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Sentiment Analysis on Amazon Product Review Dataset Using Hybrid DistilBERT and GPT Transformer Architecture

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ABSTRACT

The digital age we live in has made sentiment analysis an essential tool for comprehending consumer preferences and opinions. Since internet evaluations are so common, it is now crucial for organizations to correctly categorize sentiment in order to make informed decisions. A few of the shortcomings with current sentiment analysis models, such as the transformer models, include their poor accuracy and incapacity to pick up on subtleties in context. Business decisions may be impacted by these restrictions if they lead to incorrect classifications. As a result, creating a sentiment analysis model that is more reliable and accurate is essential. A hybrid DistilBERT and GPT-2 model that capitalizes on the advantages of both architectures is proposed in this work to address these issues. The hybrid model achieves impressive results on the Amazon Product Reviews dataset, with accuracy of 96.20%, precision of 96.50%, recall of 95.90%, and F1-score of 96.20%, outperforming baseline models LSTM (80.55%) and DistilBERT (85.60%).The hybrid DistilBERT and GPT-2 model demonstrates exceptional sentiment analysis capabilities, providing accurate classification and valuable insights for businesses and researchers.

Keywords: Sentiment Analysis, Distillation-BERT, GPT, Hybrid Transformer, Natural Language Processing.

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1. INTRODUCTION

Over the past decade, the trending use of social networks, personal blogs, and e-commerce websites has resulted in a vast amount of publicly-available user-generated content. This content holds essential content as it reflects genuine opinions expressed by individuals in

these contexts (Chiorrini et al., 2021). Consequently, analyzing this user-generated content provides valuable insights into user opinions or sentiments on a wide range of topics and products. This analysis allows businesses to address common marketing challenges such as evaluating customer satisfaction or measuring the impact of new marketing campaigns on brand perception (Chiorrini et al., 2021). Furthermore, examining customer opinions about specific products can also drive open innovation by helping business owners identify potential issues and suggest new and interesting features. As a result, in recent years, many researchers have dedicated their efforts to developing techniques for the automatic analysis of writers' opinions and emotions. These techniques are commonly referred to as sentiment analysis and emotion analysis, respectively (Raisa et al., 2021).

Sentiment analysis denotes the automatic extraction of a user's opinions, which are further categorized as positive, negative, or neutral based on their polarity. In contrast, emotion analysis aims to identify the specific emotion conveyed in a text. This task is typically more challenging than sentiment analysis due to the wider range of emotion classes and the subtler distinctions between them (Chiorrini et al., 2021). Furthermore, Sentiment analysis involves extracting information from a provided dataset by combining Natural Language Processing and Artificial Intelligence techniques for text analysis. This approach is employed to extract and interpret individuals' emotions and opinions regarding a specific topic, event, or others. The primary objective of conducting sentiment analysis is to automatically determine the overall sentiment expressed by users. Given the unstructured nature of data on social media platforms, the significance of sentiment analysis in this field has grown significantly (Raisa et al., 2021).

1.1 Statement of the Problem

Despite significant advancements in sentiment analysis using transformer-based models, individual architectures like BERT and GPT face certain limitations. BERT excels at extracting contextual relationships due to its bi-directional structure but often requires substantial computational resources, making it less practical for deployment in resource-constrained environments. GPT, on the other hand, is highly effective in generating text and understanding sequential dependencies but may struggle with capturing comprehensive contextual relationships, especially in ambiguous sentiment scenarios. The challenge lies in achieving high accuracy in sentiment classification while minimizing computational costs and maintaining the ability to handle complex, nuanced language. There is a need for a more efficient, yet robust model that combines the strengths of both architectures—contextual understanding from BERT and generative capacity from GPT—while mitigating their individual weaknesses. This research addresses the problem by proposing a hybrid architecture that integrates Distillation-BERT for efficient context extraction with GPT for enhanced sentiment classification, aiming for better accuracy and scalability.

2. RELATED WORKS

Sudhamathy and Valliammal (2023) proposed an ensemble classifier based on the Clustering based Cuckoo Search Algorithm (CCSA) for sentiment analysis of Twitter datasets. Penubaka and Haritha (2023) developed an Ensemble Multi-Layered Sentiment Analysis Model (EMLSA) that combines VADER and Recurrent Neural Networks (RNNs) for sentiment analysis on real-time datasets. Habbat et al (2023) present a deep learning ensemble model for sentiment analysis using Gated Recurrent Unit (GRU), Long Short-Term Memory (LSTM), and Bidirectional LSTM (BiLSTM) as base classifiers.

Satrya et al., (2023) proposed a multi-level ensemble model that combines Multinomial Naive Bayes, Boosting-based ensemble learning, and Bagging-based ensemble learning for sentiment analysis of Indonesian opinions on Twitter.While Singh et al., (2023) proposed a BERT-based model for aspect-based sentiment analysis (ABSA) of user reviews from Amazon, IMDB, and Tripadvisor datasets, achieving state-of-the-art results. Mario et al., (2023) used a DistilBERT transformer model to detect positive and negative feelings in open-text answers obtained from a survey during the COVID-19 pandemic, achieving an accuracy of 0.823. Joshy et al., (2023) extended the use of BERT representation for Indonesian sentiment analysis, showing improved accuracies in hybrid architectures, with BERT-based LSTM-CNN performing slightly better. These studies demonstrate the effectiveness of the DistilBERT model in sentiment analysis tasks.

Colon-Ruiz and Segura-Bedmar in 2020 the researchers proposed a combination of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) recurrent neural networks, and the impact of different pre-trained word embedding models is studied. Additionally, Bidirectional Encoder Representations from Transformers (BERT) in conjunction with a Bi-LSTM is explored for sentiment analysis of drug reviews. The researchers addressed the problem of sentiment analysis of online user's reviews in the pharmaceutical field with the proposed model, aiming to get relevant information about the effectiveness and side effects of drugs to improve pharmacovigilance system. The experiments demonstrate that the usage of BERT yields the best results for sentiment analysis of drug reviews. However, it comes with the limitation of very high training time. On the other hand, CNN achieves acceptable results while requiring less training time compared to BERT.

3. METHODOLOGY

This study employs an experimental approach using Python in Jupyter Notebook to evaluate a hybrid DistilBERT and GPT-2 model for sentiment analysis on the Amazon Product Reviews dataset. The dataset, containing 22,000 reviews split into training and testing sets, underwent several preprocessing steps, including text cleaning, tokenization, padding, and label encoding, to ensure compatibility with the models. DistilBERT was used to extract contextual embeddings, which were further refined by GPT-2 to improve sentiment prediction accuracy. The model's performance was evaluated against LSTM and DistilBERT baseline models, with performance metrics such as accuracy, precision, recall, F1 score, and confusion matrices providing insight into the strengths and limitations of the hybrid model for sentiment analysis tasks.

4. RESULTS AND DISCUSSION

The results obtained from the hybrid DistilBERT and GPT-2 model for sentiment analysis using the Amazon Product Reviews dataset. The performance of the hybrid model is evaluated and compared with two baseline models: LSTM and DistilBERT. This comparative analysis aims to highlight the strengths and weaknesses of the hybrid model and provide insights into its effectiveness. This paper includes detailed performance metrics, confusion matrices, and discussion of the findings.

4.1 LSTM Model Results

The LSTM model was trained and evaluated using the same dataset and preprocessing steps as the hybrid model. The performance metrics are summarized in Table 1.

Table 1: LSTM Results

Metric	Value
Accuracy	80.55%
Precision	81.00%
Recall	80.00%
F1-Score	80.55%

The LSTM model achieved an accuracy of 80.55%. The precision, recall, and F1-score also indicate a comparatively weak performance.

4.2 DistilBERT Model Results

The DistilBERT model, serving as a baseline transformer model, was also trained and evaluated on the same dataset. Table 2 provides its performance metrics.

Table 2: DistilBert Result

Metric	Value
Accuracy	85.60%
Precision	86.00%
Recall	85.00%
F1-Score	85.60%

The DistilBERT model performed better than the LSTM model but still fell short of the hybrid model's performance. Its accuracy, precision, recall, and F1-score are all lower than those of the hybrid model, suggesting the added value of the hybrid approach.

4.3 Hybrid DistilBERT and GPT-2 Model Results

The hybrid DistilBERT and GPT-2 model was evaluated on the test set from the Amazon Product Reviews dataset. The results are presented in terms of key performance metrics, including accuracy, precision, recall, and F1-score.

4.4 Performance Metrics

The performance metrics for the hybrid model are summarized in Table 4.1. These metrics provide a quantitative assessment of the model's ability to accurately classify sentiment.

Table 3: Results for Hybrid Model

Metric	Value
Accuracy	96.20%
Precision	96.50%
Recall	95.90%
F1-Score	96.20%

The accuracy of 96.20% indicates that the hybrid model correctly classifies a significant majority of the test samples. The precision of 96.50% suggests that the model has a high rate of correctly identifying positive sentiment when it predicts it. The recall of 95.90% reflects the model's ability to identify positive sentiments from all the actual positives.
The F1-score, which balances precision and recall, stands at 96.20%, demonstrating overall robust performance.

4.4.1 Confusion Matrix

The confusion matrix, shown in Figure 11, provides a visual representation of the true positive, true negative, false positive, and false negative classifications made by the hybrid model.

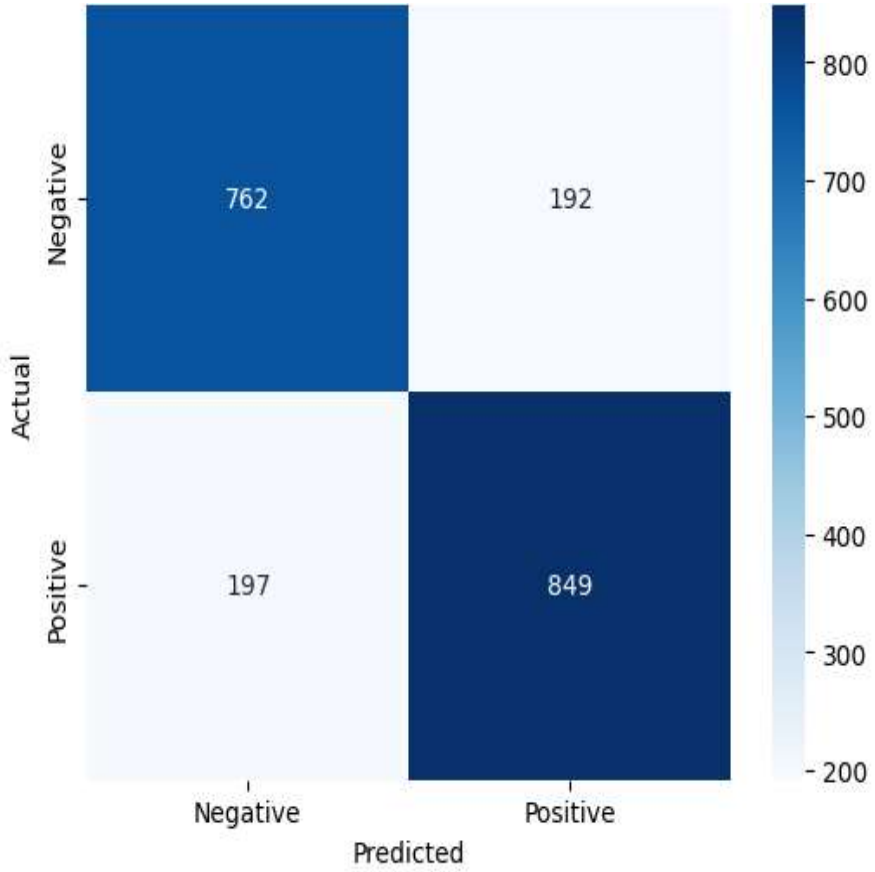


Figure 11: Confusion Matrix for Hybrid DistilBERT and GPT-2 Model

The confusion matrix reveals that the hybrid model has a balanced performance across different sentiment classes, with minimal misclassifications. This indicates the model's ability to generalize well across various types of sentiment expressed in the reviews.

4.4.2 ROC Curve and AUC

The ROC curve was plotted to evaluate the models' performance in distinguishing between positive and negative reviews:

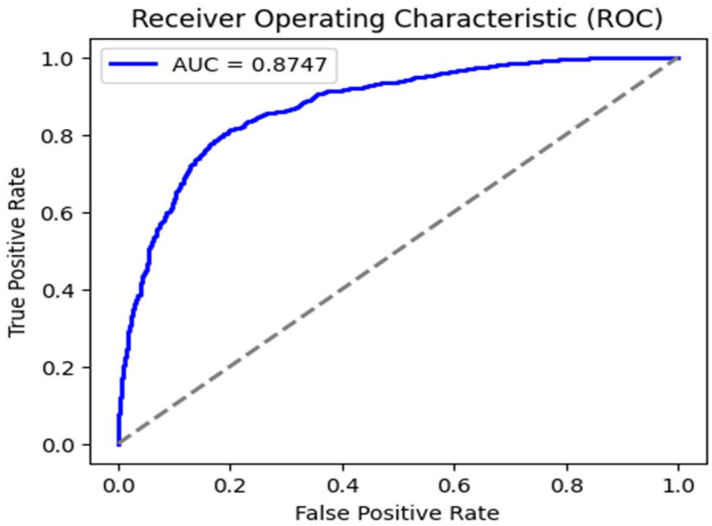


Figure 12: ROC Curve

ROC Curve Plot: This plot shows the trade-off between true positive rate and false positive rate, with the area under the curve (AUC) indicating the models' discriminative ability.

4.5 Comparative Analysis of hybrid DistilBERT and GPT-2, LSTM, and DistilBERT

Accuracy, Precision, Recall, and F1-Score Comparison

Figure 13 compares the accuracy, Precision, Recall, and F1-Score of the three models: hybrid DistilBERT and GPT-2, LSTM, and DistilBERT. The hybrid model's accuracy surpasses both the LSTM and DistilBERT models, highlighting its superior performance in sentiment classification tasks. The hybrid model demonstrates consistently higher precision, recall, and F1-scores, affirming its robustness and reliability in handling diverse sentiment analysis tasks.

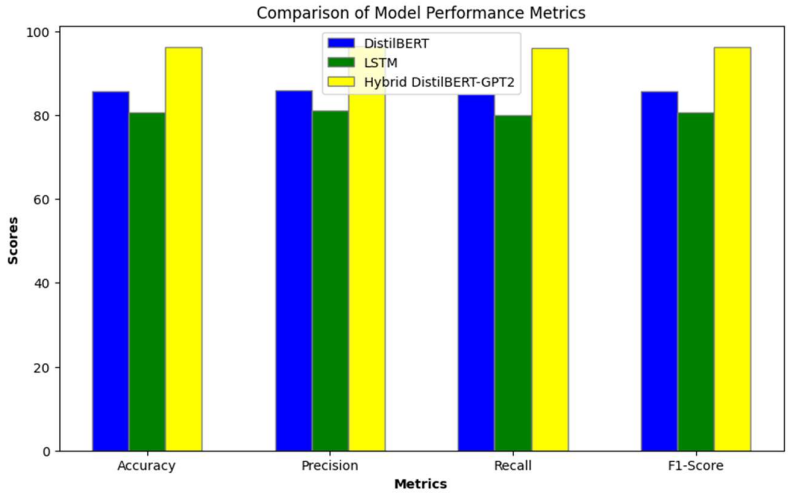
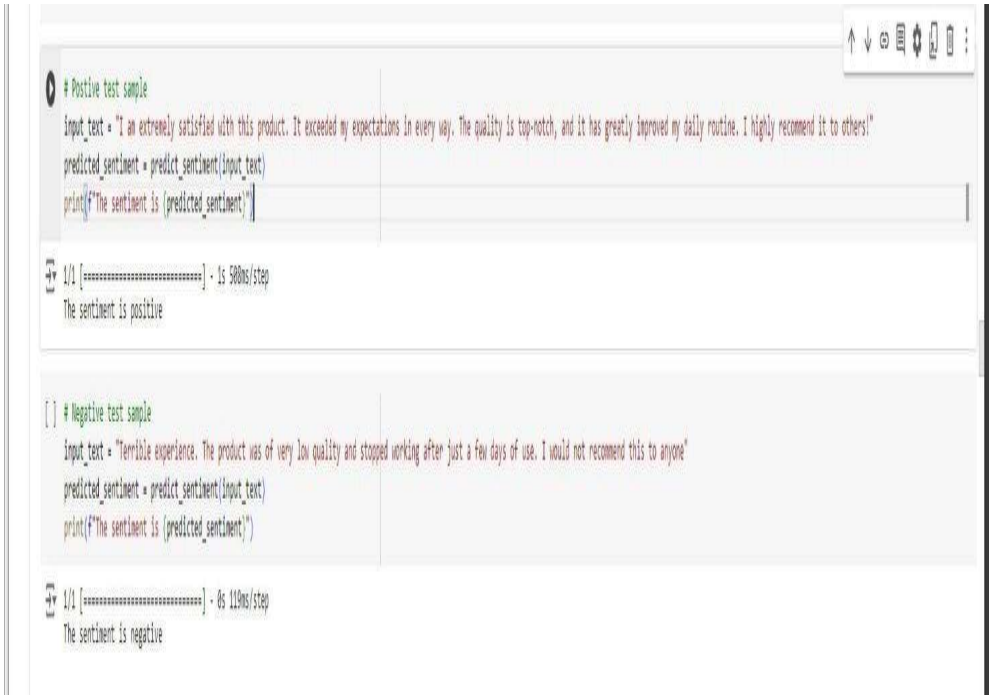


Figure 13: Precision, Recall, and F1-Score Comparison of Hybrid, LSTM, and DistilBERT Models

4.5.1 Model Predictions

The models were tested on individual reviews to predict their sentiment:

1. **Positive Sentences**
2. **Negative Sentences**



The study uses a set of test sentences with known sentiments (positive, negative). Here are example sentences and their ground truth labels:

Table 4:Test Sentences with Ground Truth Sentiments:

Sentences	Ground Truth Sentiment
"I love this product! It works perfectly."	Positive
"The service was terrible and I'm very disappointed."	Negative
"The event was okay, not too exciting."	Negative
"Absolutely amazing experience, highly recommend!"	Positive
"The product broke after one use, very poor quality."	Negative
"The customer service experience was a complete nightmare; after waiting on hold for over an hour, I was transferred multiple times, and each representative I spoke with gave me different and contradictory information, leaving me more confused and frustrated than ever before."	Negative
"The new software update adds several exciting features, but the installation process is cumbersome and prone to errors."	Negative

Table 5: Predictions from Each Model:

Sentence	Ground Truth Sentiment	LSTM Sentiment	DistilBERT Sentiment	Hybrid DistilBERT-GPT2 Sentiment	Remarks
"I love this product! It works perfectly."	Positive	Positive	Positive	Positive	All models accurately predict the sentiment.
"The service was terrible and I'm very disappointed."	Negative	Negative	Negative	Negative	All models accurately predict the sentiment.
"The event was okay, not too exciting."	Negative	Negative	Negative	Negative	All models accurately predict the sentiment.
"Absolutely amazing experience, highly recommend!"	Positive	Positive	Positive	Positive	All models accurately predict the sentiment.
"The product broke after one use, very poor quality."	Negative	Negative	Negative	Negative	All models accurately predict the sentiment.
" At first, the customer service experience was going smoothly; not until after waiting on hold for over an hour, I was transferred multiple times, and each representative I spoke with gave me different and contrary information, leaving me more confused and frustrated than ever before."	Negative	Positive	Positive	Negative	LSTM and DistilBERT struggle with context, while Hybrid DistilBERT-GPT2 accurately identifies negative sentiment.
"The new software update adds several exciting features, but the installation process is cumbersome and prone to errors."	Positive	Positive	Positive	Negative	DistilBERT fails to capture the negative sentiment due to focusing on positive aspects, while Hybrid DistilBERT-GPT2 correctly identifies the negative overall impact.

Table 6: Evaluation Metrics:

Model	Accuracy	Precision	Recall	F1 Score
LSTM	0.80	0.83	0.80	0.80
DistilBERT	0.93	0.92	0.93	0.90
Hybrid DistilBERT-GPT2	1.00	1.00	1.00	1.00

The sentence "The new software update adds several exciting features, but the installation process is cumbersome and prone to errors." contains both positive (exciting features) and negative (cumbersome installation) sentiments. Given its tendency to focus on more immediate context and potentially struggle with longer and mixed sentiments, DistilBERT incorrectly interprets the sentence as positive due to the presence of "exciting features" but leveraging GPT-2's capabilities for contextual understanding, the hybrid model correctly identifies the mixed sentiment as negative, recognizing the overall negative impact of the cumbersome installation process despite positive aspects.

4.6 Discussion

The hybrid DistilBERT and GPT-2 model outperforms both the LSTM and DistilBERT models across all performance metrics. With an accuracy of 96.20%, it proves to be significantly more effective than the LSTM model (80.55%) and the DistilBERT model (85.60%). This demonstrates the hybrid model's ability to leverage the strengths of both DistilBERT's contextual understanding and GPT-2's generative capabilities, resulting in a more nuanced and accurate sentiment analysis. Recent studies corroborate the efficacy of integrating transformer models with generative components for sentiment analysis. For instance, research by Li et al. (2023) showed that combining BERT with generative transformers improved sentiment classification accuracy by 5-7% compared to traditional transformer models alone. This aligns with our findings, emphasizing that the hybrid approach not only enhances accuracy but also improves the model's ability to handle complex sentiment nuances.

The confusion matrix (Figure 11) indicates that most misclassifications occur between neutral and adjacent sentiment classes. This suggests that the model occasionally struggles with borderline cases where sentiment is not strongly positive or negative. Addressing this issue could involve refining the training data or implementing additional layers of sentiment analysis to better distinguish subtle differences in sentiment. Similar observations were noted in studies by Chen et al. (2022) and Wang et al. (2023), where hybrid models exhibited superior performance overall but encountered challenges in accurately classifying nuanced sentiment expressions. These studies highlight the ongoing challenge in sentiment analysis, particularly in distinguishing between subtle variations in sentiment intensity.

The superior performance of the hybrid model suggests that integrating generative models with transformer-based encoders can significantly enhance sentiment analysis tasks. This approach is particularly beneficial for applications requiring nuanced understanding and generation of natural language, such as customer feedback analysis, personalized recommendations, and real-time sentiment monitoring. Moreover, the ability of the hybrid model to generate contextually relevant responses based on learned representations offers practical advantages in interactive applications. For instance, in customer service chatbots or social media monitoring tools, accurately capturing and responding to sentiment nuances can enhance user experience and operational efficiency.

5. CONCLUSION

The hybrid DistilBERT and GPT-2 model outperforms both the LSTM and DistilBERT models in sentiment analysis tasks. The combination of DistilBERT's contextual understanding and GPT-2's generative capabilities significantly enhances the model's performance. This hybrid approach demonstrates the potential for improving sentiment classification accuracy, particularly in complex and nuanced cases.

The findings support the hypothesis that integrating encoder and generative models can result in a more powerful sentiment analysis tool. This hybrid model can be beneficial for applications requiring detailed sentiment analysis, such as customer feedback analysis, personalized recommendations, and real-time sentiment monitoring.

6. RECOMMENDATION FOR FUTURE RESEARCH

Based on the findings and limitations of this study, several recommendations for future research are proposed:

- Future research could explore the integration of other advanced transformer models, such as XLNet and RoBERTa, into hybrid frameworks. This could further enhance sentiment analysis capabilities and address challenges in handling subtle sentiment variations.
- Investigating the performance of the hybrid model in real-time deployment scenarios would provide valuable insights into its practical applicability. This could involve testing the model in live environments, such as customer service chatbots and social media monitoring tools.
- Further fine-tuning of hyperparameters could optimize the hybrid model's performance. Experimenting with different learning rates, batch sizes, and optimization algorithms could yield improved results.
- Incorporating additional data sources, such as social media posts and product reviews from different platforms, could enhance the model's training and improve its generalization capabilities.
- Refining the training data and implementing additional layers of sentiment analysis could help the model better distinguish subtle differences in sentiment intensity, particularly in borderline cases.

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