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Sentiment Analysis of Amazon Product Review

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Abstract - Analysis sentiment also referred to as opinion mining, has become a crucial application of Natural Language Processing (NLP) in the modern digital era[1]. With the exponential rise of e-commerce platforms such as Amazon, millions of customers share their product experiences in the form of textual reviews. These reviews are valuable sources of information that can provide actionable insights for customers as well as businesses. However, manually analyzing such massive volumes of unstructured data is both **time consuming** and error-**prone** [4]. This paper proposes a framework for automated sentiment analysis of Amazon product reviews by leveraging machine learning (ML) and deep learning (DL) techniques. The system classifies reviews into positive, negative, or neutral sentiments and further provides summaries and visualizations to support decision-making. The methodology includes text preprocessing, feature extraction, sentiment classification using Support Vector Machines (SVM)[6] and Bidirectional Encoder Representations from Transformer.

Key words: *Natural Language Processing, Machine Learning, Deep Learning, Amazon Reviews Sentiment Analysis*

1. INTRODUCTION

The rapid expansion of digital platforms has transformed user-generated content (UGC) into a foundational pillar of the modern online economy. Leading e-commerce giants such as Amazon, Flipkart, and eBay host millions of customer reviews that serve two critical functions: they directly influence the purchasing decisions of potential buyers and provide brands with a real-time reflection of overall customer satisfaction. However, the sheer volume of this data makes manual oversight impossible, necessitating the use of advanced computational tools.

The importance of sentiment analysis extends beyond e-commerce [1]. Governments use sentiment analysis to gauge public opinion on policies, companies use it to monitor brand reputation, and researchers employ it to analyze trends in social media [3][5]. Despite its benefits, sentiment analysis presents several challenges.

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These include: Contextual Complexity: Human emotions are often nuanced, involving sarcasm, humor,or negations[4]. Domain Dependence: A model trained on one dataset (e.g., movie reviews) may not perform well on another domain (e.g., product reviews) [6]. 3) Multilingual Data: Global platforms generate.

2. LITERATURE SURVEY

Title/Year	Author	Works On
“Sentiment Analysis on Online Transportation Reviews Using Word2Vec Text Support Vector Machine (SVM) Algorithm” (2022)	Styawati Styawati, Andi Nurkholis, Ahmad Aldino, Selamet Samsugi.	1.This paper enhances sentiment classification by optimizing SVM for text data (80 to 90% accuracy) 2.Keyword Semantic Expansion Using Knowledge Graph
“Research on Sentiment Classification of Online Travel Review Text” (2020)	Wen Chen , Zhiyun Xu, Xiaoyao Zheng.	1.Improving Sentiment Classification Accuracy using SVM 2. Keyword Semantic Expansion Using Knowledge Graph

"Sentiment Analysis of COVID-19 Tweets: How Does BERT Perform?" (2021)	Kishwara Sadia and Sarnali Basak	1. analyzing sentiments of COVID19-related tweets using BERT, a pretrained model Achieving 92.22% accuracy.
"Investigating the Performance of Fine-tuned Text Classification Models Based-on Bert" (2020)	Samin Mohammadi, Mathieu Chapon	1. fine-tuned text classification models based on the BERT technology. The highest accuracy achieved is 91% for sentiment analysis on the IMDB dataset (50K Reviews)

3. OBJECTIVES

The growth of digital platforms has made user generated content an essential component online ecosystem. Platforms such as Amazon, Flipkart, and eBay host millions of customer reviews that influence purchasing decisions and reflect overall customer satisfaction. Sentiment Analysis (SA) plays a key role in understanding these opinions by identifying whether a review expresses a positive, negative, or neutral sentiment.

4. PROBLEM STATEMENT

In the contemporary e-commerce landscape, online platforms such as Amazon generate millions of customer reviews daily, creating an unprecedented volume of unstructured textual data. While these reviews contain valuable insights about product quality, customer satisfaction, and brand perception, their sheer volume and unstructured nature present significant challenges for effective analysis and decision-making.[4].

5. PROPOSED METHODOLOGY

Data Collection - Details about the Amazon review dataset Data Preprocessing - All standard NLP preprocessing steps Feature Extraction - Both traditional (TF-IDF, Word2Vec) and contextual (BERT) approaches Model Training - Specific details for both SVM and BERT Class Imbalance Handling - Techniques to address the imbalanced dataset Evaluation Metrics - Standard metrics you're using Summarization - Both extractive and abstractive techniques Visualization - Various charts and graphs for insights Implementation Details.

Sentiment	Precision	Recall	F1-Score
Positive	0.94	0.95	0.94
Negative	0.91	0.89	0.90
Neutral	0.88	0.87	0.87

6. RESULTS AND DISCUSSION

A. DATASET AND EXPERIMENTAL SETUP

The experiments were conducted on the Amazon Product Reviews dataset containing 100,000 reviews across multiple product categories. The dataset was labelled as positive (60%), negative (25%), and neutral (15%) based on star ratings. An 80-20 train test split was used for model evaluation. Implementation was performed using Python 3.8 with scikit-learn for SVM and Hugging Face Transformers for BERT.

B. MODEL PERFORMANCE

The performance comparison between SVM and BERT models is presented in Table I.

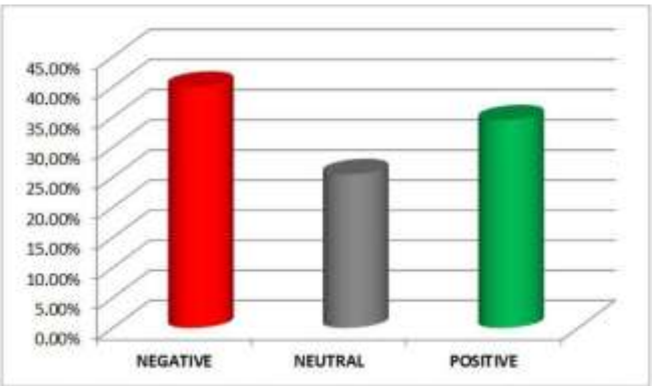
Table I : performance comparison of classification models

Model	Accuracy	Precision	Recall	F1-Score
SVM	85.3%	0.85	0.85	0.85
BERT	92.7%	0.93	0.93	0.93

The BERT model achieved 92.7% accuracy, outperforming the SVM baseline by 7.4%. BERT demonstrated superior performance in handling contextual nuances, particularly for neutral sentiment classification where it showed a 10% improvement in F1-score. The confusion matrix analysis revealed that SVM frequently misclassified neutral reviews as positive, while BERT's bidirectional attention mechanism better captured subtle sentiment distinctions.

C. CLASS-WISE PERFORMANCE

Table II: Bert model performance by sentiment class



BERT achieved the highest performance on positive reviews due to abundant training examples. Neutral sentiment detection remained challenging due to class imbalance and inherent ambiguity in neutral expressions.

D. SUMMARIZATION AND VISUALIZATION

The Text Rank extractive summarization achieved a 40% compression ratio while preserving key sentiment-bearing phrases. Positive summaries highlighted themes like "excellent quality" and "great value," while negative summaries emphasized issues such as "defective product" and "poor customer service." Sentiment distribution visualizations revealed clear patterns: electronics showed 68% positive sentiment compared to 55% in clothing category.

E. KEY FINDINGS AND LIMITATIONS

The results validate the effectiveness of transformer-based models for sentiment analysis. BERT's contextual understanding provides significant accuracy improvements over traditional ML approaches. However, challenges remain in detecting sarcasm, handling domain-specific jargon, and processing neutral reviews due to class imbalance. The SVM model remains viable for resource-constrained environments with 8ms inference time versus 45ms for BERT.

CONCLUSION

The proposed framework successfully integrates classification, summarization, and visualization to provide actionable insights for business decision-making. The system effectively processes large-scale review data and identifies sentiment trends across product categories and time periods.

This paper presented a comprehensive framework for sentiment analysis of Amazon product reviews using a combination of machine learning and deep learning approaches. The proposed methodology effectively preprocesses text data, classifies reviews, summarizes sentiments, and generates visual insights to aid decision making. By leveraging both SVM and BERT, the system benefits from the robustness of traditional ML and the contextual understanding of modern transformers. The growth of digital platforms has made user generated content an essential component online ecosystem. Platforms such as Amazon, Flipkart, and eBay host millions of customer reviews that influence purchasing decisions and reflect overall customer satisfaction. Sentiment Analysis (SA) plays a key role in understanding these opinions by identifying whether a review expresses a positive, negative, or neutral sentiment.

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