Part I:

Mental Health Sentiment Analysis Using BERT

1. Introduction

This project aims to develop a sentiment analysis model to detect signs of mental health issues in social media posts, particularly focusing on Twitter data. The goal aligns with SDG 3 (Good Health and Well-Being) by leveraging natural language processing (NLP) to provide insights into public mental health trends.

2. Project Objective

The objective is to fine-tune a pre-trained BERT model on a dataset of tweets to identify sentiments related to mental health issues such as depression and anxiety. The model's performance is evaluated before and after fine-tuning to measure its effectiveness in detecting these sentiments.

3. Methodology

- **Data Collection:**
  The Sentiment140 dataset was used, containing 1.6 million tweets labeled as positive or negative. For this project, the dataset was filtered to focus on tweets containing mental health-related keywords.
- **Model Selection:**
  The BERT model (`bert-base-uncased`) was selected from the Hugging Face model hub due to its strong performance in various NLP tasks.
- **Data Preprocessing:**
  The tweets were tokenized using BERT's tokenizer, and the data was split into training and testing sets.
- **Fine-Tuning:**
  The BERT model was fine-tuned on the prepared dataset over 3 epochs with a learning rate of 2e-5. The training process was optimized using cross-entropy loss.

4. Implementation

The project was implemented using the Hugging Face `transformers` library in Python. The key steps included loading the dataset, tokenizing the text, fine-tuning the model, and evaluating its performance.

- **Code Implementation:**
  The full implementation is provided in the `mental_health_sentiment_analysis.py` script. This script handles data loading, preprocessing, model training, and evaluation.

5. Results

- **Evaluation Metrics:**
  The model was evaluated using accuracy, precision, recall, and F1 score. These metrics were calculated before and after fine-tuning to assess improvements.
- **Model Performance:**
  - **Before Fine-Tuning:**
    The pre-trained BERT model achieved an accuracy of X% on the test set.
  - **After Fine-Tuning:**
    Post fine-tuning, the model's accuracy improved to Y%, with an F1 score of Z%. These improvements demonstrate the model's enhanced ability to detect sentiments related to mental health issues.

6. Conclusion

The fine-tuned BERT model showed significant improvements in detecting mental health-related sentiments on social media. This project highlights the potential of NLP in contributing to mental health monitoring and intervention strategies.

7. Future Work

- Further fine-tuning on larger datasets containing more diverse mental health-related content.
- Implementation of additional models or ensemble methods to further improve accuracy.
- Deployment of the model as a real-time monitoring tool for mental health trends.

Part II:

Fine-Tuning GPT-2 for Climate Change Awareness

1. Introduction

This project fine-tunes a pre-trained GPT-2 model to generate content related to climate change, aiming to raise awareness and encourage action on environmental issues. The project aligns with SDG 13 (Climate Action) by promoting sustainable practices and providing information on climate change through generated text.

2. Project Objective

The objective is to fine-tune the GPT-2 model on a dataset focused on climate change topics. The goal is to improve the model's ability to generate relevant and meaningful content that can be used to raise awareness about climate change, provide tips on reducing carbon footprints, and encourage sustainable practices.

3. Methodology

Data Collection:

The Climate Fever dataset was used, containing claims related to climate change. This dataset was selected for its focus on environmental topics and relevance to the project's goals.

Model Selection:

The GPT-2 model (gpt2) was selected from the Hugging Face model hub for fine-tuning. GPT-2 is known for its strong text generation capabilities, making it suitable for this task.

Data Preprocessing:

The dataset was tokenized using GPT-2's tokenizer, and the data was split into training and validation sets.

Fine-Tuning:

The GPT-2 model was fine-tuned on the Climate Fever dataset over 3 epochs with a learning rate of 5e-5. The training process was optimized using cross-entropy loss.

4. Implementation

The project was implemented using the Hugging Face transformers library in Python. The key steps included loading the dataset, tokenizing the text, fine-tuning the model, and evaluating its performance.

Code Implementation:

The full implementation is provided in the climate_change_gpt2_finetuning.py script. This script handles data loading, preprocessing, model training, and evaluation.

5. Results

Evaluation Metrics:

The model was evaluated using perplexity and other relevant metrics before and after fine-tuning.

Model Performance: Before Fine-Tuning:
The pre-trained GPT-2 model had a perplexity of X on the validation set.
After Fine-Tuning:
After fine-tuning, the model's perplexity improved to Y, indicating better text generation quality.
The model was also qualitatively evaluated to ensure the relevance and coherence of the generated content.

6. Conclusion

The fine-tuned GPT-2 model demonstrated significant improvements in generating climate change-related content. This project highlights the potential of language models in contributing to climate action by spreading awareness and providing actionable insights through generated text.

7. Future Work

Future work could involve further fine-tuning the model on a more diverse dataset that includes various aspects of climate change. Additionally, deploying the model as a chatbot or content generation tool could help in actively engaging the public on climate-related issues.