive datasets in search of complex relationships and patterns in text data. RNNs, LSTMs, and CNNs are just a few examples. Thanks to these cutting-edge designs, researchers can improve sentiment classification, leading to a more sophisticated knowledge of customers' thoughts and feelings.

D. Hybrid Approaches

An effective strategy for sentiment categorisation that makes use of the strengths of both deep learning and traditional machine learning algorithms is to combine the two. For instance, by recording the semantic meanings and contextual links between words, word embeddings can greatly improve the performance of classical classifiers when used as input data. Combining the interpretability and efficiency of standard machine learning with the dense representations of deep learning can strengthen sentiment analysis models and make them more accurate. We can learn more subtle aspects about text tone and generate better generalisations across datasets by combining the two approaches [24], [25].

E. Preprocessing Techniques

To guarantee that the text data is clean and suitable for further investigation, good preprocessing is crucial for effective sentiment analysis. Tokenising, which separates text into individual words, deleting stop words, stemming, which gets to the roots of words, and lemmatising, which gets to the base or dictionary forms, are all important preprocessing procedures. The collaboration of these technologies improves the accuracy and efficiency of sentiment classification algorithms by standardising text formats, reducing noise, and focused on the most instructive components of the data.

F. Ensemble Methods

By combining predictions from many methods, ensemble learning improves classification performance when applied to multiple models. This approach leverages the strengths of many models, leading to more robust and precise sentiment classification outcomes. In contrast to stacking, which requires training a new model to synthesise the predictions of base models, voting classifiers and similar algorithms offer a majority decision-making process in which the predictions of each model contribute to the final classification. Ensemble approaches improve the interpretation of consumer attitudes and opinions in many various applications by incorporating numerous points of view and minimising individual model biases. This increases the general dependability of sentiment analysis [26], [27].

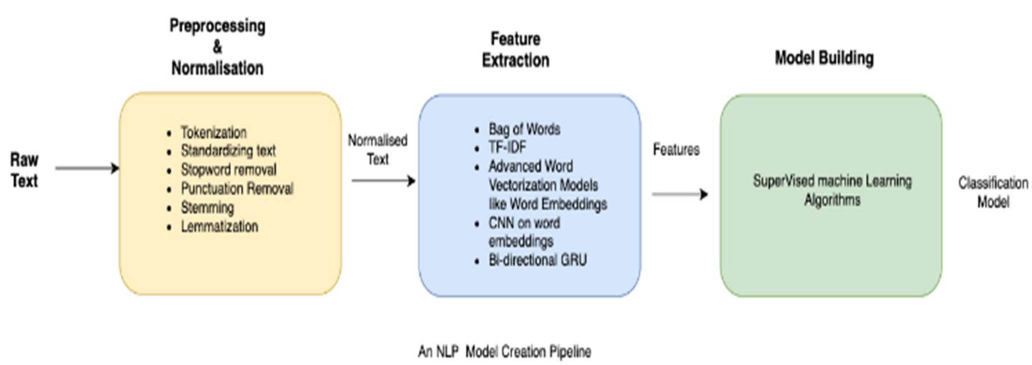

Figure 2 NLP for sentiment classification [28]

IV. CHALLENGES AND LIMITATIONS IN SENTIMENT CLASSIFICATION

A. Sarcasm and Irony Detection

Accurately spotting sarcasm and irony is one of the most important difficulties in sentiment classification. These kinds of expression help models to understand the actual emotional intent behind the text since they might transmit feelings different from the exact meaning of the words.

B. Contextual Nuances

Context can drastically affect sentiment. Positive words used in one context could have a bad connotation in another. Traditional models might find these subtleties difficult, which would cause misclassification [29]–[31].

C. Domain-Specific Language

Many disciplines—including finance, healthcare, technology—have particular terminology and jargon. Sentiment classification algorithms may not be relevant for domain-specific texts even if they have been trained on large datasets, therefore restricting their usefulness.

D. Ambiguity in Language

Natural language is by nature ambiguous; words can have several interpretations (polysemy). This uncertainty might hinder sentiment analysis since the same word might convey different emotions in several situations or sentences.

E. Data Imbalance

Class imbalance, in which one sentiment class—e.g., positive—much exceeds another—e.g., negative—affects many sentiment datasets. This imbalance can tilt the model towards the more common class, therefore lowering the general classification accuracy [32]–[34].

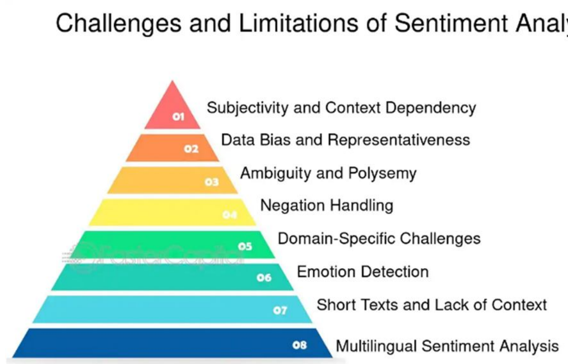

Figure 3 Challenges and limitations in sentiment classification [35]

V. FUTURE TRENDS IN NLP FOR SENTIMENT CLASSIFICATION

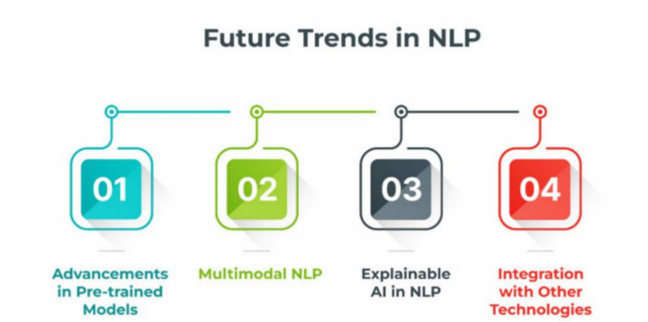

Figure 4 Future trends in NLP [36]

Motivated by fresh technologies and methods, Natural Language Processing (NLP) for sentiment classification has bright future possibilities. Among the most significant developments are rising contextualised word embeddings, best shown by models such as BERT and GPT, which offer a fuller knowledge of words based on their context, therefore enhancing the accuracy of sentiment analysis. Moreover, the application of transformer architectures with attention mechanisms lets models focus on the most relevant parts of the input text, thereby boosting the sentiment classification outcomes. Combining textual data with visual inputs such as photographs and videos, multimodal sentiment analysis provides a whole picture of consumer sentiment in the progressively multimedia-rich online environment [37], [38]. Transparency is becoming more and more crucial in artificial intelligence, hence the focus on Explainable AI (XAI) will help to improve sentiment categorisation so models may clear their decision-making process and boost user confidence. Domain-specific sentiment models will also find resonance as businesses hunt for tailored solutions leveraging specialist vocabularies and contextual knowledge to boost classification accuracy across many sectors, including healthcare, finance, and e-commerce. Constant learning is a fundamental ability that will help sentiment analysis models to adapt with linguistic trends and changing client opinions without major retraining on fresh data. Emotion detection will simultaneously modify sentiment classification so that models may not only classify emotions as positive or negative but also identify individual emotions like pleasure, rage, or sadness, therefore providing a fuller knowledge of human opinions. Ethical questions around bias in sentiment analysis will demand ongoing research targeted at developing techniques to identify and reduce biases in training data and model predictions. Furthermore there are better preprocessing techniques, which will enhance feature extraction and noise reduction techniques to maximise input data quality for sentiment models. Finally, cross-lingual sentiment analysis will take front stage since it will allow sentiment classification across various languages and enhance global consumer insights. Targeting models that are not only accurate but also interpretable, context-aware, and responsive to the shifting landscape of human feeling, these trends taken together promise a bright future for NLP in sentiment classification [39], [40].

VI. CONCLUSION

Natural Language Processing (NLP) sentiment classification is rapidly expanding in importance, particularly for e-commerce and online customer interactions. Through accurate analysis and interpretation of customer attitudes from massive volumes of textual data, businesses may improve customer experiences, influence product offers, and allow informed decisions. But this has a lot of repercussions. This paper showcases a variety of sentiment analysis methods, including deep learning models, unique preprocessing techniques, and more typical machine learning applications. Word embeddings, TF-IDF, and the Bag of Words are a few methods that scholars and practitioners use to capture the intricacies of expressing sentiment in text. Results in classifications that are more consistent as a result. The use of transformer topologies in conjunction with contextualised embeddings has also made great strides in the area, improving the capacity to understand language and identify sentiment. Expanding the breadth of possible sentiment classifications, multimodal sentiment analysis incorporates insights from a wide variety of data sources, including visual ones like images and videos. In contrast, the discipline faces substantial obstacles in removing biases from training data, adjusting to linguistic shifts, and guaranteeing model interpretability. As sentiment classification advances, research into emotion identification, explainable AI methods, and strong models that can function effectively across languages and domains should be prioritised. The use of sentiment analysis extends beyond e-commerce into fields such as public opinion research, social media monitoring, and customer service automation. As sentiment analysis is used increasingly often by corporations to evaluate consumer attitude, the necessity to solve ethical challenges and reduce discrimination will only increase. Collectively, new concepts and tools that aim to enhance our comprehension of human feelings and viewpoints are encouraging for the trajectory of sentiment classification in NLP. Professionals and academics might make better use of sentiment analysis in the digital era if they accepted these advancements, which would lead to more effective customer interaction strategies and decision-making.

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