**Design Document**

**Part B: Detailed Approach, Workflows, and Enhancements**

**1. Introduction**

This document outlines the approach for improving the performance of a question-answering model using different word embedding techniques. The document will discuss the steps and workflows involved, the impact of various word embedding techniques on model performance, and propose enhancements and alternative strategies to generalize the model. Additionally, contemporary methodologies will be reviewed, and relevant references will be compiled.

**2. Approach and Workflows**

**2.1 Data Preprocessing**

* **Tokenization**: Convert text into tokens using a tokenizer compatible with the chosen embedding technique (e.g., BERT tokenizer for BERT embeddings).
* **Padding and Truncation**: Ensure all sequences are of the same length by padding shorter sequences and truncating longer ones.
* **Encoding**: Convert tokens into their respective indices based on the embedding vocabulary.

**2.2 Embedding Techniques**

* **BERT Embeddings**: Use pre-trained BERT embeddings to capture contextual information.
* **GloVe Embeddings**: Use pre-trained GloVe embeddings to capture global word co-occurrence statistics.
* **Comparison**: Evaluate the performance of both embeddings on the same dataset to understand their impact.

**2.3 Model Training**

* **Architecture**: Use a transformer-based architecture for BERT embeddings and a simpler neural network for GloVe embeddings.
* **Training**: Train the model on the dataset, monitoring loss and accuracy.
* **Evaluation**: Evaluate the model using metrics such as accuracy and F1 score.

**2.4 Post-Processing**

* **Answer Extraction**: Extract the answer from the model's output.
* **Handling Overflowing Tokens**: Implement strategies to manage overflowing tokens, ensuring no loss of critical information.

**3. Impact of Word Embedding Techniques**

**3.1 BERT Embeddings**

* **Contextual Understanding**: BERT embeddings provide a deep understanding of context, improving the model's ability to handle complex queries.
* **Performance**: Typically result in higher accuracy and F1 scores due to their ability to capture nuanced meanings.

**3.2 GloVe Embeddings**

* **Efficiency**: GloVe embeddings are computationally less intensive compared to BERT.
* **Performance**: May not capture context as effectively as BERT, potentially leading to lower accuracy and F1 scores.

**4. Enhancements and Alternative Strategies**

**4.1 Data Augmentation**

* **Synonym Replacement**: Increase dataset size by replacing words with their synonyms.
* **Paraphrasing**: Generate paraphrased versions of questions to improve model robustness.

**4.2 Hybrid Embeddings**

* **Combining BERT and GloVe**: Use a combination of BERT and GloVe embeddings to leverage the strengths of both techniques.

**4.3 Transfer Learning**

* **Pre-trained Models**: Fine-tune pre-trained models on the specific dataset to improve performance.

**4.4 Advanced Architectures**

* **Attention Mechanisms**: Incorporate attention mechanisms to better capture relationships between words.
* **Ensemble Methods**: Use ensemble methods to combine predictions from multiple models.

**5. Contemporary Methodologies and References**

**5.1 Methodologies**

* **Transformers**: Review the latest advancements in transformer architectures.
* **Self-Supervised Learning**: Explore self-supervised learning techniques for better pre-training.

**6. Evaluation Results**

**6.1 Original Embeddings**

* Start Accuracy: 0.0000
* End Accuracy: 0.0500
* Start F1 Score: 0.0000
* End F1 Score: 0.0200

**6.2 GloVe60d Embeddings**

* Start Accuracy: 0.0000
* End Accuracy: 0.1000
* Start F1 Score: 0.0000
* End F1 Score: 0.0583

**6.3 Performance Comparison**

Based on the evaluation results, the GloVe60d embeddings performed better than the original embeddings. The GloVe60d embeddings achieved higher end accuracy (0.1000) and end F1 score (0.0583) compared to the original embeddings' end accuracy (0.0500) and end F1 score (0.0200).

**Conclusion**

This design document outlines a comprehensive approach to improving a question-answering model using different word embedding techniques. By following the detailed steps and workflows, and considering the proposed enhancements and alternative strategies, the model's performance can be significantly improved. Reviewing contemporary methodologies and relevant references will ensure the solution is aligned with the latest advancements in the field.