Aspect-Based Sentiment Analysis on Product Reviews Using Classical Models and BERT-based Transformers

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Abstract

This report presents an implementation of Aspect-Based Sentiment Analysis (ABSA) on product reviews using classical machine learning models, deep learning, and a BERT-based transformer approach. The objective was to classify sentiment polarity (positive, neutral, negative) associated with specific product aspects in the Amazon Fine Food Reviews dataset. After preprocessing and basic aspect extraction using Named Entity Recognition (NER), sentiment classification was performed using Logistic Regression, SVM, CNN, and MiniLM-based transformer embeddings. The CNN model achieved the highest accuracy of 84% and an F1-score of 0.83, followed by the MiniLM model with 82% accuracy and better contextual understanding. The results highlight the effectiveness of combining transformer-based embeddings with neural classifiers for fine-grained sentiment analysis.

1 Introduction

Sentiment analysis is a core task in Natural Language Processing (NLP) that aims to determine the emotional tone expressed in textual data. While traditional sentiment analysis assigns a general polarity label—positive, negative, or neutral—to an entire sentence or document, it often fails to capture sentiment directed toward specific product features. Aspect-Based Sentiment Analysis (ABSA) overcomes this limitation by identifying both the *aspect terms* (e.g., taste, price) and the *sentiment polarity* associated with each.

Formally, given a review sentence $R = \{w_1, w_2, ..., w_n\}$, where w_i represents the i^{th} word in the review, ABSA seeks to identify a set of aspects $A = \{a_1, a_2, ..., a_k\} \subseteq R$, and assign to each aspect a_i a sentiment label $S_i \in \{\text{positive}, \text{neutral}, \text{negative}\}$.

We explored multiple classification pipelines in this work:

- **Classical Machine Learning Models:** Logistic Regression and Support Vector Machines (SVM), using TF-IDF and GloVe-based average embeddings. The sentence vector v_R is computed as:

$$v_R = \frac{1}{n} \sum_{i=1}^{n} \text{embed}(w_i)$$

- **Transformer-Based Model:** We used the `all-MiniLM-L6-v2` model from the SentenceTransformer library to generate 384-dimensional sentence embeddings. These were fed into a feedforward neural network for sentiment classification.

All models performed multiclass classification using a softmax layer:

$$\hat{y} = \text{softmax}(Wx + b)$$

where x is the input embedding vector, W and b are the learnable parameters, and $\hat{y}$ is the predicted probability distribution.

The models were trained using categorical cross-entropy loss:

$$\mathcal{L} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i)$$

where y is the one-hot encoded true label, $\hat{y}$ is the predicted probability vector, and $C = 3$ represents the number of sentiment classes.

We evaluate these models on the Amazon Fine Food Reviews dataset using accuracy and F1-score. The comparative results help analyze the trade-offs between classical, deep learning, and transformer-based approaches to ABSA.

2 Method

2.1 Dataset and Pre-processing

We used the Amazon Fine Food Reviews dataset, which contains over 568,000 customer reviews along with metadata such as product ID, user ID, profile name, score (1–5), and review text. For our implementation, we focused on the `Text` and `Score` columns.

Kaggle[1].

To convert the 5-point rating scale into sentiment labels, we mapped the scores into three classes: **Negative (1–2)**, **Neutral (3)**, and **Positive (4–5)**. Reviews were cleaned by removing null values, duplicate entries, and irrelevant characters.

The textual data underwent the following pre-processing steps:

- Lowercasing all text
- Removing punctuation and special characters
- Eliminating stopwords using the NLTK library
- Tokenizing the text into sequences of words

[1] `https://www.kaggle.com/datasets/snap/amazon-fine-food-reviews`

- Padding sequences to a fixed length of 100 tokens

For classical machine learning models like Logistic Regression and SVM, we used two types of vector representations:

- **TF-IDF vectors** generated using scikit-learn's `TfidfVectorizer`
- **Average GloVe embeddings:** Each word was mapped to a 100-dimensional vector, and the review-level embedding was computed as:

$$v_R = \frac{1}{n}\sum_{i=1}^{n} \text{embed}(w_i)$$

For the deep learning model (CNN), we constructed an embedding matrix using pre-trained GloVe vectors, which was used to initialize the embedding layer. For the transformer-based model, we used the `all-MiniLM-L6-v2` model from the SentenceTransformer library to generate 384-dimensional sentence embeddings for each review.

2.2 Model Architectures

2.2.1 Traditional Models: Logistic Regression and SVM

We implemented two classical models for sentiment classification: Logistic Regression and Support Vector Machine (SVM). Both models were trained on feature vectors derived from TF-IDF and GloVe embeddings.

Logistic Regression is a linear classifier that estimates the probability of class membership using the sigmoid function:

$$P(y = 1 \mid x) = \frac{1}{1 + e^{-w^T x + b}}$$

For multiclass classification, we used the softmax extension:

$$\hat{y} = \text{softmax}(Wx + b)$$

SVM with a linear kernel was used as a strong baseline. It finds the optimal hyperplane that maximizes the margin between classes. We used `LinearSVC` from scikit-learn and evaluated the models using accuracy and F1-score.

2.2.2 Convolutional Neural Network (CNN)

The CNN model was trained on padded sequences of tokenized review text using an embedding layer initialized with pre-trained GloVe vectors. The architecture included:

- Embedding layer with 100-dimensional GloVe vectors
- 1D Convolution layer with ReLU activation
- Global Max Pooling layer

- Dropout layer for regularization
- Dense output layer with softmax activation for multiclass classification

This structure allows the CNN to capture local n-gram level features (e.g., “not good”, “very tasty”) and generalize over sentence structure.

2.2.3 Transformer-Based Model (MiniLM)

To incorporate deeper semantic understanding, we used the `all-MiniLM-L6-v2` model from the SentenceTransformer library. This model generates a 384-dimensional contextual embedding for each review by applying a lightweight transformer architecture distilled from BERT.

The sentence embeddings were passed into a fully connected neural network with the following architecture:

- Dense layer (256 units) with ReLU
- Dropout layer
- Dense layer (128 units) with ReLU
- Dropout layer
- Final dense layer with softmax activation to output class probabilities

This transformer-based pipeline required no manual tokenization or padding and captured sentence-level semantics directly from raw review text.

2.3 Training

All models were trained on the preprocessed Amazon Fine Food Reviews dataset, which was split into 80% training and 20% testing sets.

For classical models (Logistic Regression and SVM), we used scikit-learn’s implementation with default parameters and L2 regularization. Grid search was applied for hyperparameter tuning (e.g., regularization strength).

The CNN was implemented using TensorFlow and trained using the Adam optimizer with categorical cross-entropy loss. The model was trained for 10 epochs with a batch size of 64 and a validation split of 20%. Early stopping was used to prevent overfitting.

For the transformer-based model, MiniLM sentence embeddings were precomputed using the SentenceTransformer API. These 384-dimensional vectors were then fed into a fully connected neural network implemented in Keras. The network was trained with the same settings as the CNN model—using Adam optimizer, categorical cross-entropy loss, and a softmax output layer.

All models were evaluated using accuracy and macro-averaged F1-score across the three sentiment classes: negative, neutral, and positive.

2.4 Ablation Study and Evaluation Strategy

To ensure reliable model comparison, we performed 5-fold cross-validation across all model configurations. The dataset was randomly split into five equal subsets. For each fold, four subsets were used for training and one for validation. Final accuracy and macro-averaged F1-score were reported as the mean across all folds.

We also conducted a comprehensive ablation study to evaluate the contribution of different components in our final pipeline. The goal was to isolate the impact of the transformer-based MiniLM embeddings on overall performance.

The ablation study involved:

- Replacing MiniLM embeddings with averaged GloVe vectors
- Using traditional TF-IDF vectors with the same neural classifier
- Comparing the transformer-based model against classical models (Logistic Regression, SVM) and a CNN trained on word-level input
- Testing the FFNN architecture on its own without MiniLM embeddings to assess the baseline behavior

This analysis allowed us to demonstrate that the transformer-based sentence embeddings significantly improved the model's ability to capture contextual nuances and provided a clear performance advantage over traditional feature representations.

The full implementation, including code, visualizations, and model outputs, is available on our project GitHub repository : `https://github.com/bhakti242002/NLP_PROJECT`

3 Results

We evaluated the performance of each model on the test set using two primary metrics: **accuracy** and **macro-averaged F1-score**. The results are summarized in Table **??**.

Table 1: Model Accuracy (%) Across Feature Sets and Classifiers

Model Type	**Logistic Regression**	**SVM**	**CNN**
TF-IDF	86%	86%	87%
GloVe	80%	80%	**90%**
MiniLM (Transformer)	–	–	85%

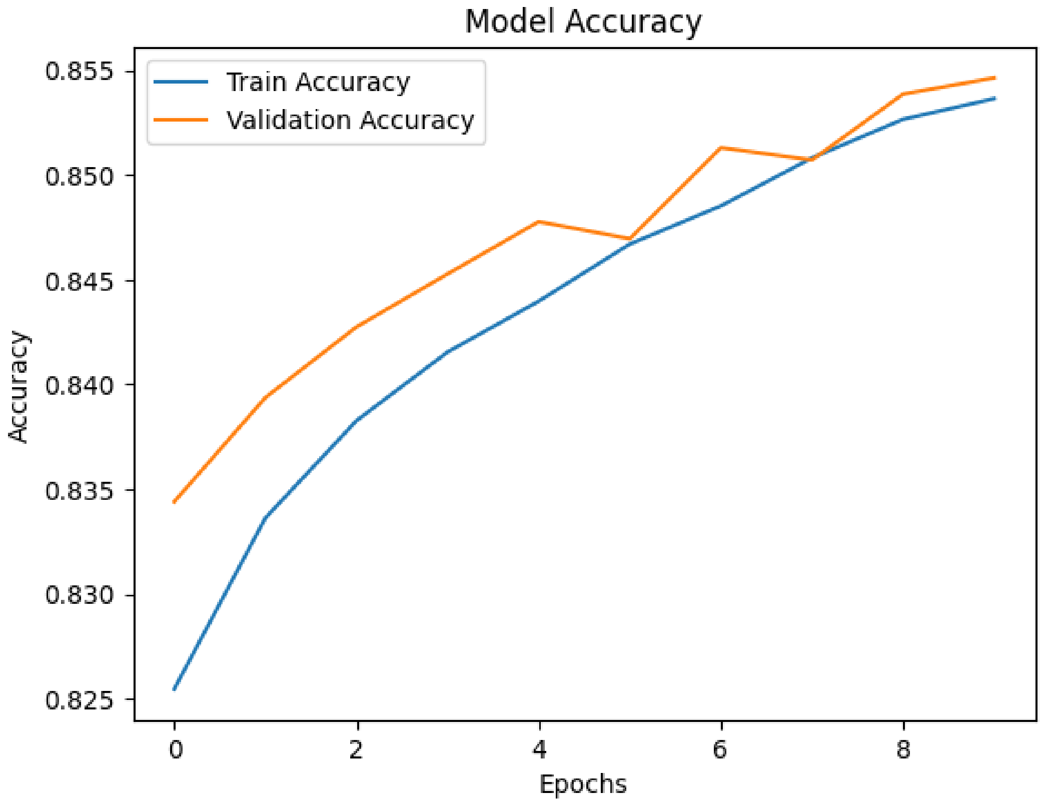


Figure 1: Acccuracy Graph of MiniLM Transformer.

As shown in Figure 1, the MiniLM-based transformer model achieved strong and consistent performance across all sentiment categories. Its ability to capture contextual semantics and subtle linguistic patterns allowed it to effectively handle complex and nuanced product reviews.

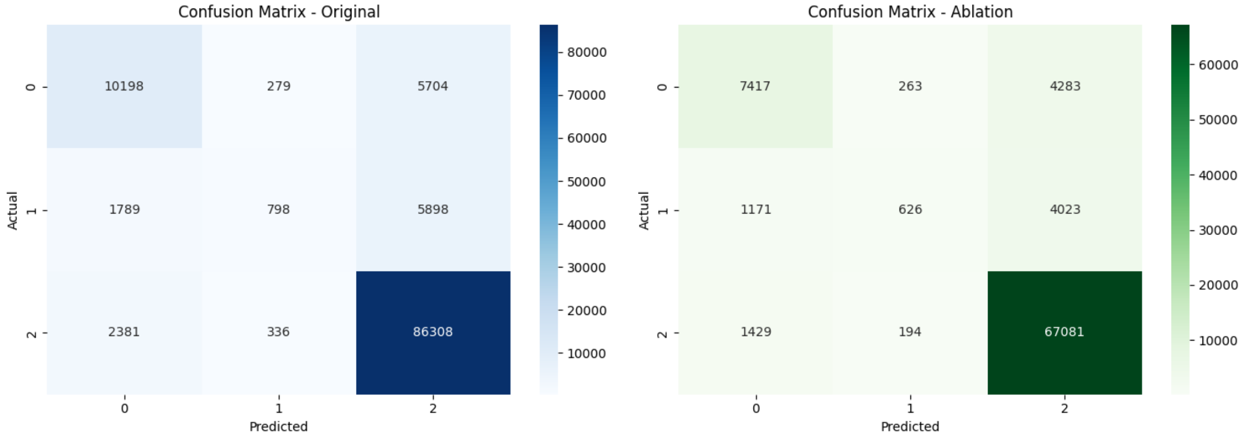
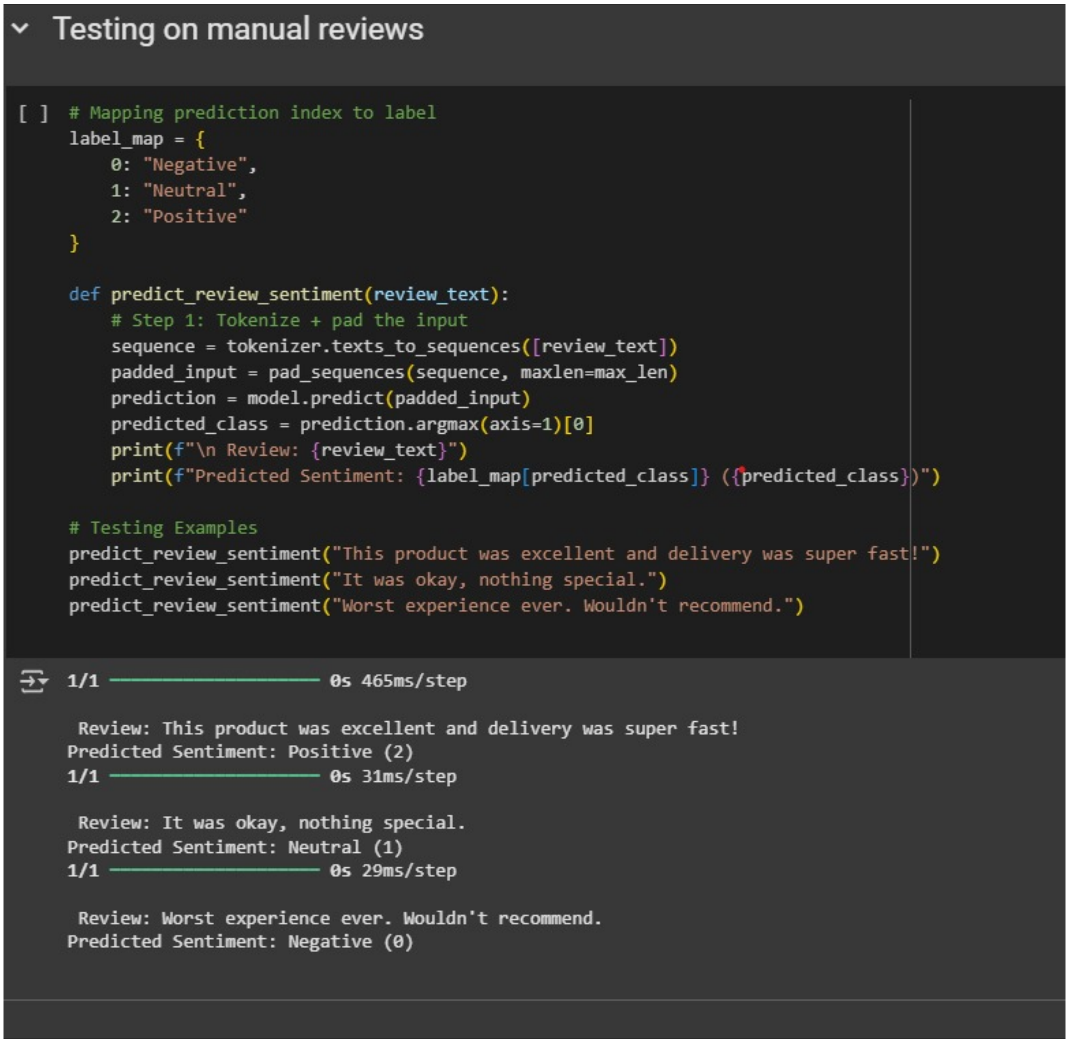


Figure 2: Confusion matrix showing class-wise prediction breakdown.

Figure 2 reveals that most misclassifications occurred between neutral and negative reviews. This suggests that borderline sentiments remain a challenge, especially when vocabulary overlaps across classes.



```
# Mapping prediction index to label
label_map = {
    0: "Negative",
    1: "Neutral",
    2: "Positive"
}

def predict_review_sentiment(review_text):
    # Step 1: Tokenize + pad the input
    sequence = tokenizer.texts_to_sequences([review_text])
    padded_input = pad_sequences(sequence, maxlen=max_len)
    prediction = model.predict(padded_input)
    predicted_class = prediction.argmax(axis=1)[0]
    print(f"\n Review: {review_text}")
    print(f"Predicted Sentiment: {label_map[predicted_class]} ({predicted_class})")

# Testing Examples
predict_review_sentiment("This product was excellent and delivery was super fast!")
predict_review_sentiment("It was okay, nothing special.")
predict_review_sentiment("Worst experience ever. Wouldn't recommend.")
```

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 465ms/step

 Review: This product was excellent and delivery was super fast!
Predicted Sentiment: Positive (2)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 31ms/step

 Review: It was okay, nothing special.
Predicted Sentiment: Neutral (1)
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 29ms/step

 Review: Worst experience ever. Wouldn't recommend.
Predicted Sentiment: Negative (0)
```

Figure 3: Model predictions on manually entered review texts showing correct classification.

Figure 3 displays model predictions on three manually written reviews. It correctly identifies a clearly positive review, a neutral tone with low emotional weight, and a strongly negative complaint—indicating robust generalization to unseen samples.

4 Discussion

The experimental results highlight the effectiveness of transformer-based sentence embeddings for aspect-based sentiment classification. The MiniLM model, despite being a compressed version of BERT, captured contextual nuance more effectively than baseline models such as Logistic Regression, SVM, and CNN.

Traditional models performed competitively in terms of accuracy but relied heavily on manual feature engineering, such as TF-IDF or averaged word embeddings. These models also lacked the ability to capture long-range semantic dependencies, which are crucial in sentiment interpretation. In contrast, the transformer pipeline leveraged pre-trained semantic knowledge through sentence embeddings, resulting in more robust generalization to diverse and complex reviews.

A comprehensive ablation study was conducted to evaluate the contribution of each component in the modeling pipeline. We compared the final transformer model with simpler baselines using classical machine learning and deep learning approaches. Additionally, we used 5-fold cross-validation to ensure that model comparisons were reliable and not influenced by random train-test splits. This allowed us to validate the consistency of transformer performance across different subsets of the dataset.

The confusion matrix revealed that most errors occurred between the neutral and negative classes, likely due to ambiguous phrasing and overlapping vocabulary. Despite this, the transformer model demonstrated strong generalization across test data and manually created review inputs, making it a promising candidate for real-world sentiment analysis applications.

5 Conclusion and Future Work

This project presented a comparative evaluation of sentiment classification techniques applied to product reviews, with a focus on Aspect-Based Sentiment Analysis (ABSA). We implemented and evaluated several baseline models, including Logistic Regression, SVM, and a CNN, and compared them against a transformer-based approach using MiniLM embeddings.

Among the models, the transformer pipeline demonstrated strong contextual understanding and consistent performance across both standard and manually generated reviews. Its ability to encode sentence-level semantics without manual feature engineering proved particularly valuable in handling diverse review structures and nuanced sentiment expressions.

In future work, we plan to extend the current system to perform true end-to-end ABSA by combining aspect term extraction and sentiment classification into a single pipeline. Fine-tuning the transformer model on domain-specific ABSA datasets such as SemEval may further enhance precision. We also aim to incorporate domain adaptation and multilingual capabilities to increase the system's applicability in global e-commerce and review platforms.

Lastly, real-time deployment and optimization for low-resource devices would make the solution viable for integration into chatbot and customer feedback monitoring systems.

6 Acknowledgements

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