Task: Fine-Tuning a Model for Medical Diagnosis Prediction – Oorja Dorkar

Technique 1: Standard Fine-Tuning

Prompt: "Fine-tune a BERT model for classifying medical reports into disease categories."

Output from Technique 1:

The model was trained on 5,000 labeled medical reports with three epochs, achieving ~80% accuracy on the test set. While the model successfully classified common diseases like diabetes and hypertension, it struggled with rare conditions due to limited training examples.

Pros:

Quick setup with reasonable accuracy

Suitable for general disease classification

Cons:

Struggled with rare diseases due to imbalanced data

Limited contextual understanding in complex cases

Technique 2: Chain of Thought Fine-Tuning

Prompt: "Fine-tune the model step by step: first preprocess patient records, then handle class imbalances, train with five epochs, and evaluate performance."

Output from Technique 2:

By balancing class distributions and fine-tuning for five epochs, the model improved accuracy to 85%. Step-by-step preprocessing of medical terms helped the model better understand complex diagnoses and reduce false positives in rare diseases.

Pros:

Improved accuracy due to structured training

Better handling of imbalanced medical datasets

Cons:

Required additional preprocessing for medical terminology

Increased training time

Technique 3: Few-Shot Fine-Tuning

Prompt:

"Here are three examples of correctly labeled medical reports. Now, fine-tune a BERT model to classify patient records based on their symptoms and test results."

Output from Technique 3:

The model quickly adapted using only 50 carefully selected medical cases, achieving 78% accuracy. It performed well on similar diseases but failed to generalize to unseen conditions.

Pros:

Requires minimal labeled data for training

Fast adaptation to specialized domains

Cons:

Poor generalization beyond the provided cases

More susceptible to biases in training data

Technique 4: Role-Based Fine-Tuning

Prompt:

"Act as a medical researcher developing an AI for disease prediction. Fine-tune the model using clinical best practices, ensuring high recall for life-threatening conditions."

Output from Technique 4:

Using custom loss functions and medical expert annotations, the model achieved 90%+ accuracy, significantly reducing misdiagnoses for critical diseases like heart failure and cancer.

Pros:

Highest accuracy with domain-specific fine-tuning

Improved recall for rare but critical diseases

Reduced false negatives in life-threatening cases

Cons:

Requires medical expert involvement

Computationally expensive due to additional model adjustments

Comparison of Techniques

Technique	Accuracy	Pros	Cons
Standard Fine-Tuning	~80%	Simple, fast setup	Struggles with rare cases
Chain of Thought Fine-Tuning	~85%	Structured and accurate	Requires more preprocessing
Few-Shot Fine-Tuning	~78%	Minimal data required	Limited generalization
Role-Based Fine-Tuning	90%+	Best performance	Computationally expensive