Technical Report

1. Model Architecture

- Sentiment Analysis Module (Fine-Tuned LLM):
 - o **Model:** A SimpleRNN model fine-tuned on the IMDB movie review dataset.
 - Custom Component: A custom SimpleRNN class (which removes the unsupported time_major parameter) is used to load the pre-trained model from simple_rnn_imdb.h5.
 - o **Pipeline:** Input reviews are preprocessed (lowercased, tokenized, and padded to a fixed length of 500 tokens) before being fed into the model to predict sentiment.

• Text Generation Explanation (RAG-Inspired):

- Model: GPT-2 from Hugging Face is used via the Transformers pipeline to generate explanations based on the provided movie review.
- o **Prompting Strategy:** The prompt is structured as "Review: [user review] \nSentiment:" so that GPT-2 generates a sentiment explanation.
- o Generation Parameters: The pipeline is configured with parameters (max_length, temperature, top_p, top_k, no_repeat_ngram_size, repetition_penalty) to control output length and reduce repetition.

Embedding Demo Module:

- o **Approach:** Demonstrates one-hot encoding of a sample sentence followed by padding and embedding conversion using a simple Keras Embedding layer.
- Model: A minimal Sequential model is built to convert one-hot encoded inputs into dense embedding vectors.

2. Dataset & Preprocessing

Dataset:

 The IMDB movie review dataset is used for training and testing the sentiment analysis model.

• Preprocessing for Sentiment Analysis:

o **Text Normalization:** Reviews are converted to lowercase and split into words.

- Encoding: Words are encoded using the IMDb word index. Unknown words are assigned a default index (2), and indices are shifted by 3 (to account for reserved tokens).
- o **Padding:** Encoded reviews are padded to a maximum length of 500 tokens.

Preprocessing for Embedding Demo:

- One-Hot Encoding: Sample sentences are converted into one-hot representations using a specified vocabulary size (10,000).
- o **Padding:** Sequences are padded to a fixed length (e.g., 8 tokens) before being processed by the embedding layer.

3. Design Decisions

• Model Selection:

- The SimpleRNN model was selected for its simplicity and effective performance on the IMDB dataset, making it suitable for a domain-specific task.
- GPT-2 was chosen for text generation because it can produce coherent explanations based on prompts even without fine-tuning on sentiment explanations.

• Frameworks and Libraries:

- TensorFlow/Keras: Used for building and training the sentiment analysis and embedding models.
- o **Hugging Face Transformers:** Used for leveraging GPT-2 for text generation.
- Streamlit: Selected as the web framework to build an interactive multi-page application that integrates all modules.

• Integration Techniques:

- The project uses modular functions for each component (sentiment analysis, text generation, embedding demo) and integrates them into a single Streamlit app (app.py).
- New caching decorators (st.cache_resource for resource-intensive objects and st.cache_data for serializable data) are implemented to optimize performance and resource management.

4. Performance Evaluation

• Quantitative Evaluation:

- o The SimpleRNN model, as shown in the training notebooks (simplernn.ipynb and prediction.ipynb), achieved a validation accuracy of approximately 81%.
- The prediction function uses a threshold (set to 0.7 in the app) to classify reviews as Positive or Negative.

• Qualitative Evaluation:

- Sentiment Analysis: For example, a review like "This movie was fantastic!" yields a prediction score (e.g., 0.81) and is classified as Positive.
- Text Generation: The GPT-2-based module produces explanations that provide rationale for the predicted sentiment, though further fine-tuning may improve consistency.
- o **Embedding Demo:** The one-hot encoded inputs are transformed into dense embeddings and displayed in a clear tabulated format via Streamlit.

Deployment Link:

Streamlit

Results:





