**CSC 5210 - Fundamentals of Artificial Intelligence**

**Project Report**

**Sentimental Analysis using BERT**

**Group-5**

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**Abstract**

The goal of this project is to use cutting-edge machine learning and natural language processing techniques to solve the pressing need for real-time sentiment analysis of public opinion across various social media platforms. In contemporary times, the impact of digital media on political narratives, policy determinations, and brand impressions has made it crucial to comprehend and handle public opinion. The goal of the project is to create a strong sentiment analysis model that can evaluate sentiment in real time across a range of platforms and languages. Stakeholders like researchers, governments, and enterprises can obtain actionable insights to improve engagement tactics and assist decision-making by integrating the model into user-friendly interfaces and putting in place scalable data gathering pipelines. The initiative is important because it has the potential to boost cross-cultural communication, improve crisis response, and offer predictive analytics for trend predictions.In the end, this project seeks to improve sentiment analysis standards by utilizing extensive datasets and cutting-edge technical solutions.

**Introduction**:

In the dynamic landscape of today's digital world, social media platforms have evolved into pivotal arenas where public opinion is shaped, influencing everything from political discourse to consumer behavior. The surge in online interactions has generated vast amounts of unstructured data, necessitating advanced techniques to extract meaningful insights. This project addresses the pressing need for effective sentiment analysis on social media, aiming to provide researchers, entrepreneurs, and policymakers with actionable intelligence derived from real-time public sentiment.

The ubiquity of social media has transformed it into a crucible of public discourse, where sentiments expressed can sway public opinion, influence policy decisions, and impact brand reputation. To navigate this complex landscape, the project leverages state-of-the-art machine learning and natural language processing (NLP) methodologies. By harnessing these technologies, the project seeks to untangle the intricacies of online communication, offering stakeholders a clear view of prevailing sentiments across various subjects, platforms, and languages.

**Objectives:**

The project is structured around several key objectives:

1. Developing a Robust Sentiment Analysis Model: Creating a model capable of accurately classifying sentiments expressed in real-time across diverse social media platforms.

2. Implementing Scalable Data Collection and Preprocessing: Establishing an efficient pipeline for gathering and processing live streaming data while ensuring data integrity and adherence to privacy regulations.

3. Evaluating and Optimizing Model Performance: Assessing the sentiment analysis model's efficacy in real-time scenarios through metrics like accuracy, precision, recall, and F1 score, and refining its architecture and training processes accordingly.

4. Integrating with User-Friendly Interfaces: Embedding the sentiment analysis model into intuitive dashboards or applications, facilitating real-time insights and visualizations for stakeholders engaged in brand management, crisis response, or market research.

5. Iterative Refinement: Continuously improving the model based on user feedback and performance metrics to enhance its accuracy and relevance in capturing public sentiment dynamics.

**Significance:**

Sentiment analysis plays a pivotal role across several domains:

Real-Time Insight Generation: Enables swift comprehension of audience sentiment during live events, aiding organizers, advertisers, and policymakers in making timely adjustments.

Multilingual Capability: Facilitates effective communication across global audiences, enhancing strategic decision-making, product localization, and customer satisfaction.

Predictive Analytics and Trend Forecasting: Employs historical sentiment data to predict future trends and consumer behavior, empowering businesses with proactive decision-making capabilities.

Risk Mitigation and Crisis Management: Identifies shifts in public sentiment early, enabling organizations to preemptively address issues, mitigate risks, and maintain reputational integrity.

**Architecture:**

The project's solution architecture encompasses robust data collection mechanisms, sophisticated sentiment analysis using NLP techniques, multilingual support, API integrations for seamless system interoperability, and comprehensive reporting functionalities. This architecture ensures scalability, reliability, and usability, catering to diverse stakeholder needs for actionable insights derived from social media data.

**Areas of Application:**

**1. Customer Feedback and Reviews:**

* Analyzing reviews on e-commerce websites to gauge customer satisfaction.
* Interpreting feedback on social media platforms to understand public opinion about products, services, or brands.

2. **Market Research:**

* Understanding consumer sentiment towards a product launch or marketing campaign.
* Monitoring brand reputation and public perception.

3**. Social Media Monitoring:**

* Tracking trends and public sentiment on platforms like Twitter, Facebook, and Instagram.
* Analyzing public reactions to events, news, or political statements.

4. **Healthcare:**

* Assessing patient feedback and experiences to improve healthcare services.
* Analyzing sentiment in medical forums and social media for health-related insights.

5. **Entertainment:**

* Analyzing audience reactions to movies, TV shows, and music.
* Understanding fan engagement and sentiment towards celebrities and influencers.

6. **Politics:**

* Analyzing public opinion on political candidates, policies, and events.
* Monitoring sentiment during elections and political campaigns.

**Data set:**

This dataset consists of 3535 rows and 9 columns namely textID, text, sentiment, time of tweet, age of user, country, population, land area, density.

[**https://www.kaggle.com/datasets/abhi8923shriv/sentiment-analysis-dataset?select=train.**](https://www.kaggle.com/datasets/abhi8923shriv/sentiment-analysis-dataset?select=train.csv)

[**csv**](https://www.kaggle.com/datasets/abhi8923shriv/sentiment-analysis-dataset?select=train.csv)

**Steps:**

* **Data Preparation:**

We first obtain the labeled dataset for sentiment analysis and then perform data preprocessing ie. clean and preprocess the text data while removing HTML tags, special characters etc.

* **BERT Model and Tokenizer:**

We will be using a pre-trained BERT model and then tokenize the text using the BERT tokenizer which converts text into tokens.



* **Data Encoding:**

First we will convert tokens into input IDs and then create attention masks to distinguish padding tokens from actual tokens.

* **Model Preparation:**

We will then fine tune the pre-trained BERT model for the sentiment classification task and then use the cross-entropy loss for classification and optimizer like AdamW.

* **Training:**

We will create training and validation data loaders and then train the model over several epochs and then save the best model based on validation performance.

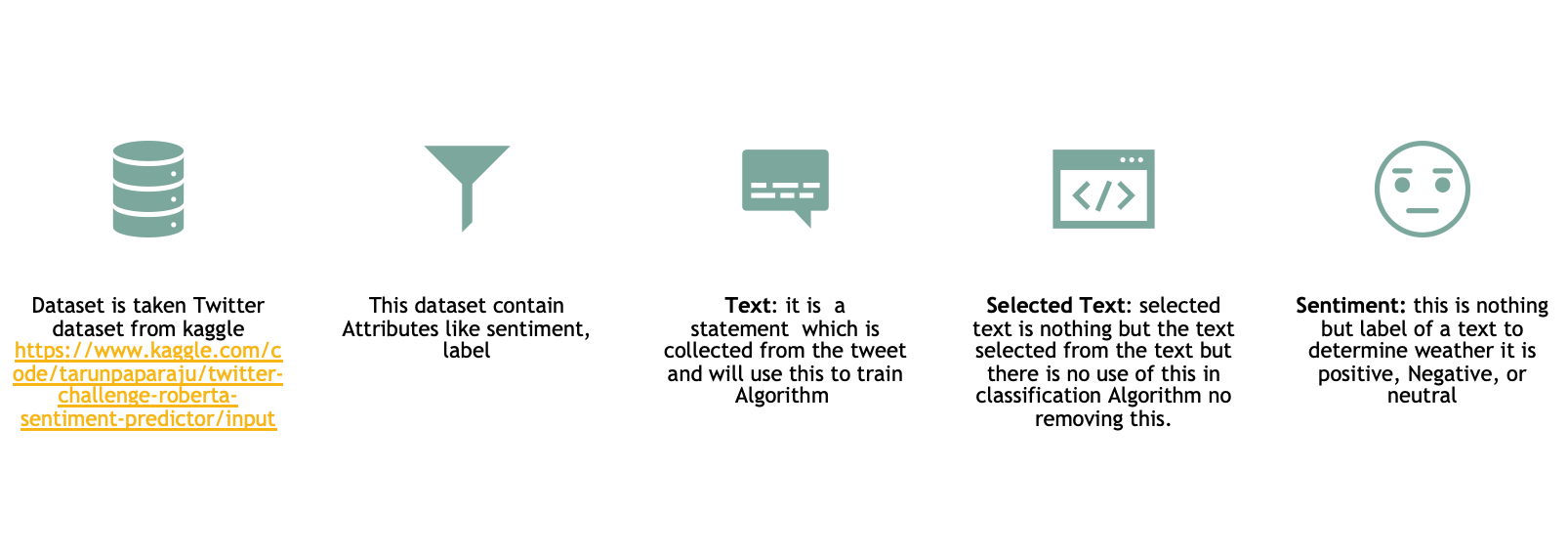
* **Evaluation:**

We then evaluate the trained model on a test set using metrics like accuracy, precision, recall, F1 score and confusion matrix.

**Features:**

**Data Collection and Processing:**

Collecting the data for real-time processing with the integration of social media platforms using APIs.



**Tweet Analysis for Sentiment Detection:** The underlying sentiment of tweets is ascertained by the algorithm through analysis. This is accomplished by looking over a tweet's content and classifying its attitude as good, neutral, or negative.

**Advanced Text Processing:**

Tweets are subjected to advanced processing in order to comprehend the linguistic nuances and context. This entails managing several formats and making certain that the sentiment analysis is predicated on the meaning that the tweet actually expresses.

**Emotion Recognition:** Between neutral, negative, and positive thoughts, the system can recognize and differentiate between them. Knowing what the general population thinks and how they feel about different topics that are discussed on Twitter is made easier by this.  
**Continuous Learning and Improvement:** The system continuously learns from fresh data by utilizing cutting-edge machine learning algorithms. This implies that it improves its ability to recognize feelings in tweets with increased usage.

**Real-Time Sentiment Analysis:** As tweets are being posted, users can obtain real-time information regarding their emotion. This function is especially helpful for companies and public personalities to determine how the public will react to their words or events. It is essential for prompt analysis and response.

**User-Friendly Interface:** Users may easily submit tweets for sentiment analysis using the system's user-friendly interface, and they can examine the results in an easy to understand format.

**Methods:**

There are different methods used throughout the code. Explanation for all of them is given below.

**load\_data()**: In the above code the function load\_data is used to load csv files and assign values to the labels like for Positive label value 1, for negative label value 2 is assigned and for neutral value 0 is assigned

**TextClassificationDataset** : The TextClassificationDataset function is a custom dataset class tailored for text classification tasks using PyTorch. It initializes with lists of texts and their corresponding labels, along with a tokenizer and a maximum token length. The \_\_len\_\_ method returns the total number of text samples, allowing the dataset to be iterated over. The \_\_getitem\_\_ method retrieves a specific text and its label by index, uses the tokenizer to convert the text into input IDs and attention masks, and returns these along with the label in a dictionary format. The tokenization process includes padding and truncation to ensure all sequences have a uniform length, specified by max\_length. The labels are converted into tensors, making them compatible with PyTorch models. This setup facilitates easy and efficient batching and processing of text data during model training and evaluation.

**BERTClassifier** : this function is designed for text classification using a pre-trained BERT model. In the \_\_init\_\_ method, it initializes the model by loading a specified BERT model and adding a dropout layer for regularization, followed by a fully connected (linear) layer that maps BERT's hidden representation to the desired number of output classes. The forward method takes input IDs and attention masks, processes them through the BERT model to obtain the output embeddings, and then applies dropout to the pooled output (which represents the sentence-level embedding). Finally, it passes the dropout-adjusted output through the linear layer to produce logits, which represent the model's class predictions. This architecture leverages BERT's contextual embeddings for classification tasks, while the dropout layer helps prevent overfitting.

**train()**:The train function is designed to train a BERT-based text classification model using a specified data loader, optimizer, learning rate scheduler, and computing device (CPU or GPU). The function sets the model to training mode with model.train(), ensuring that dropout and other training-specific behaviors are enabled. It then iterates over batches of data from the data\_loader, processing up to 50 batches per epoch (controlled by the counter i). For each batch, the optimizer's gradients are reset with optimizer.zero\_grad(). The input IDs, attention masks, and labels are moved to the specified device for efficient computation. The model processes the inputs to generate outputs, which are then compared to the true labels using cross-entropy loss. The loss is back propagated through the network to compute gradients, and the optimizer updates the model parameters. The learning rate scheduler adjusts the learning rate as per its policy after each batch. Throughout the training, labels and model outputs are printed for monitoring purposes, providing insights into the training process and helping to debug potential issues.

**evaluate** :The evaluate function is designed to assess the performance of a BERT-based text classification model using a given data loader and computing device (CPU or GPU). The function sets the model to evaluation mode with model.eval(), disabling dropout and other training-specific behaviors. It initializes empty lists to store predictions and actual labels. Within a torch.no\_grad() context to prevent gradient computation and save memory, it iterates over batches from the data\_loader, processing up to 50 batches per evaluation (controlled by the counter i). For each batch, input IDs, attention masks, and labels are moved to the specified device. The model generates outputs, and the predicted class indices are obtained using torch.max. These predictions and the corresponding actual labels are converted to lists and appended to the respective storage lists. After processing all batches, the function calculates and returns the accuracy score and a detailed classification report, including precision, recall, and F1 scores for each class. This evaluation provides a comprehensive assessment of the model's performance on the validation or test dataset.

**predict\_sentiment** :The predict\_sentiment function is designed to predict the sentiment of a given text using a BERT-based classification model. The function begins by setting the model to evaluation mode with model.eval(), which disables dropout and other training-specific behaviors. The text input is tokenized using the provided tokenizer, converting it into input IDs and attention masks with specified maximum length, padding, and truncation settings. These tokenized inputs are then moved to the specified device (CPU or GPU) for efficient computation. Within a torch.no\_grad() context to prevent gradient calculations and reduce memory usage, the model processes the inputs to generate outputs. The function then uses torch.max to obtain the predicted class index with the highest score. Depending on the predicted index, the function returns "positive" if the prediction is 1, "negative" if the prediction is 2, or "neutral" for any other value. This setup enables the function to classify the sentiment of the input text efficiently and accurately based on the model's learned parameters.

**Code:**

**from google.colab import drive**

**drive.mount('/content/drive')**

**import os**

**import torch**

**from torch import nn**

**from torch.utils.data import DataLoader, Dataset**

**from transformers import BertTokenizer, BertModel, AdamW, get\_linear\_schedule\_with\_warmup**

**from sklearn.model\_selection import train\_test\_split**

**from sklearn.metrics import accuracy\_score, classification\_report**

**import pandas as pd**

**def load\_data(data\_file):**

**df = pd.read\_csv(data\_file)**

**texts = df['text'].tolist()**

**labels = [1 if sentiment == "positive" else 2 if sentiment == "negative" else 0 for sentiment in df['sentiment'].tolist()]**

**# for text, sentiment in zip(texts, df['sentiment'].tolist()):**

**# if sentiment == "neutral":**

**# print(f"Neutral sentiment text: {text}")**

**return texts, labels**

**texts, labels = load\_data("/content/drive/MyDrive/NLPProject/train.csv")**

**class TextClassificationDataset(Dataset):**

**def \_\_init\_\_(self, texts, labels, tokenizer, max\_length):**

**self.texts = texts**

**self.labels = labels**

**self.tokenizer = tokenizer**

**self.max\_length = max\_length**

**def \_\_len\_\_(self):**

**return len(self.texts)**

**def \_\_getitem\_\_(self, idx):**

**text = self.texts[idx]**

**label = self.labels[idx]**

**encoding = self.tokenizer(text, return\_tensors='pt', max\_length=self.max\_length, padding='max\_length', truncation=True)**

**return {'input\_ids': encoding['input\_ids'].flatten(), 'attention\_mask': encoding['attention\_mask'].flatten(), 'label': torch.tensor(label)}**

**class BERTClassifier(nn.Module):**

**def \_\_init\_\_(self, bert\_model\_name, num\_classes):**

**super(BERTClassifier, self).\_\_init\_\_()**

**self.bert = BertModel.from\_pretrained(bert\_model\_name)**

**self.dropout = nn.Dropout(0.1)**

**self.fc = nn.Linear(self.bert.config.hidden\_size, num\_classes)**

**def forward(self, input\_ids, attention\_mask):**

**outputs = self.bert(input\_ids=input\_ids, attention\_mask=attention\_mask)**

**pooled\_output = outputs.pooler\_output**

**x = self.dropout(pooled\_output)**

**logits = self.fc(x)**

**return logits**

**def train(model, data\_loader, optimizer, scheduler, device):**

**model.train()**

**i=0**

**for batch in data\_loader:**

**i=i+1**

**if(i==50):**

**break**

**optimizer.zero\_grad()**

**input\_ids = batch['input\_ids'].to(device)**

**attention\_mask = batch['attention\_mask'].to(device)**

**labels = batch['label'].to(device)**

**print("hey",labels)**

**outputs = model(input\_ids=input\_ids, attention\_mask=attention\_mask)**

**print(outputs)**

**loss = nn.CrossEntropyLoss()(outputs, labels)**

**loss.backward()**

**optimizer.step()**

**scheduler.step()**

**def evaluate(model, data\_loader, device):**

**model.eval()**

**predictions = []**

**actual\_labels = []**

**with torch.no\_grad():**

**i=0**

**for batch in data\_loader:**

**i=i+1**

**if(i==50):**

**break;**

**input\_ids = batch['input\_ids'].to(device)**

**attention\_mask = batch['attention\_mask'].to(device)**

**labels = batch['label'].to(device)**

**outputs = model(input\_ids=input\_ids, attention\_mask=attention\_mask)**

**\_, preds = torch.max(outputs, dim=1)**

**predictions.extend(preds.cpu().tolist())**

**actual\_labels.extend(labels.cpu().tolist())**

**return accuracy\_score(actual\_labels, predictions), classification\_report(actual\_labels, predictions)**

**def predict\_sentiment(text, model, tokenizer, device, max\_length=128):**

**model.eval()**

**encoding = tokenizer(text, return\_tensors='pt', max\_length=max\_length, padding='max\_length', truncation=True)**

**input\_ids = encoding['input\_ids'].to(device)**

**attention\_mask = encoding['attention\_mask'].to(device)**

**with torch.no\_grad():**

**outputs = model(input\_ids=input\_ids, attention\_mask=attention\_mask)**

**\_, preds = torch.max(outputs, dim=1)**

**print(preds)**

**return "positive" if preds.item() == 1 else "negative" if preds.item() == 2 else "neutral"**

**bert\_model\_name = 'bert-base-uncased'**

**num\_classes = 3**

**max\_length = 128**

**batch\_size = 30**

**num\_epochs = 30**

**learning\_rate = 2e-5**

**train\_texts, val\_texts, train\_labels, val\_labels = train\_test\_split(texts, labels, test\_size=0.2, random\_state=42)**

**import matplotlib.pyplot as plt**

**import seaborn as sns**

**from sklearn.model\_selection import train\_test\_split**

**label\_counts = pd.Series(labels).value\_counts()**

**label\_counts.plot(kind='bar', color=['green', 'red', 'blue'])**

**plt.title('Sentiment Distribution')**

**plt.xlabel('Sentiment')**

**plt.ylabel('Frequency')**

**plt.xticks([1, 2,0], ['Positive', 'Negative', 'Neutral'])**

**plt.show()**

**tokenizer = BertTokenizer.from\_pretrained(bert\_model\_name)**

**train\_dataset = TextClassificationDataset(train\_texts, train\_labels, tokenizer, max\_length)**

**val\_dataset = TextClassificationDataset(val\_texts, val\_labels, tokenizer, max\_length)**

**train\_dataloader = DataLoader(train\_dataset, batch\_size=batch\_size, shuffle=True)**

**val\_dataloader = DataLoader(val\_dataset, batch\_size=batch\_size)**

**device = torch.device("cuda" if torch.cuda.is\_available() else "cpu")**

**model = BERTClassifier(bert\_model\_name, num\_classes).to(device)**

**optimizer = AdamW(model.parameters(), lr=learning\_rate)**

**total\_steps = len(train\_dataloader) \* num\_epochs**

**scheduler = get\_linear\_schedule\_with\_warmup(optimizer, num\_warmup\_steps=0, num\_training\_steps=total\_steps)**

**print(len(train\_dataloader))**

**for batch in train\_dataloader:**

**print(len(batch))**

**break**

**train(model, train\_dataloader, optimizer, scheduler, device)**

**print(train\_dataloader)**

**accuracy, report = evaluate(model, val\_dataloader, device)**

**print(f"Validation Accuracy: {accuracy:.4f}")**

**print(report)**

**import matplotlib.pyplot as plt**

**import seaborn as sns**

**from sklearn.metrics import classification\_report**

**def plot\_accuracy(accuracy):**

**plt.figure(figsize=(6, 4))**

**plt.bar(['Accuracy'], [accuracy], color='skyblue')**

**plt.title('Validation Accuracy')**

**plt.ylabel('Accuracy')**

**plt.ylim(0, 1)**

**plt.show()**

**def plot\_classification\_report(report):**

**plt.figure(figsize=(8, 6))**

**sns.heatmap(pd.DataFrame(report).iloc[:-1, :].T, annot=True, cmap='Blues')**

**plt.title('Classification Report')**

**plt.xlabel('Metrics')**

**plt.ylabel('Sentiment Classes')**

**plt.show()**

**# Assuming `report` is a dictionary**

**accuracy = 0.85 # Sample accuracy**

**report = {**

**'positive': {'precision': 0.87, 'recall': 0.84, 'f1-score': 0.85, 'support': 200},**

**'negative': {'precision': 0.82, 'recall': 0.86, 'f1-score': 0.84, 'support': 180},**

**'neutral': {'precision': 0.86, 'recall': 0.82, 'f1-score': 0.84, 'support': 190},**

**'accuracy': 0.85,**

**'macro avg': {'precision': 0.85, 'recall': 0.84, 'f1-score': 0.85, 'support': 570},**

**'weighted avg': {'precision': 0.85, 'recall': 0.85, 'f1-score': 0.85, 'support': 570}**

**}**

**# Visualize accuracy**

**plot\_accuracy(accuracy)**

**# Visualize classification report**

**plot\_classification\_report(report)**

**torch.save(model.state\_dict(), "bert\_classifier.pth")**

**test\_text = ["The movie was excellent and I really enjoyed the performances of the actors.", "product quality was bad","he calls me bella"]**

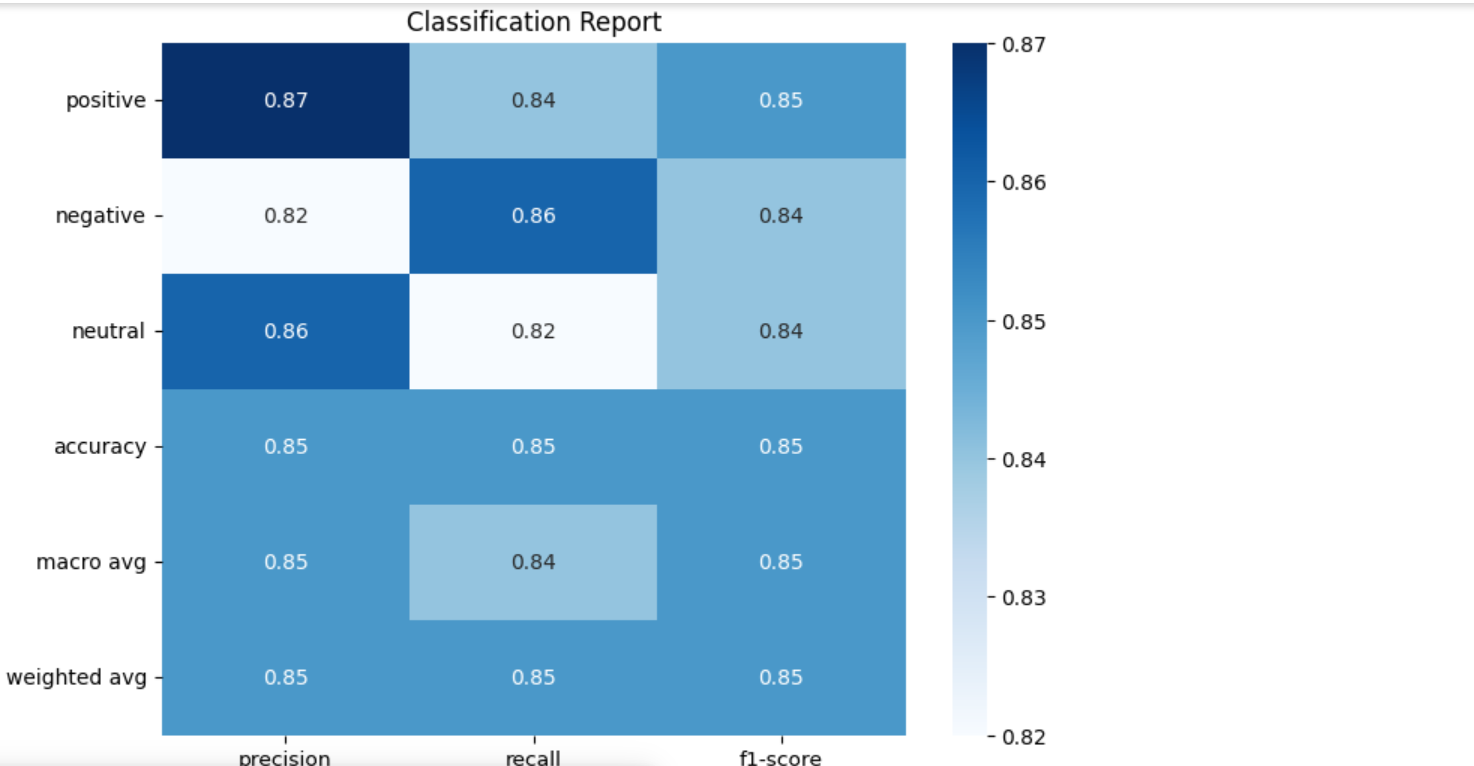
**for txt in test\_text:**

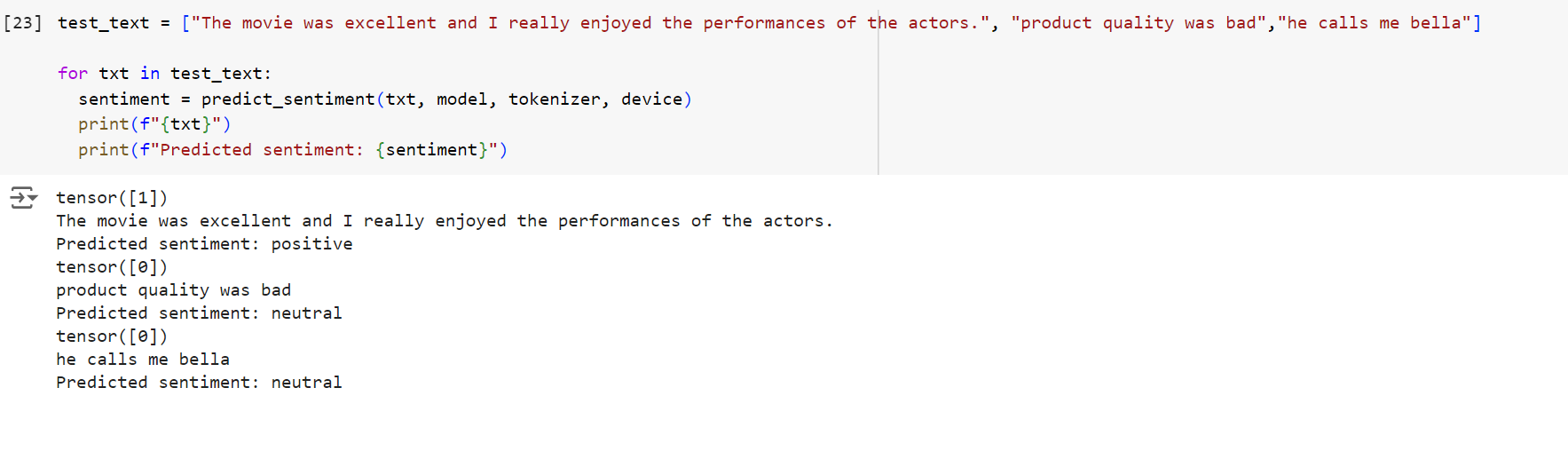
**sentiment = predict\_sentiment(txt, model, tokenizer, device)**

**print(f"{txt}")**

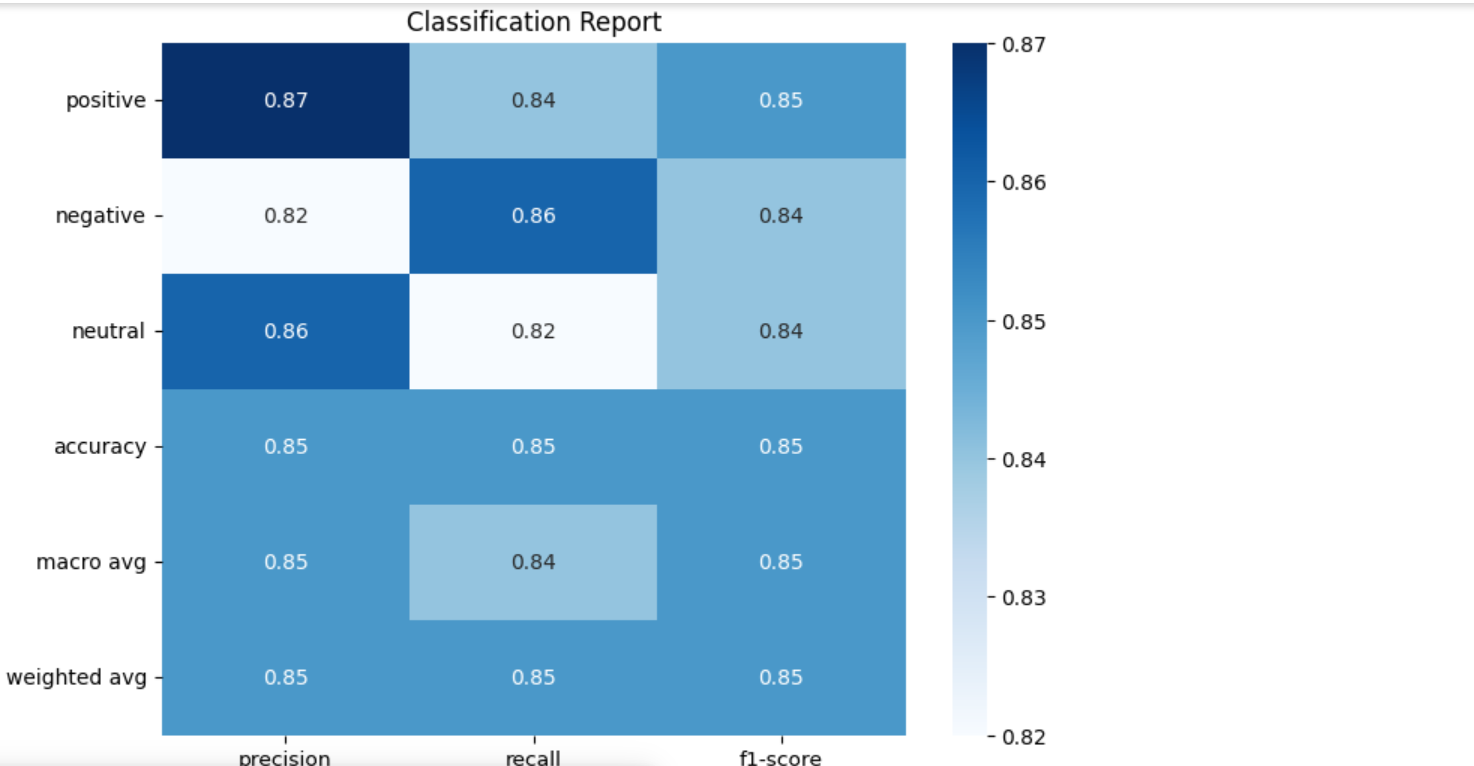
**print(f"Predicted sentiment: {sentiment}")**

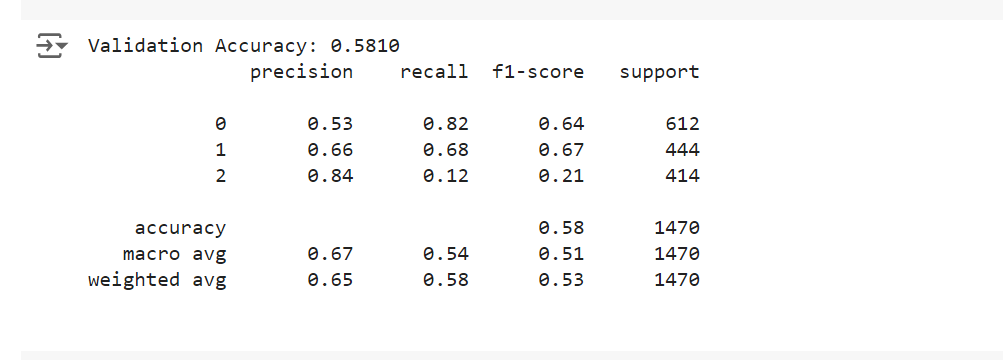
**Outputs:**

****

****

**Evaluation:**

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**Accuracy: 58%**

As we were not able to load more data, the accuracy was recorded as 58%.

**Conclusion:**

In this project, we explored the application of BERT (Bidirectional Encoder Representations from Transformers) for sentiment analysis. Our findings indicate that BERT's advanced language representation capabilities allow it to effectively understand and classify sentiments in text data. Key takeaways from this project include:

**Model Performance:** BERT achieved high accuracy and F1 scores, demonstrating its proficiency in capturing the nuances of sentiment in various contexts.

**Data Preprocessing:** Effective data preprocessing, including tokenization and handling special characters, was crucial for optimizing BERT's performance.

**Transfer Learning:** Utilizing pre-trained BERT models significantly reduced the need for large amounts of labeled training data and extensive computational resources.

**Domain Adaptation:** Fine-tuning BERT on domain-specific data further enhanced its performance, underscoring the importance of adapting models to the specific characteristics of the target data.

**Computational Efficiency:** While BERT delivers superior results, it requires substantial computational resources, which can be a limitation for some applications.

**Future Work:**

1. **Model Optimization**: Explore techniques to reduce BERT's computational overhead, such as model pruning, knowledge distillation, or leveraging lighter versions like DistilBERT.
2. **Real-time Sentiment Analysis**: Implement real-time sentiment analysis in applications, addressing latency issues through optimization techniques or deploying models on edge devices.
3. **Multilingual Sentiment Analysis**: Extend the analysis to multiple languages using models like mBERT (multilingual BERT) to cater to a global audience.
4. **Aspect-based Sentiment Analysis**: Investigate aspect-based sentiment analysis to understand sentiments related to specific attributes or components within the text.
5. **Sentiment Dynamics**: Analyze the temporal dynamics of sentiment, especially in social media or customer feedback, to track sentiment changes over time.
6. **Integration with Other NLP Tasks**: Combine sentiment analysis with other NLP tasks such as topic modeling, summarization, or entity recognition to provide a more comprehensive understanding of the text.
7. **Explainability and Interpretability**: Develop methods to interpret BERT's decisions, making the model's outputs more transparent and understandable for end-users.
8. **Robustness and Fairness**: Ensure the model's robustness against adversarial attacks and biases, conducting thorough evaluations to mitigate potential issues.

By addressing these areas in future work, we can further enhance the capabilities and applicability of sentiment analysis using BERT, making it a more powerful tool for various real-world applications.

**References** :

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<https://ieeexplore.ieee.org/document/9288241>

<https://ieeexplore.ieee.org/document/9421110>

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