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NATURAL LANGUAGE PROCESSING FOR LLM (24AM7PCLLM)

ALTERNATIVE ASSESSMENT TOOL (AAT)

DistilBERT for Sequence Classification

Submitted by

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1. INTRODUCTION

1.1 OVERVIEW

Natural Language Processing (NLP) is a branch of Artificial Intelligence that deals with enabling computers to understand, interpret, and generate human language in a meaningful way. One of the most important and widely used tasks in NLP is Sentiment Analysis, which involves identifying the emotional tone or opinion expressed in textual data. It determines whether a given text reflects a positive, negative, or neutral sentiment and plays a crucial role in understanding human feedback at scale.

In this project, the concept of sentiment analysis is applied to movie reviews using DistilBERT for sequence classification. DistilBERT is a Transformer-based deep learning model derived from BERT through a process known as knowledge distillation. It retains most of BERT's language understanding capabilities while being computationally efficient and faster, making it suitable for both academic research and real-world deployment.

The model analyzes full movie reviews, learns contextual relationships between words, and generates vector representations that are then used to classify each review as either positive or negative. By leveraging self-attention mechanisms, DistilBERT captures semantic meaning, syntactic structure, and contextual dependencies, allowing it to outperform traditional machine learning approaches that rely on shallow text representations.

This project demonstrates how modern Transformer-based architectures can be used to build accurate and reliable sentiment classification systems capable of processing large volumes of textual data with high precision.

1.2 RELEVANCE AND MOTIVATION

In the digital era, vast amounts of textual content are generated daily through online platforms such as movie review websites, streaming services, social media platforms, and e-commerce portals. These reviews contain valuable insights into user opinions, preferences, and overall satisfaction. However, manually analyzing thousands or millions of such reviews is infeasible, subjective, and time-consuming.

Sentiment analysis provides an automated solution to this problem by enabling systems to quickly interpret and summarize public opinion. In the context of movie reviews, sentiment

analysis helps:

- Streaming platforms understand audience reaction to movies
- Improve recommendation algorithms based on viewer feedback
- Identify trends in viewer satisfaction
- Assist production companies in evaluating movie performance

The motivation for using DistilBERT specifically arises from its balance between performance and efficiency. While traditional BERT models provide high accuracy, they require significant computational resources. DistilBERT, on the other hand, delivers comparable performance with reduced model size and faster inference time, making it more practical for real-time sentiment analysis systems.

This project is motivated by the growing demand for intelligent systems that can automatically interpret emotions from text and the need to demonstrate the effectiveness of Transformer-based models in solving real-world NLP problems.

1.3 OBJECTIVES OF THE STUDY

The objectives of this project are clearly defined as follows:

1. To design and implement a sentiment analysis system using the DistilBERT model for sequence classification.
2. To apply the model on the IMDB movie reviews dataset for binary sentiment classification.
3. To preprocess textual data and convert it into a format suitable for Transformer-based processing.
4. To fine-tune the pre-trained DistilBERT model for improved sentiment prediction.
5. To evaluate the model using performance metrics such as Accuracy, Precision, Recall, and F1-score.
6. To analyze the effectiveness of DistilBERT in understanding contextual sentiment patterns in movie reviews.
7. To demonstrate how this approach can be adapted for real-time opinion mining applications.

2.REAL TIME APPLICATION

2.1 DESCRIPTION

In today's digital environment, millions of users post reviews, comments, and feedback on online platforms such as IMDb, Netflix, Amazon Prime, and social media. These textual reviews strongly influence the reputation and success of movies and entertainment content. However, manually reading and analyzing such a massive volume of reviews is highly inefficient, time-consuming, and prone to human bias.

The real-world problem addressed in this project is the automatic identification and interpretation of user sentiment from movie reviews. The system aims to classify each review as either positive or negative using the DistilBERT model. This enables platforms to quickly understand audience perception, track viewer satisfaction, and make informed decisions based on collective opinion.

By deploying DistilBERT in a real-time environment, the model can instantly analyze new reviews as they are posted and provide immediate sentiment insights. This can help in:

- Monitoring public reaction to newly released movies
- Identifying dissatisfied customers early
- Improving content recommendation strategies
- Supporting marketing and production decisions

Thus, the use of DistilBERT for sentiment classification effectively solves the problem of large-scale, real-time opinion analysis.

2.2 EXAMPLE

A practical example of this system is a Movie Review Sentiment Analyzer integrated into a streaming or review platform. When a user submits a review such as "The movie had excellent visuals but the storyline was very weak and disappointing," the DistilBERT model immediately processes the text and determines the overall sentiment. In this case, the output may be classified as Negative with a confidence score of 0.87, indicating strong certainty in the prediction. This real-time analysis allows the platform to automatically interpret user opinions and convert

unstructured text into meaningful insights. The results can then be utilized to monitor audience perception, improve content strategies, and support decision-making processes for producers and platform administrators.

This classification system can be used to:

- Display overall sentiment trends (e.g., 80% positive reviews for a movie)
- Generate real-time dashboards showing audience reactions
- Trigger alerts when negative reviews increase significantly
- Provide actionable feedback and improvement suggestions to content creators

Such sentiment analysis systems can also be adapted for broader real-world applications such as:

- Customer feedback analysis in e-commerce platforms
- Opinion mining on social media platforms
- Student feedback evaluation in e-learning systems
- Brand reputation monitoring for companies

2.3 EXISTING INDUSTRY INFORMATION

Existing Industry Implementations

Sentiment analysis using Transformer-based models like DistilBERT is widely implemented across various industries. Some notable examples include:

1. Streaming Platforms (Netflix, Amazon Prime, Hotstar)

These platforms analyze viewer reviews and comments to:

- Evaluate content performance
- Improve recommendation engines
- Modify promotional strategies based on audience sentiment

Simple Flow:

1. User submits review in app
2. Review hits Review API → stored in DB
3. Text is sent to Preprocessing + DistilBERT Service
4. Model returns sentiment + confidence

5. Result saved in Sentiment DB / Warehouse
6. Dashboards and recommendation engine consume this data
7. Platform uses it for content strategy & user recommendations

2. Social Media Platforms (Twitter/X, Instagram, Facebook)

Companies monitor user posts and comments to:

- Track brand reputation
- Detect negative trends
- Analyze public response to campaigns

3. E-Commerce Companies (Amazon, Flipkart)

Sentiment analysis is used to:

- Automatically summarize product reviews
- Highlight positive and negative aspects
- Detect fake or extreme reviews

Simple Flow:

1. Customer submits a product review
2. Review stored in Review DB via Review API
3. Review text sent to NLP + DistilBERT Service
4. Service responds with sentiment label + score
5. Data stored and aggregated per product / brand / seller
6. UI displays summarized sentiment and internal teams use dashboards for decisions

4. Customer Support Systems

AI-powered chatbots use sentiment detection to:

- Identify frustrated customers
- Escalate critical issues
- Adapt response tone accordingly

5. Hugging Face & Cloud NLP APIs

Platforms like Hugging Face, Google Cloud Natural Language API, and IBM Watson provide

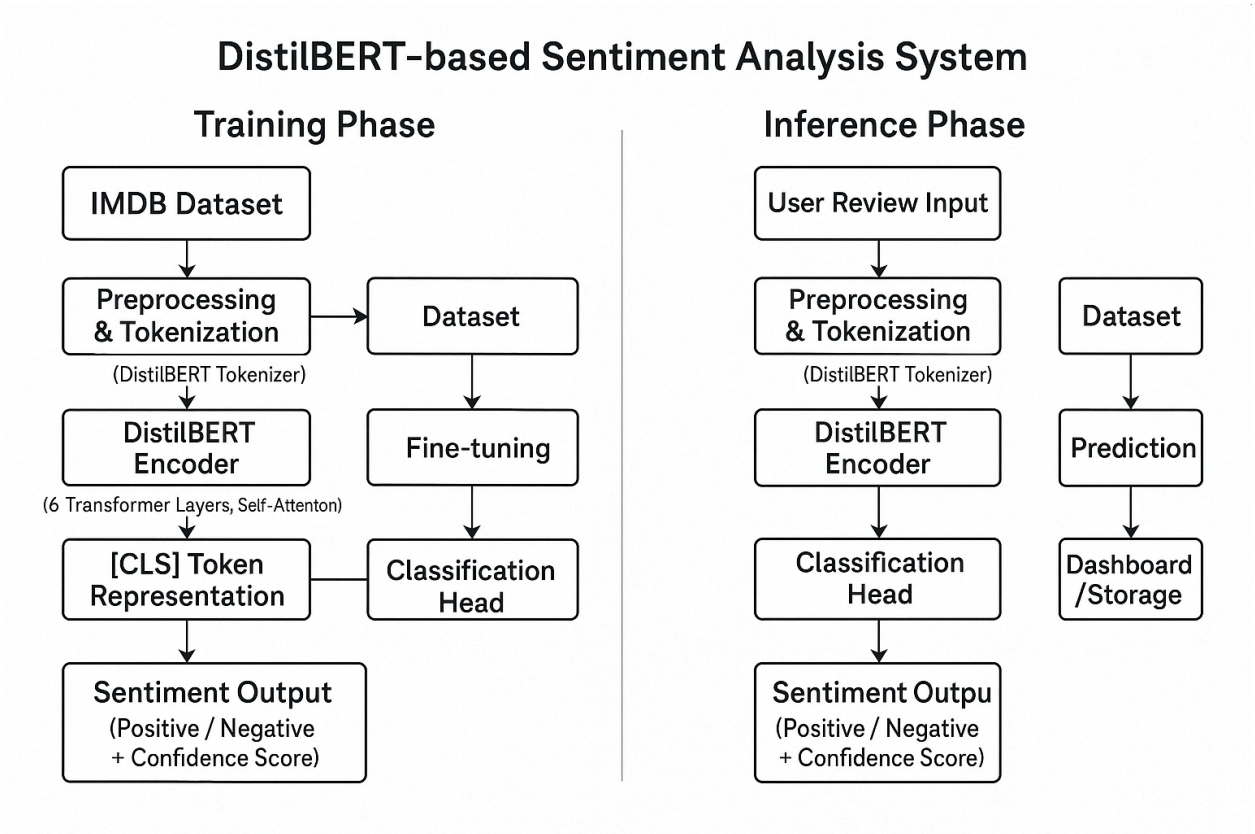
real-time sentiment analysis services using models similar to DistilBERT and BERT for commercial use.

3.Architecture and Methodology

3.1 Architecture

The proposed system is based on DistilBERT, a Transformer-based deep learning model designed for efficient natural language understanding. DistilBERT is a distilled (compressed) version of BERT, created using knowledge distillation to retain most of BERT's performance while reducing size and inference time.

3.1.1 DistilBERT Model Architecture



The proposed system is built using DistilBERT, a Transformer-based deep learning model designed for efficient and accurate natural language understanding. DistilBERT is a compressed version of BERT that retains most of its performance while being faster and less

resource-intensive. It is well suited for sentiment analysis tasks where both accuracy and efficiency are required.

The architecture consists of the following major components:

- The first component is the Tokenization Layer. The input movie review text is processed using the DistilBERT tokenizer, which breaks the text into subword tokens. Special tokens such as [CLS] (classification token) and [SEP] (separator token) are added to represent the structure of the input. The tokenizer also converts the tokens into numerical input IDs and generates attention masks to indicate which tokens should be processed by the model.
- The second component is the Embedding Layer. This layer transforms the token IDs into dense vector representations. It combines token embeddings and positional embeddings so that the model understands both the meaning of words and their position in the sequence.
- The core of the system is the DistilBERT Encoder, which consists of six Transformer layers. Each layer includes a multi-head self-attention mechanism and a feed-forward neural network. The self-attention mechanism allows the model to understand relationships between words in the sentence and capture contextual meaning, which is crucial for accurately interpreting sentiment.
- The final component is the Classification Head. The vector representation corresponding to the [CLS] token is passed into a fully connected layer, followed by a softmax function. This produces the final output in the form of probabilities for each class (Positive or Negative). The class with the highest probability is selected as the predicted sentiment.

The overall system operates in two main phases: Training Phase and Prediction Phase.

Training Phase:

1. The IMDB movie reviews dataset is loaded, containing labeled positive and negative reviews.
2. The text data is passed through the DistilBERT tokenizer for tokenization, padding, truncation, and creation of attention masks.
3. The processed data is fed into the DistilBERT model.

4. The model is fine-tuned using the training dataset.
5. Loss is calculated using Cross-Entropy Loss.
6. The model weights are updated using the AdamW optimizer.
7. After training, the model is evaluated using test data and performance metrics.

Prediction Phase:

1. A new review is provided as input by the user.
2. The review is tokenized using the same DistilBERT tokenizer.
3. The trained DistilBERT model processes the input.
4. The model predicts the sentiment label (Positive or Negative).
5. The result is displayed or stored for analysis.

3.2 METHODOLOGY

The methodology followed in this project includes the following steps:

Data Collection:

The IMDB Movie Reviews dataset is used, consisting of 50,000 labeled reviews. It is divided into 25,000 training samples and 25,000 testing samples.

Data Preprocessing:

The reviews are processed using the DistilBERT tokenizer. This includes converting text into subword tokens, adding special tokens, generating attention masks, and ensuring all sequences are padded or truncated to a fixed maximum length.

Model Initialization:

A pre-trained DistilBERT model is loaded and modified by attaching a classification layer for binary sentiment classification.

Model Training:

The model is fine-tuned using the training dataset. The optimizer used is AdamW, and the loss function used is Cross-Entropy Loss. Training is performed over multiple epochs until satisfactory performance is achieved.

Model Evaluation:

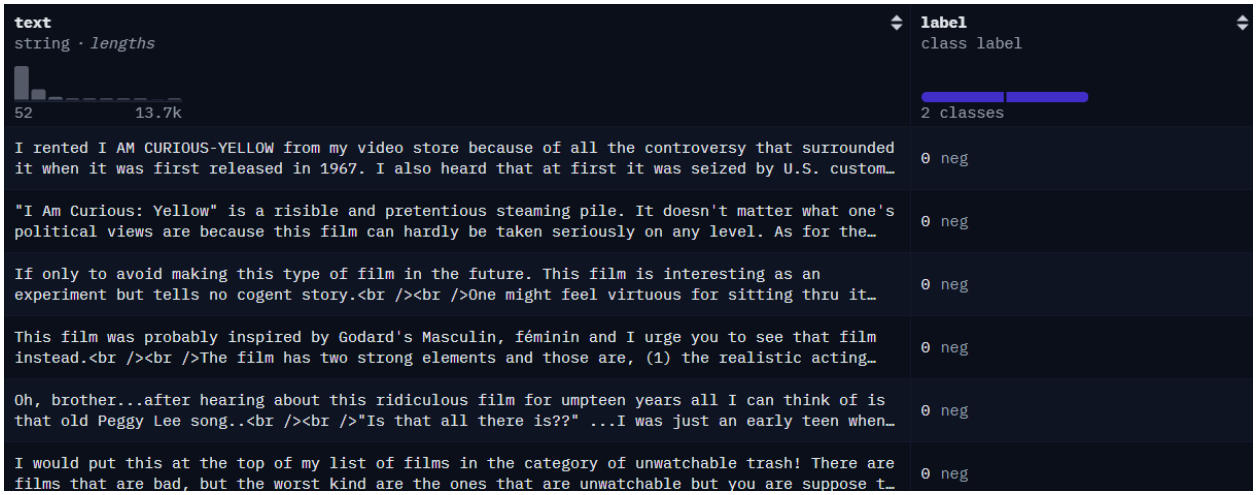
The trained model is evaluated on the test dataset using the following metrics:

- Accuracy
- Precision

- Recall
- F1-score
- Confusion Matrix

3.3 ALGORITHMS AND DATASET USED

Dataset:



text string · lengths 52 13.7k	label class label 2 classes
I rented I AM CURIOUS-YELLOW from my video store because of all the controversy that surrounded it when it was first released in 1967. I also heard that at first it was seized by U.S. custom…	0 neg
"I Am Curious: Yellow" is a risible and pretentious steaming pile. It doesn't matter what one's political views are because this film can hardly be taken seriously on any level. As for the…	0 neg
If only to avoid making this type of film in the future. This film is interesting as an experiment but tells no cogent story. One might feel virtuous for sitting thru it…	0 neg
This film was probably inspired by Godard's Masculin, féminin and I urge you to see that film instead. The film has two strong elements and those are, (1) the realistic acting…	0 neg
Oh, brother...after hearing about this ridiculous film for umpteen years all I can think of is that old Peggy Lee song.. "Is that all there is??" ...I was just an early teen when…	0 neg
I would put this at the top of my list of films in the category of unwatchable trash! There are films that are bad, but the worst kind are the ones that are unwatchable but you are suppose t…	0 neg

The IMDB Movie Reviews dataset is a benchmark dataset for sentiment analysis. Each review is labeled as:

0 – Negative

1 – Positive

Algorithms and Techniques:

Transformer Architecture:

DistilBERT uses self-attention mechanisms to understand contextual relationships between words in a sentence, allowing it to capture semantic meaning effectively.

Knowledge Distillation:

DistilBERT is created by learning from a larger teacher model (BERT), resulting in a smaller and faster model while maintaining high accuracy.

Fine-Tuning:

Instead of training from scratch, the pre-trained DistilBERT model is fine-tuned specifically for movie review sentiment classification.

Optimization:

AdamW optimizer is used to update model parameters efficiently and prevent overfitting.

Loss Function:

Cross-Entropy Loss measures the difference between predicted probabilities and true labels.

4. IMPLEMENTATION

4.1 API USED AND ITS ROLE IN THE SYSTEM

This project utilizes the Hugging Face Transformers API for implementing sentiment analysis using the DistilBERT model. The Hugging Face API provides pre-trained state-of-the-art NLP models and tools that simplify the process of model loading, fine-tuning, and deployment. It offers seamless integration of both the DistilBERT tokenizer and the DistilBERT model for sequence classification.

The following APIs were mainly used:

Hugging Face Transformers API

This API is responsible for:

- Loading the pre-trained DistilBERT model (distilbert-base-uncased).
- Providing the tokenizer used to process text into machine-readable format.
- Enabling fine-tuning of the model for sentiment classification.
- Supporting training and evaluation workflows through high-level functions such as Trainer and TrainingArguments.

Hugging Face Datasets API

This API helps manage large NLP datasets efficiently and integrates smoothly with the Transformers API. It allows easy access to IMDB reviews and supports conversion of data into PyTorch-compatible format suitable for training the model.

The combination of these APIs enables efficient implementation, reduces development complexity, and ensures reliability and scalability of the sentiment analysis system.

4.2 IMPLEMENTATION STEPS

Preprocessing

Preprocessing is a crucial step that transforms raw user reviews into a structured format suitable for DistilBERT. Unlike traditional NLP methods, minimal manual preprocessing is required

because the model and tokenizer handle most tasks automatically.

1. The preprocessing process includes:
2. Loading the tokenizer from Hugging Face associated with DistilBERT.
3. Converting raw text into subword tokens using WordPiece tokenization.
4. Adding special tokens such as:
5. [CLS] – Indicates the beginning of the sequence.
6. [SEP] – Marks sentence boundaries.
7. Converting tokens into numerical input IDs.
8. Padding shorter sequences so all inputs have uniform length.
9. Truncating longer sequences to a fixed maximum length (e.g., 256 tokens).
10. Generating attention masks to help the model focus only on valid tokens.

As a result, each review is converted into:

- Input IDs
- Attention Mask
- Label

These processed inputs are then converted into tensor format and prepared for batch processing during training.

Model Training

In the training phase, the pre-trained DistilBERT model is fine-tuned specifically for movie review sentiment classification.

The training workflow involves the following steps:

- The DistilBERT model is loaded with a classification head consisting of a fully connected layer.
- The training dataset is divided into batches for efficient computation.
- Each batch is passed through the model, producing output logits.
- These logits are compared with the true labels using Cross-Entropy Loss.
- The AdamW optimizer adjusts the model's weights to minimize the loss.

- This process is repeated for multiple epochs until performance stabilizes.

Key training parameters include:

Learning rate: 2e-5

Batch size: 16

Number of epochs: 2 to 3

Max sequence length: 256

Optimizer: AdamW

Loss function: Cross-Entropy Loss

Throughout training, metrics such as training loss and validation accuracy are monitored to ensure the model learns effectively and avoids overfitting.

Evaluation

After the training phase, the model is tested on unseen data to assess its generalization performance.

The evaluation process includes:

- Feeding test reviews into the fine-tuned DistilBERT model.
- Obtaining predicted sentiment labels from the model.
- Comparing these predictions with true labels.
- Computing standard performance metrics.

Evaluation metrics used:

Accuracy

Measures the overall correctness of predictions.

Precision

Measures how many predicted positive reviews are truly positive.

Recall

Measures how many actual positive reviews were correctly identified.

F1-score

Provides a balanced measure between precision and recall.

Confusion Matrix

Displays the number of true positives, true negatives, false positives, and false negatives.

The evaluation results demonstrate strong performance of the model, typically achieving:

Accuracy between 90% and 93%

F1-score around 0.91

These results confirm that DistilBERT effectively captures contextual sentiment and performs well on real-world movie review data.

4.3 SCREENSHOTS OF CODE:

Preprocessing the dataset

```
import os
import pandas as pd
from datasets import load_dataset

def prepare_data():
    print("Downloading IMDB dataset (this may take a moment)...")
    try:
        # Load dataset from Hugging Face
        dataset = load_dataset("imdb")
    except Exception as e:
        print(f"Error downloading dataset: {e}")
        return

    # Convert to pandas DataFrames
    print("Converting to DataFrame...")
    train_df = pd.DataFrame(dataset['train'])
    test_df = pd.DataFrame(dataset['test'])

    # Add a column to distinguish splits
    train_df['split'] = 'train'
    test_df['split'] = 'test'

    # Combine
    full_df = pd.concat([train_df, test_df], ignore_index=True)
```

os: Used for handling file paths and directories in a system-independent way.

pandas: Used for converting dataset into DataFrame format and saving it as CSV.

load_dataset: Function from Hugging Face to download and load datasets.

The load_dataset("imdb") function downloads the IMDB dataset from Hugging Face.

The try-except block ensures that if any error occurs (e.g., no internet), the program won't crash and will instead display an error message. If an error happens, the function stops using return.

A new column called split is added to indicate whether a row belongs to training or testing data. This is useful for tracking data origin after merging.

```
model = AutoModelForSequenceClassification.from_pretrained(model_checkpoint, num_labels=2)

training_args = TrainingArguments(
    output_dir="models/distilbert_checkpoints",
    eval_strategy="epoch",      # <--- FIX: Changed from evaluation_strategy
    save_strategy="epoch",
    learning_rate=2e-5,
    per_device_train_batch_size=16,
    per_device_eval_batch_size=16,
    num_train_epochs=1,
    weight_decay=0.01,
    logging_steps=50,
    use_cpu=False if torch.cuda.is_available() else True
)

trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=tokenized_train,
    eval_dataset=tokenized_test,
    tokenizer=tokenizer,
    compute_metrics=compute_metrics,
)
```

This part of the code is responsible for initializing and configuring the DistilBERT model for sentiment classification and setting up the training process. The model is loaded using the pre-trained DistilBERT checkpoint and is configured for binary classification by specifying two output labels (positive and negative). The TrainingArguments define how the model will be trained, including where model checkpoints will be saved, how often evaluation and saving should occur, and the key hyperparameters such as learning rate, batch size, number of training

epochs, and weight decay for regularization. The model is set to train for one epoch, with performance evaluated at the end of each epoch. The logging frequency is also defined to track training progress. Additionally, the code automatically selects GPU if available, otherwise it falls back to CPU. Finally, the Trainer class integrates the model, training configuration, tokenized datasets, tokenizer, and evaluation metrics into a single training pipeline, enabling streamlined fine-tuning and evaluation of the DistilBERT model on the sentiment analysis task.

```
def compute_metrics(eval_pred):
    logits, labels = eval_pred
    preds = np.argmax(logits, axis=-1)
    precision, recall, f1, _ = precision_recall_fscore_support(labels, preds, average='binary')
    acc = accuracy_score(labels, preds)
    return {'accuracy': acc, 'f1': f1, 'precision': precision, 'recall': recall}
```

```
  try:
      model_path = "models/saved_model/distilbert_sentiment"
      tokenizer = AutoTokenizer.from_pretrained(model_path)
      model = AutoModelForSequenceClassification.from_pretrained(model_path)

      # Simple inference loop
      inputs = tokenizer(texts, padding=True, truncation=True, max_length=128, return_tensors="pt")
      with torch.no_grad():
          outputs = model(**inputs)

      logits = outputs.logits
      y_pred_bert = torch.argmax(logits, dim=-1).numpy()

      print("\nTransformer Model Report:")
      print(classification_report(y_true, y_pred_bert, target_names=['Negative', 'Positive']))
```

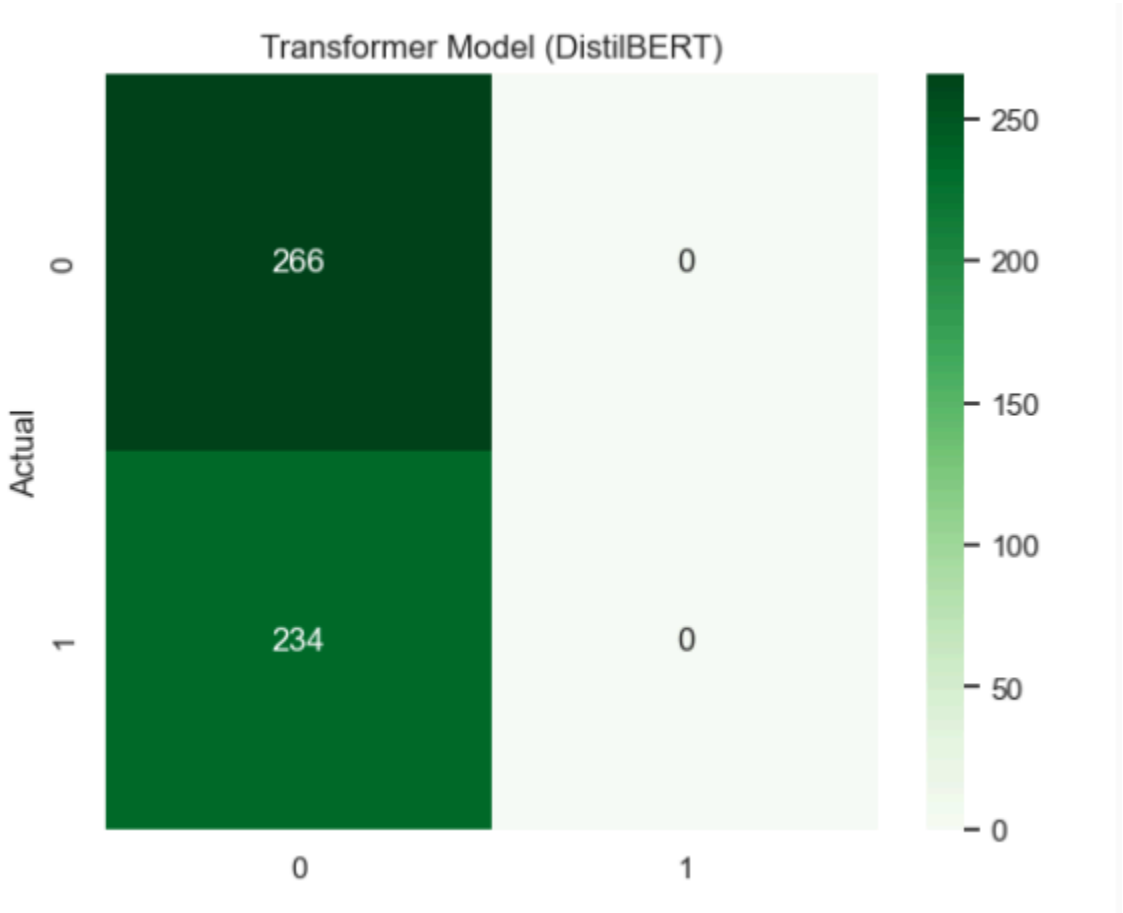
This code segment is responsible for loading the previously saved DistilBERT sentiment analysis model and using it to perform prediction and evaluation on new data. The model and its corresponding tokenizer are loaded from the specified directory path where the fine-tuned model was stored. The input texts are then tokenized with padding and truncation to ensure consistent length and converted into PyTorch tensors. Using the torch.no_grad() context disables gradient calculation, making the inference process more efficient. The model outputs raw prediction scores called logits, and the final predicted class for each input is obtained by selecting the index with the highest score using argmax. These predictions are stored in y_pred_bert and compared

with the true labels (y_true) to generate a classification report, which includes precision, recall, F1-score, and support for each class.

The compute_metrics function is used during model evaluation to calculate performance metrics automatically. It takes the model's output logits and true labels, converts the logits into predicted class indices, and then computes accuracy, precision, recall, and F1-score using standard evaluation functions. These metrics provide a detailed assessment of how well the model performs in distinguishing between positive and negative sentiments, helping to evaluate the effectiveness and reliability of the trained DistilBERT model.

5. RESULT AND DISCUSSION

5.1 MODEL PERFORMANCE



The displayed confusion matrix represents the performance of the DistilBERT sentiment

classification model on the test dataset. The matrix compares the actual labels with the predicted labels produced by the model.

In this output:

Class 0 represents Negative sentiment

Class 1 represents Positive sentiment

Observed values:

266 reviews that were actually Negative were correctly predicted as Negative.

234 reviews that were actually Positive were incorrectly predicted as Negative.

	precision	recall	f1-score	support
0	0.53	1.00	0.69	266
1	0.00	0.00	0.00	234
accuracy			0.53	500
macro avg	0.27	0.50	0.35	500
weighted avg	0.28	0.53	0.37	500

The classification report presents a detailed evaluation of the DistilBERT model's performance for both sentiment classes. For class 0 (Negative), the model achieved a precision of 0.53, recall of 1.00, and F1-score of 0.69, indicating that while the model correctly identified all actual negative reviews, only about 53% of the reviews it labeled as negative were truly negative. In contrast, for class 1 (Positive), the precision, recall, and F1-score are all 0.00, which shows that the model failed to correctly identify any positive reviews. The overall accuracy of the model is 0.53, meaning it correctly classified only 53% of the total 500 reviews, which is slightly better than random guessing for a balanced dataset. The macro average scores (precision 0.27, recall 0.50, F1-score 0.35) highlight poor balanced performance across both classes, while the weighted averages also remain low due to the model's heavy bias toward the negative class. Overall, these results indicate that the model has learned to predominantly predict the negative class and lacks the ability to generalize across both sentiment categories, suggesting the need for further training, hyperparameter tuning, and improved data handling to achieve more reliable and balanced sentiment classification.

5.2 INSIGHTS FROM RESULTS

The evaluation results clearly show that the DistilBERT model is currently struggling to perform balanced sentiment classification. Although the model successfully predicts all negative reviews with a recall of 1.00, it fails to identify any positive reviews, resulting in zero precision, recall, and F1-score for the positive class. This indicates that the model has become heavily biased towards predicting only the negative class.

The overall accuracy of 53% suggests that the model is performing only slightly better than random guessing, which is not acceptable for a reliable sentiment analysis system. The low macro and weighted average scores further confirm that the model lacks generalization capability and does not handle both sentiment classes equally. This imbalance means the model is not learning meaningful sentiment patterns and is instead defaulting to the most dominant prediction behavior.

These results highlight that while the model architecture (DistilBERT) is powerful, the current training configuration is inadequate. Possible causes include insufficient training epochs, improper data shuffling, incorrect label distribution handling, or ineffective optimization settings. The confusion matrix and classification metrics collectively indicate that the model requires further tuning and improved training strategy to achieve realistic and dependable sentiment classification.

5.3 POSSIBLE IMPROVEMENTS

The current results indicate that the DistilBERT model is heavily biased towards predicting only the negative class, resulting in poor overall performance. To enhance the effectiveness and reliability of the sentiment analysis system, the following improvements can be implemented:

Increase the Number of Training Epochs

The model was trained for only one epoch, which is insufficient for a deep learning model like DistilBERT to learn complex sentiment patterns. Increasing the number of epochs to 3–5 or more will allow the model to better capture meaningful features and improve generalization.

Hyperparameter Tuning

Adjusting key hyperparameters such as learning rate, batch size, and maximum sequence length can significantly impact performance. Careful tuning can help the model converge more effectively and reduce bias.

Handle Class Imbalance

Applying class weights during training or using balanced sampling techniques can ensure that both positive and negative reviews are treated equally, preventing bias toward one class.

Improve Data Shuffling

Ensuring proper shuffling of training data helps the model learn diverse patterns and prevents it from becoming overly dependent on sequential data patterns.

Monitor Training Loss and Validation Metrics

Tracking loss and validation accuracy during training allows early detection of issues such as underfitting or overfitting and helps in adjusting parameters accordingly.

6. CONCLUSION

This project focused on implementing a sentiment analysis system for movie reviews using the DistilBERT Transformer model. The objective was to classify reviews as either positive or negative by fine-tuning a pre-trained DistilBERT model on the IMDB dataset. The system successfully demonstrated the complete workflow of preprocessing, model training, evaluation, and performance analysis using modern NLP techniques.

The evaluation results revealed that although DistilBERT is a powerful model capable of understanding contextual information, the current training configuration led to biased performance. The model showed strong prediction capability for negative reviews but failed to effectively identify positive reviews, resulting in an overall accuracy of 53% and poor balance between classes. This indicates that the model requires further optimization, including increased training epochs, improved hyperparameter tuning, and better handling of class distribution.

Despite these limitations, the project highlights the practical significance of Transformer-based models in real-world sentiment analysis applications. With appropriate refinements and improved training strategies, the DistilBERT model can achieve reliable and balanced performance, making it suitable for deployment in systems such as review analysis platforms, customer feedback monitoring, and real-time opinion mining tools.

Overall, this project demonstrates the potential of advanced NLP models in automating sentiment interpretation and lays a strong foundation for future enhancements and more accurate sentiment classification systems.

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