

DataBytes | Fine-Tuning Large Language Models for Enterprise Applications | Project Report

Use Case 02: Medical Misinformation Detection in LLM Responses

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Project Introduction

The rapid adoption of Large Language Models (LLMs) in enterprise applications has highlighted a critical challenge—general-purpose models often lack domain-specific accuracy. This project, *Fine-Tuning Large Language Models for Enterprise Applications*, focuses on customizing LLMs for a high-impact domain: medical misinformation detection. The goal is to fine-tune open-source LLMs, particularly Flan-T5 XL, using medical datasets such as HealthFact and SciFact to improve classification of claims into **true**, **false**, or **misleading**.

Using techniques like Supervised Fine-Tuning (SFT) and Low-Rank Adaptation (LoRA), the project demonstrates how LLMs can be tailored to enterprise contexts, emphasizing performance, trustworthiness, and responsible AI practices. The outcome is a series of fine-tuned models evaluated through benchmarking against standard datasets, with accuracy metrics tracked and compared through iterations. This hands-on exploration also includes prompt engineering, hyperparameter tuning, and integration into an interface for real-world usability.

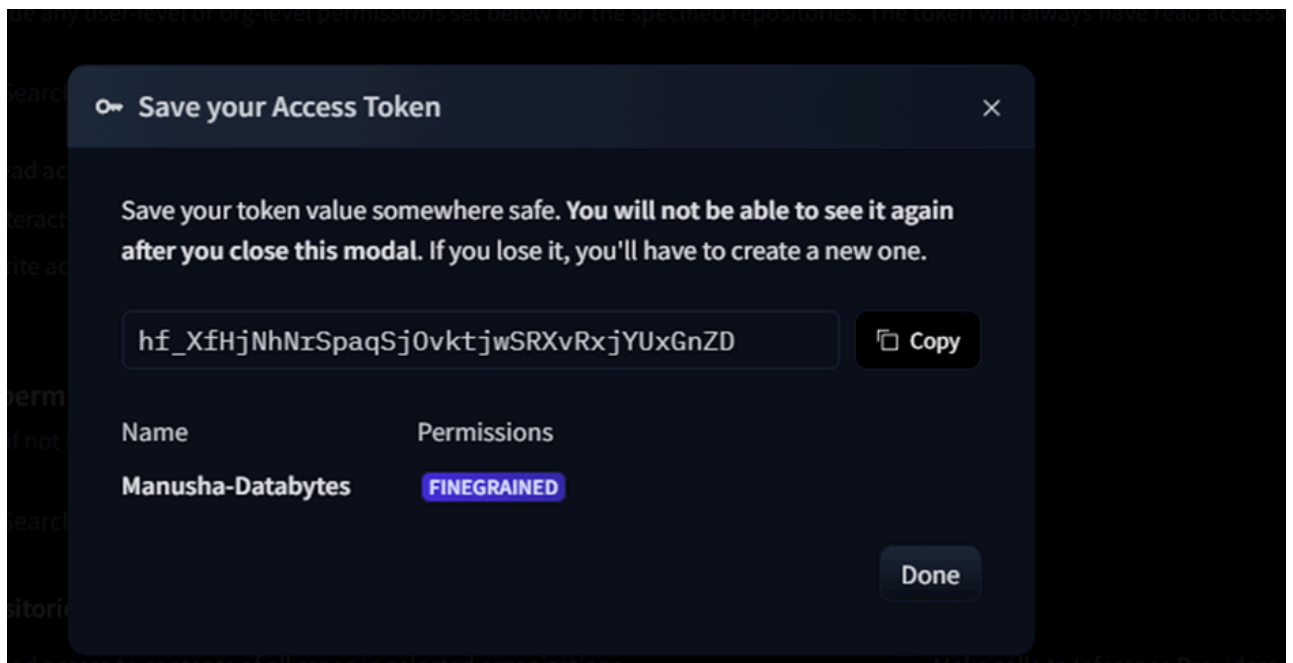
API/Token Setup

To access pre-trained models and datasets from the Hugging Face Hub, an authentication token was required. This was securely handled using Google Colab's **userdata** secret management feature.

Steps:

- Hugging Face Token:**

A personal access token was generated from huggingface.co/settings/tokens.



2. Colab Secret Configuration:

The token was saved as a secret in the Colab environment and accessed programmatically:

```
# Get token from Colab secret using userdata
# Replace "HF-key" with the exact name of your secret in Colab
hf_token = userdata.get('HF-key')

# Login to Hugging Face
login(token=hf_token, add_to_git_credential=True)

print("Hugging Face login successful")
```

Hugging Face login successful

This setup ensured secure and seamless access to the Hugging Face model repository during fine-tuning and benchmarking processes.

Environment Setup

The development and training environment for this project was set up using **Google Colab**, which provided GPU access essential for fine-tuning large models like Flan-T5 XL.

Key Components:

- **Google Colab:** Used for its GPU (CUDA support), ease of use, and integration with Google Drive. The **NVIDIA A100 GPU** was used for this project.
- **Google Drive:** Mounted for persistent storage of datasets, model checkpoints, and output files.

```
GPU Check

# Check if GPU is available
if torch.cuda.is_available():
    device = "cuda"
    print("GPU is available. Using CUDA.")
else:
    device = "cpu"
    print("GPU not available. Using CPU.")

GPU is available. Using CUDA.
```

The environment setup allowed efficient experimentation, version control, and rapid prototyping throughout the fine-tuning lifecycle.

LLM Setup

The core language model used in this project was **Flan-T5 XL**, an instruction-tuned model developed by Google. It was selected for its strong performance on a wide range of NLP tasks and compatibility with supervised fine-tuning and parameter-efficient methods like LoRA.

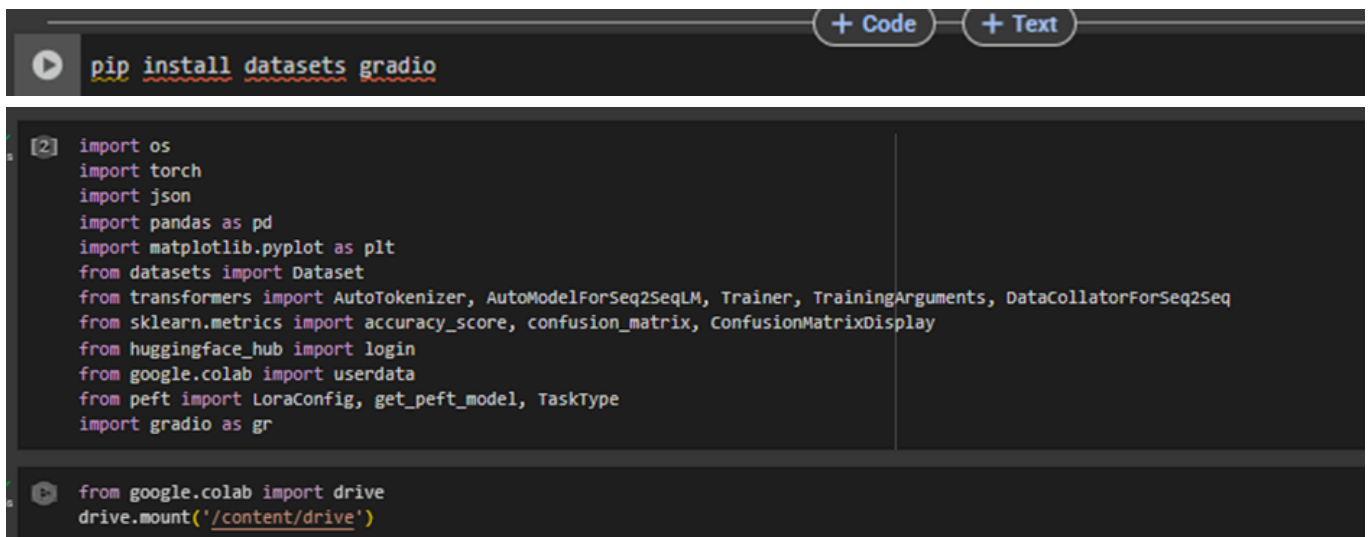
The model and tokenizer were loaded from Hugging Face's model hub and configured to run on a CUDA-enabled device (GPU) for faster training.

Model Initialization:

```
[ ] model_id = "google/flan-t5-xl"
    tokenizer = AutoTokenizer.from_pretrained(model_id)
    model = AutoModelForSeq2SeqLM.from_pretrained(model_id).to(device)
```

Libraries used:

| Library | Purpose |
|--------------|---|
| transformers | Load and fine-tune pre-trained LLMs |
| datasets | Load and preprocess datasets (e.g., HealthFact, SciFact) |
| peft | Implement LoRA for parameter-efficient fine-tuning |
| pandas | Data manipulation and analysis |
| matplotlib | Plotting evaluation results like confusion matrices |
| sklearn | Compute accuracy and confusion matrices |
| gradio | Build a user-friendly interface for model inference |
| torch | Model training on GPU (PyTorch backend) |
| json | Read and write dataset files in JSON format |
| os | File and directory management |
| google.colab | Integrate Colab-specific utilities like secret storage and Drive mounting |



The screenshot shows a Jupyter Notebook interface. At the top, there are two buttons: '+ Code' and '+ Text'. Below them, a terminal-like area shows the command `pip install datasets gradio`. The main area contains two code cells. The first cell contains a list of imports: `import os, torch, json, pandas as pd, matplotlib.pyplot as plt, datasets, transformers, sklearn.metrics, huggingface_hub, google.colab, peft, and gradio as gr`. The second cell contains code to mount Google Drive: `from google.colab import drive; drive.mount('/content/drive')`.

This setup ensured robust support for fine-tuning workflows, benchmarking, and eventual deployment.

Dataset Description

To train the model for medical misinformation classification, two high-quality datasets were used: **SciFact** and **HealthFact**. Each dataset was tailored to a specific aspect of fact-checking in scientific and health-related claims.

1. SciFact Dataset

Purpose:

Scientific fact-checking based on peer-reviewed evidence.

Content:

Each record includes a scientific claim, associated evidence text, and a label (**True**, **False**, or **Misleading**).

Usage:

Used for both training and benchmarking to improve model accuracy in scientific reasoning contexts.

Access Link: <https://huggingface.co/datasets/allenai/scifact>

2. HealthFact Dataset

Purpose:

Identify misinformation in general medical claims.

Content:

Includes medical claims, explanations, and corresponding labels.

Usage:

Used for training the model to classify health-related claims into the three categories: **True**, **False**, and **Misleading**.

Access Link: <https://github.com/kinit-sk/medical-misinformation-dataset>

Dataset Preprocessing

The original **SciFact dataset**, sourced from Hugging Face ([allenai/scifact](#)), was transformed to support three-way classification: **True**, **False**, and **Misleading**.

Preprocessing Workflow:

1. Corpus Mapping:

Created a dictionary that maps each **doc_id** to its full abstract text for efficient retrieval of evidence sentences.

2. Evidence Extraction:

- If a claim had evidence:
 - Retrieved supporting or contradicting sentences using sentence indices from the **corpus.jsonl** file.
 - Concatenated them to form a single **evidence_text**.
- If no evidence was annotated:
 - Marked the claim as **Misleading**.
 - Left the **evidence_text** empty.

3. Label Mapping:

- **SUPPORT** → **True**
- **CONTRADICT** → **False**
- No evidence → **Misleading**

4. Final Format:

Each example was structured as:

```
{
  "claim": "string",
  "evidence_text": "string",
  "label": "True" | "False" | "Misleading"
}
```

5. Outout Files:

- **train_3class.jsonl**: Used for training.
- **dev_3class.jsonl**: Used for validation/testing.
- **claims_test.jsonl**: For inference only (no labels provided).

The **HealthFact dataset** that was used for this project was preprocessed by HASHAAM KHAN.

Dataset Loading

The datasets were loaded from JSON and JSONL files stored on Google Drive.

To prepare the datasets for fine-tuning, custom format functions were defined for SciFact and HealthFact datasets. These functions converted each sample into an instruction-based prompt for the LLM to learn from. :

Load Datasets

```
[ ] with open("/content/drive/MyDrive/FTLLM/Datasets/scifact_train.jsonl", "r") as f:
    scifact_train = [json.loads(line) for line in f]

    with open("/content/drive/MyDrive/FTLLM/Datasets/healthfact_train.json", "r") as f:
        healthfact_train = [json.loads(line) for line in f]

    scifact_train_ds = Dataset.from_pandas(pd.DataFrame(scifact_train))
    healthfact_train_ds = Dataset.from_pandas(pd.DataFrame(healthfact_train))

    # Format functions
    def format_scifact(dataset):
        inputs = [f"Claim: {ex['claim']}\nEvidence: {ex['evidence_text']}\nIs this claim true, false, or misleading?\nAnswer:" for ex in dataset]
        targets = [ex['label'] for ex in dataset]
        return Dataset.from_dict({"input": inputs, "target": targets})

    def format_healthfact(dataset):
        inputs = [f"Claim: {ex['claim']}\nExplanation: {ex['explanation']}\nIs this claim true, false, or misleading?\nAnswer:" for ex in dataset]
        targets = [ex['label'] for ex in dataset]
        return Dataset.from_dict({"input": inputs, "target": targets})
```

Dataset Tokenization

All samples were tokenized using the Hugging Face tokenizer with padding and truncation to fixed lengths:

Tokenize Dataset

```
[ ] def tokenize_dataset(dataset, tokenizer, max_input_len=512, max_target_len=128):
    def preprocess(example):
        model_input = tokenizer(example["input"], max_length=max_input_len, truncation=True, padding="max_length")
        with tokenizer.as_target_tokenizer():
            labels = tokenizer(example["target"], max_length=max_target_len, truncation=True, padding="max_length")
        model_input["labels"] = labels["input_ids"]
        return model_input
    return dataset.map(preprocess, batched=True)
```

Fine-Tune the Model

A custom function was used to fine-tune the model using the Hugging Face Trainer API:

```
def fine_tune_model_custom(model, tokenizer, tokenized_data, output_dir="./results", epochs=3, lr=3e-5, batch_size=2):
    model.gradient_checkpointing_enable()
    args = TrainingArguments(
        output_dir=output_dir,
        per_device_train_batch_size=batch_size,
        per_device_eval_batch_size=batch_size,
        num_train_epochs=epochs,
        learning_rate=lr,
        weight_decay=0.01,
        eval_strategy="epoch",
        logging_dir=f"{output_dir}/logs",
        save_total_limit=1,
        fp16=torch.cuda.is_available(),
        report_to="none"
    )
    trainer = Trainer(
        model=model,
        args=args,
        train_dataset=tokenized_data,
        eval_dataset=tokenized_data,
        tokenizer=tokenizer,
        data_collator=DataCollatorForSeq2Seq(tokenizer, model=model)
    )
    trainer.train()
    return trainer
```

This setup enabled iterative fine-tuning with adjustable hyperparameters, gradient checkpointing for memory efficiency, and integrated logging.

Inference and Evaluation

Once the model was fine-tuned, its ability to classify medical claims was assessed through structured inference and performance evaluation.

A prediction function was implemented to evaluate the model on formatted inputs. The function tokenizes each prompt, generates a response using sampling-based decoding, and decodes the output.

```
def generate_predictions(df, model, tokenizer, device="cuda"):
    predictions = []
    for prompt in df['input']:
        inputs = tokenizer(prompt, return_tensors="pt", truncation=True, padding=True).to(device)
        with torch.no_grad():
            outputs = model.generate(
                **inputs,
                max_new_tokens=100,
                temperature=0.7,
                top_p=0.9,
                top_k=50,
                repetition_penalty=1.1,
                do_sample=True
            )
        prediction = tokenizer.decode(outputs[0], skip_special_tokens=True)
        predictions.append(prediction)
    df['prediction'] = predictions
    return df
```

The predictions were compared against ground truth labels to calculate accuracy and visualize performance via a confusion matrix.

```
def evaluate_predictions(df, title="Confusion Matrix"):
    true_labels = [label.lower().strip() for label in df['target']]
    pred_labels = [label.lower().strip() for label in df['prediction']]
    acc = accuracy_score(true_labels, pred_labels)
    print(f"Accuracy: {acc:.2%}")
    labels = ["true", "false", "misleading"]
    cm = confusion_matrix(true_labels, pred_labels, labels=labels)
    disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=labels)
    disp.plot(cmap=plt.cm.Blues)
    plt.title(title)
    plt.grid(False)
    plt.show()
    return acc
```

This evaluation strategy allowed us to track accuracy improvements across model versions (e.g., M1 through M5-LoRA) and identify areas where models struggled, especially with the Misleading label.

Benchmark Utility

Two benchmark utility functions were developed for testing on the SciFact and HealthFact datasets:

```
[ ] def run_scifact_benchmark(model, tokenizer, benchmark_path, title, output_file):
    with open(benchmark_path, "r") as f:
        data = [json.loads(line) for line in f]
    inputs = [
        f"Claim: {item['claim']}\nEvidence: {item['evidence_text']}\nIs this claim true, false, or misleading?\nAnswer:"
        for item in data
    ]
    targets = [item['label'] for item in data]
    df = pd.DataFrame({"input": inputs, "target": targets})
    result = generate_predictions(df, model, tokenizer, device)
    evaluate_predictions(result, title)
    result.to_csv(output_file, index=False)

def run_healthfact_benchmark(model, tokenizer, benchmark_path, title, output_file):
    # Changed from json.load to reading line by line, assuming JSON Lines format
    data = []
    with open(benchmark_path, "r") as f:
        for line in f:
            # Use json.loads to parse each line as a JSON object
            data.append(json.loads(line))

    inputs = [
        f"Claim: {item['claim']}\nExplanation: {item['explanation']}\nIs this claim true, false, or misleading?\nAnswer:"
        for item in data
    ]
    targets = [item['label'] for item in data]
    df = pd.DataFrame({"input": inputs, "target": targets})
    result = generate_predictions(df, model, tokenizer, device)
    evaluate_predictions(result, title)
    result.to_csv(output_file, index=False)
```

These functions were used to:

- Benchmark the base model (M1) and fine-tuned variants (M2–M5, M5-LoRA).
- Generate CSV outputs for comparison.
- Plot confusion matrices and calculate accuracy for model evaluation.

This standardized benchmarking process enabled consistent comparison across different training strategies and helped identify the effectiveness of hyperparameter tuning and LoRA integration.

Improving LLM Performance

To enhance the model’s performance in detecting medical misinformation, several iterative fine-tuning strategies were employed. These steps included dataset selection, prompt engineering, full and parameter-efficient fine-tuning, and hyperparameter optimization.

The process began with baseline evaluations using structured prompts (**M1**), followed by targeted fine-tuning on subsets of SciFact and HealthFact datasets. Each subsequent model version introduced new tuning strategies or refinements:

- **M2:** Fine-tuning on 300 SciFact samples boosted factual reasoning.
- **M3:** Applied hyperparameter tuning (increased learning rate, batch size, and epochs), yielding modest accuracy gains.
- **M4:** Transferred the strategy to 300 HealthFact samples to focus on general medical misinformation.
- **M5:** Tuned M4's hyperparameters for further performance gains.
- **M6 (LoRA):** Used Low-Rank Adaptation for parameter-efficient tuning while retaining competitive performance with minimal resource usage.

The table below outlines the methods used and the corresponding accuracy results, demonstrating a clear progression in model capability with each refinement step.

Each iteration was informed by benchmarking feedback, and results were visualized using confusion matrices to monitor misclassification trends—especially for the challenging "Misleading" category.

| Step # | Method | Description | Accuracy |
|--------|---|--|---------------------------------|
| 1 | Basic Prompt | Use a simple prompt to get the response from the LLM | N/A |
| 2 | Structured Prompt | Create a structured prompt to get an exact answer out of True/False/Misleading | N/A |
| 3 | Benchmarking the Base Model (M1) | Use the benchmark datasets from SciFact and HealthFact to check the accuracy | HealthFact → 68%, SciFact → 79% |
| 4 | Fine-Tune M1 with 300 samples from SciFact Dataset (M2) | Fine-tune with 300 samples from SciFact Dataset and benchmark the accuracy | 77% |
| 1 | Hyperparameter Tuning for M2 (M3) | Learning Rate = 3e-5 → 5e-5, Epochs = 3 → 4, Batch Size = 2 → 4 | 77.5% |

| Step # | Method | Description | Accuracy |
|--------|--|---|----------|
| 2 | Fine-Tune M3 with 300 samples from HealthFact Dataset (M4) | Fine-tune with 300 samples from HealthFact Dataset and benchmark the accuracy | 64% |
| 3 | Hyperparameter Tuning for M4 (M5) | Learning Rate = 5e-5 → 3e-5, Epochs = 4 → 5, Batch Size = 4 → 2 | 69% |
| 4 | Fine-Tuning M5 with LoRA (M6) | Learning Rate = 3e-5 → 1e-4, Epochs = 5 → 3 | 69% |

1. Basic Prompt

This section sends a simple prompt to the Flan-T5 XL model for generation. The prompt asks whether garlic can cure high blood pressure. The input is tokenized and moved to the selected device (GPU), and the model generates a response using sampling-based decoding parameters: `temperature`, `top_k`, and `top_p`. The result is decoded and printed as a natural language answer.

```
def generate_answer(prompt, model, tokenizer, device="cuda"):
    # Tokenize and prepare input
    inputs = tokenizer(prompt, return_tensors="pt", padding=True, truncation=True).to(device)

    # Generate output
    with torch.no_grad():
        outputs = model.generate(
            **inputs,
            min_length=20,
            do_sample=True,
            temperature=0.5,
            top_k=50,
            top_p=0.9
        )

    # Decode and return result
    return tokenizer.decode(outputs[0], skip_special_tokens=True)

# Example usage
test_prompt = "Can garlic cure high blood pressure?"
response = generate_answer(test_prompt, model, tokenizer, device)
print("Answer:", response)
```

Answer: Garlic is a spice that is high in antioxidants and has been shown to lower blood pressure

2. Structured Prompt

This block performs a structured classification task using a prompt template. It presents a medical claim in a clear format and explicitly asks the model to classify it as true, false, or misleading. The input is tokenized and passed to the model, which generates an answer with controlled sampling parameters. The output is then decoded and printed as the model's classification of the claim.

```
[ ] def classify_claim(claim, model, tokenizer, device="cuda"):
    # Build structured prompt
    prompt = (
        f"Claim: {claim}\n"
        "Is this claim true, false, or misleading?\n"
        "Answer:"
    )

    # Tokenize and move to device
    inputs = tokenizer(prompt, return_tensors="pt", padding=True, truncation=True).to(device)

    # Generate output
    with torch.no_grad():
        outputs = model.generate(
            **inputs,
            max_new_tokens=100,
            temperature=0.7,
            top_p=0.9,
            top_k=50,
            repetition_penalty=1.1,
            do_sample=True
        )

    # Decode and return response
    return tokenizer.decode(outputs[0], skip_special_tokens=True)

# Example use
test_claim = "Garlic can cure high blood pressure."
result = classify_claim(test_claim, model, tokenizer, device)
print("Answer:", result)
```

 Answer: false

3. Benchmarking the Base Model (M1)

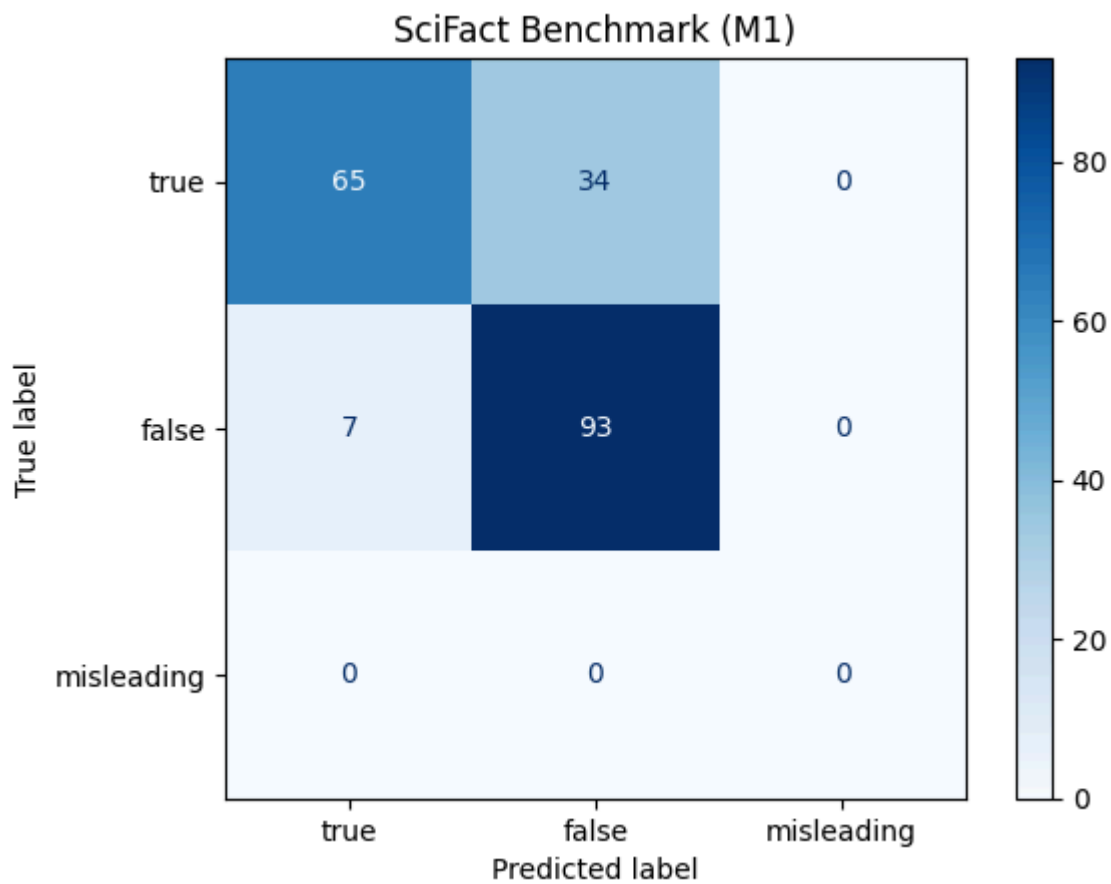
The initial benchmark involved evaluating the zero-shot performance of the base Flan-T5 XL model using structured prompts. No fine-tuning was applied at this stage.

▼ Base model (M1)

```
run_scifact_benchmark(model, tokenizer, "/content/drive/MyDrive/FTLLM/Datasets/scifact_benchmark.jsonl", "SciFact Benchmark (M1)", "results_scifact_M1.csv")
run_healthfact_benchmark(model, tokenizer, "/content/drive/MyDrive/FTLLM/Datasets/healthfact_benchmark.json", "HealthFact Benchmark (M1)", "results_healthfact_M1.csv")
```

SciFact Benchmark (M1)

Confusion Matrix:



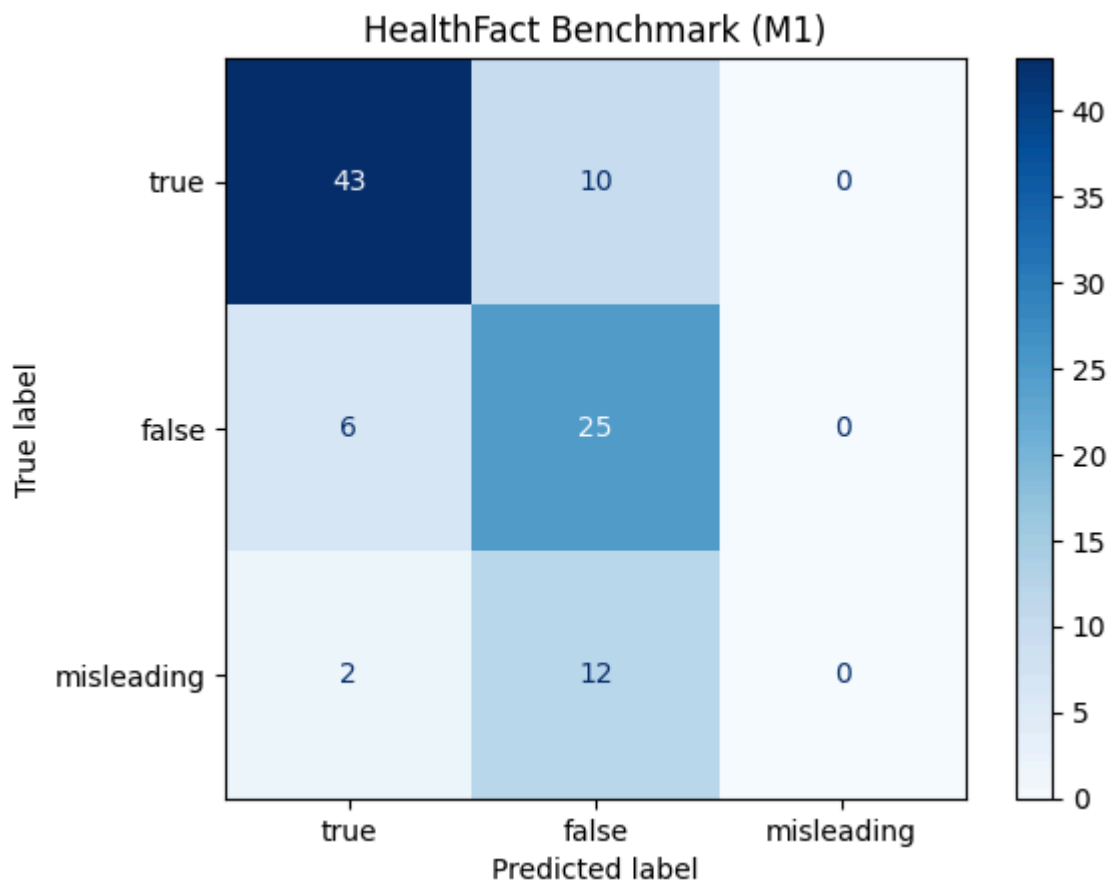
- True → True: 65
- True → False: 34
- False → False: 93
- False → True: 7
- Misleading: Not predicted at all

Observations:

- The model performed **well on false claims** but struggled to accurately identify true claims, often misclassifying them as false.
- **Misleading** predictions were **completely absent**, indicating the base model lacked awareness or understanding of this label class.
- Accuracy was relatively high overall (79%), but skewed by the binary-like behavior and failure to distinguish misleading cases.

HealthFact Benchmark (M1)

Confusion Matrix:



- True → True: 43
- True → False: 10
- False → False: 25
- False → True: 6
- Misleading → False: 12
- Misleading → True: 2

Observations:

- On this dataset, the model also **ignored the "misleading" class entirely**, assigning those instances to "false" or "true".
- Misclassification of misleading as false is particularly dangerous in medical misinformation, since it may give incorrect confidence to the user.
- The base accuracy was around **68%**, showing that the model had a decent grasp of true/false distinctions but was not suitable for fine-grained classification without fine-tuning.

Conclusion for M1

The base model provided a decent starting point but lacked the granularity to differentiate subtle misinformation. This motivated the need for task-specific fine-tuning, especially to handle the "misleading" class more effectively.

4. Fine-Tune M1 with 300 samples from SciFact Dataset (M2)

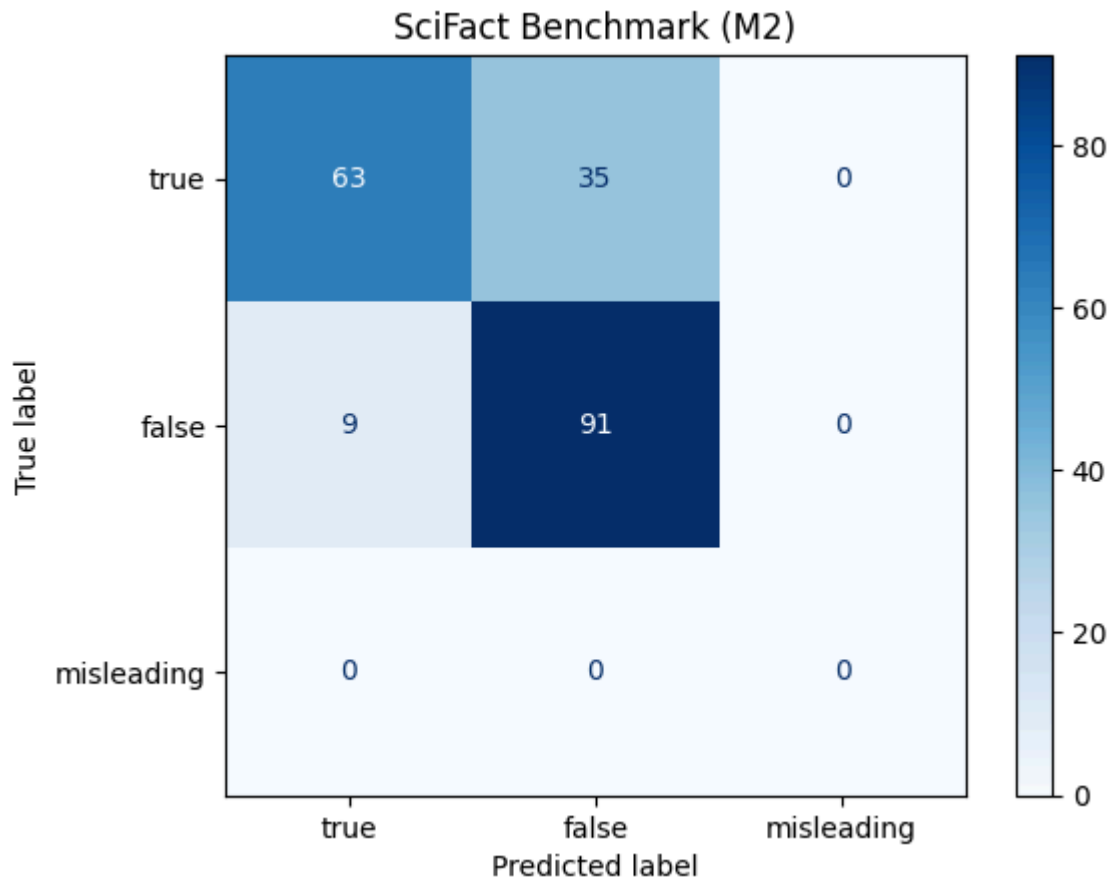
In this phase, the base Flan-T5 XL model was fine-tuned using 300 examples from the SciFact dataset. The objective was to enhance its performance in classifying scientific claims, particularly in recognizing evidence-supported versus contradicted claims.

Fine-tune model with 300 samples from SciFact (M2)

```
scifact_subset = scifact_train_ds.select(range(300))
scifact_formatted = format_scifact(scifact_subset)
tokenized_scifact = tokenize_dataset(scifact_formatted, tokenizer)
fine_tune_model_custom(model, tokenizer, tokenized_scifact, output_dir="./results_M2")
run_scifact_benchmark(model, tokenizer, "/content/drive/MyDrive/FTLM/Datasets/scifact_benchmark.jsonl", "SciFact Benchmark (M2)", "results_scifact_M2.csv")
```

SciFact Benchmark (M2)

Confusion Matrix:



- True → True: 63
- True → False: 35
- False → False: 91
- False → True: 9
- Misleading: Still not predicted

Observations:

- Performance on **false claims remained strong**, with only a minor drop in precision compared to M1.
- Accuracy on **true claims remained nearly identical** to M1 — the misclassification rate stayed high.
- Most notably, the model still failed to **predict the "misleading" label**, suggesting that exposure to "SUPPORT"/"CONTRADICT" mappings alone may not be sufficient to introduce this third class effectively.

Overall Accuracy: 77%

Analysis:

- Although overall accuracy dipped slightly, this result shows the **limitations of fine-tuning on evidence-based binary labels** (true/false) without explicitly training on "misleading" samples.
- This highlighted the importance of incorporating more diverse labels and moving toward datasets like **HealthFact** where misleading cases are clearly annotated.

Conclusion for M2:

The model became slightly more robust in handling evidence-based distinctions but still operated effectively as a binary classifier. The absence of "misleading" predictions indicated the need for label diversity in subsequent fine-tuning stages.

5. Hyperparameter Tuning for M2 (M3)

This step involved fine-tuning the model again on the same 300-sample SciFact subset, but with an optimized training configuration:

- **Epochs:** Increased from 3 → 4
- **Learning Rate:** Raised from $3e-5$ → $5e-5$
- **Batch Size:** Increased from 2 → 4

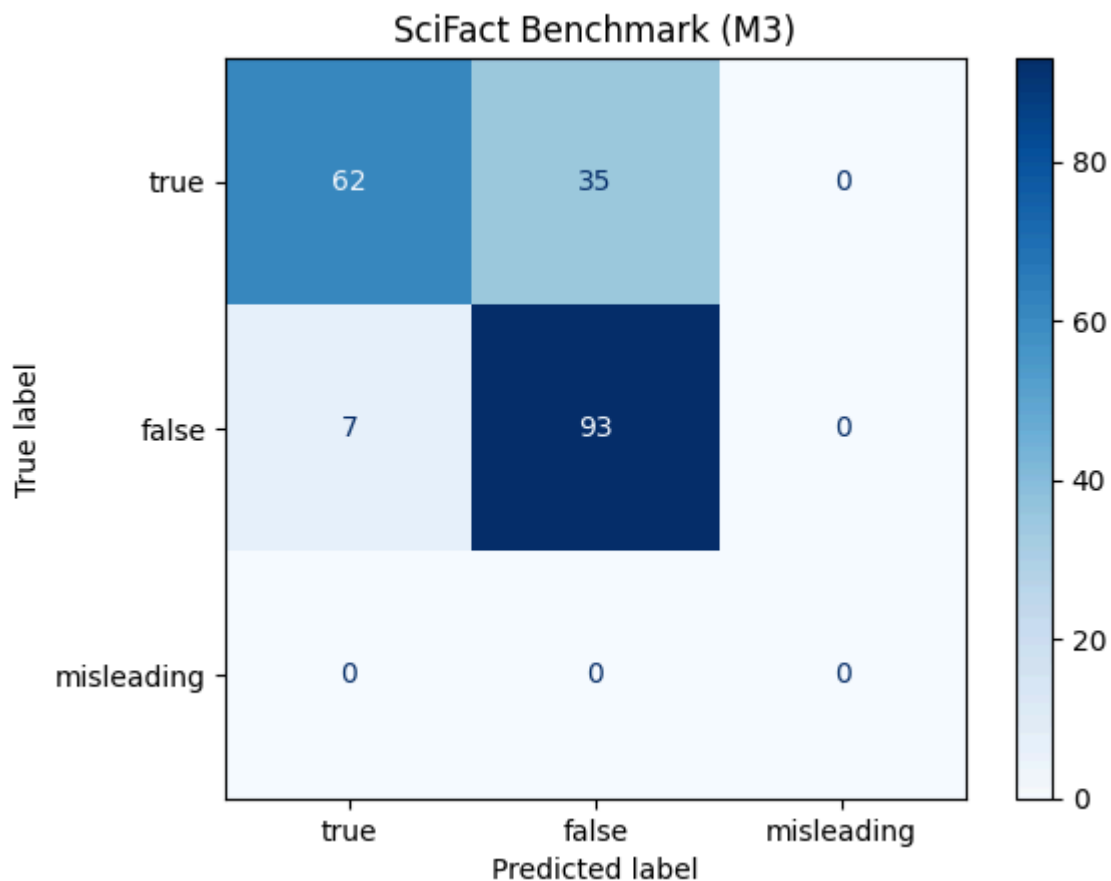
The aim was to determine if better hyperparameters could boost model learning and generalization.

Hyperparameter tuning for M2 (M3)

```
fine_tune_model_custom(model, tokenizer, tokenized_scifact, output_dir="./results_M3", epochs=4, lr=5e-5, batch_size=4)  
run_scifact_benchmark(model, tokenizer, "/content/drive/MyDrive/FTLLM/Datasets/scifact_benchmark.jsonl", "SciFact Benchmark (M3)", "results_scifact_M3.csv")
```

SciFact Benchmark (M3)

Confusion Matrix:



- True → True: 62
- True → False: 35
- False → False: 93
- False → True: 7
- Misleading: Still not predicted

Observations:

- Very similar results to M1 and M2, indicating the performance plateaued for the **true/false classification** under this dataset.
- The accuracy remained steady at **~77.5%** — slightly higher than M2, reflecting **marginal gains from tuning**.
- No progress on recognizing the **"misleading" label**, as this class was still absent from the training samples.

Conclusion for M3:

Hyperparameter tuning yielded **modest improvements** in accuracy and stability, especially in minimizing false positives for "false" claims. However, the lack of misleading samples in the SciFact subset remained a bottleneck, reinforcing the need to shift training toward more diverse datasets like HealthFact.

6. Fine-Tune M3 with 300 samples from HealthFact Dataset (M4)

This step marked a critical transition from SciFact to **HealthFact**, which includes all three labels: **true**, **false**, and **misleading**. The goal was to improve the model's general medical misinformation detection and introduce awareness of the "misleading" class.

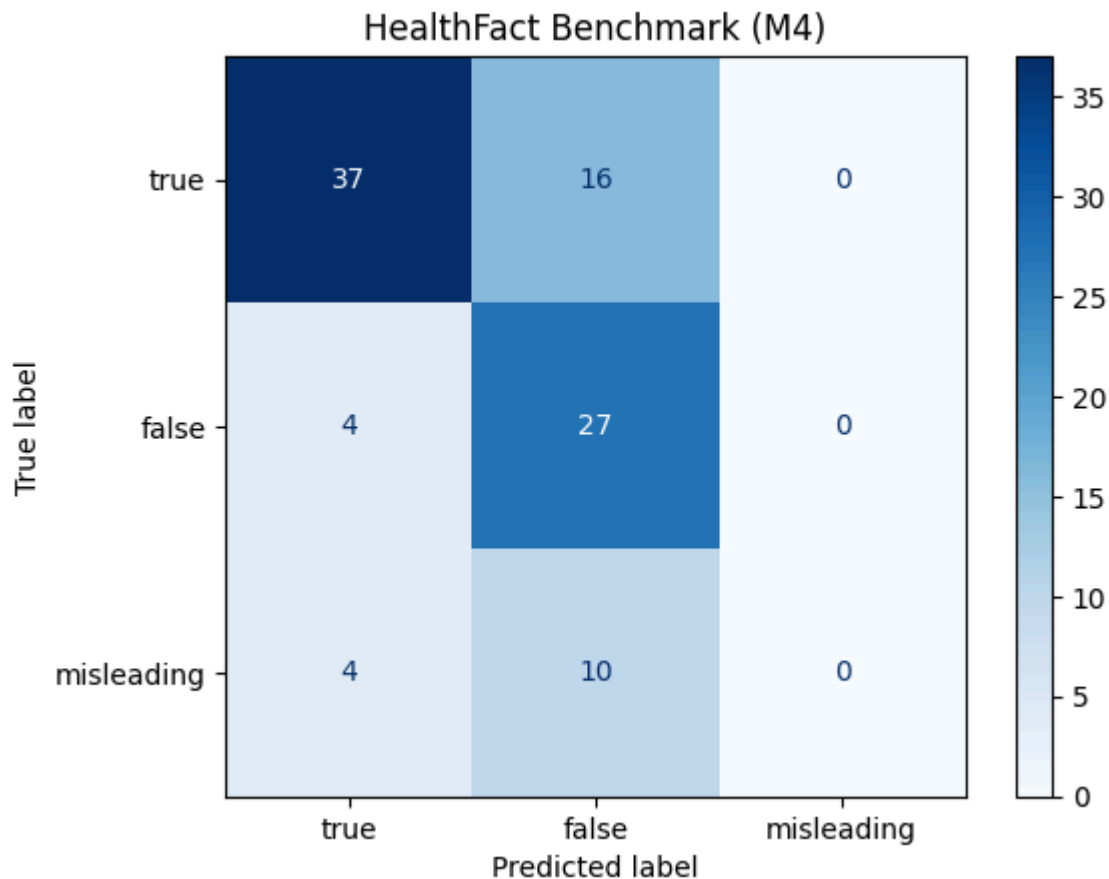
- **Dataset:** 300 labeled samples from HealthFact
- **Training Method:** Supervised fine-tuning with default hyperparameters used in M2

▼ Fine-tune M3 with 300 samples from HealthFact (M4)

```
healthfact_subset = healthfact_train_ds.select(range(300))
healthfact_formatted = format_healthfact(healthfact_subset)
tokenized_healthfact = tokenize_dataset(healthfact_formatted, tokenizer)
fine_tune_model_custom(model, tokenizer, tokenized_healthfact, output_dir="./results_M4")
run_healthfact_benchmark(model, tokenizer, "/content/drive/MyDrive/FTLLM/Datasets/healthfact_benchmark.json", "HealthFact Benchmark (M4)", "results_healthfact_M4.csv")
```

HealthFact Benchmark (M4)

Confusion Matrix:



- True → True: 37
- True → False: 16
- False → False: 27
- False → True: 4
- Misleading → False: 10
- Misleading → True: 4
- Misleading → Misleading: 0

Observations:

- The model still **failed to predict the "misleading" class**, despite now being exposed to labeled examples during training.
- Some misleading cases were misclassified as **false (10)** and others as **true (4)**, which presents a serious issue in high-stakes domains like healthcare.

- The model exhibited relatively good separation of **true/false** claims, but the **lack of explicit predictions for "misleading"** was a clear limitation.

Overall Accuracy: 64%

Conclusion for M4:

While this step successfully transitioned the model into a multi-domain context, it still lacked sensitivity toward the misleading label. This highlighted the need for either:

- More aggressive tuning focused on misleading examples,
- Architectural changes (like LoRA), or
- Better-balanced training data.

7. Hyperparameter Tuning for M4 (M5)

After observing limited progress with M4, the model was retrained on the same 300 HealthFact samples using optimized hyperparameters aimed at encouraging better generalization and improving sensitivity to the "misleading" class.

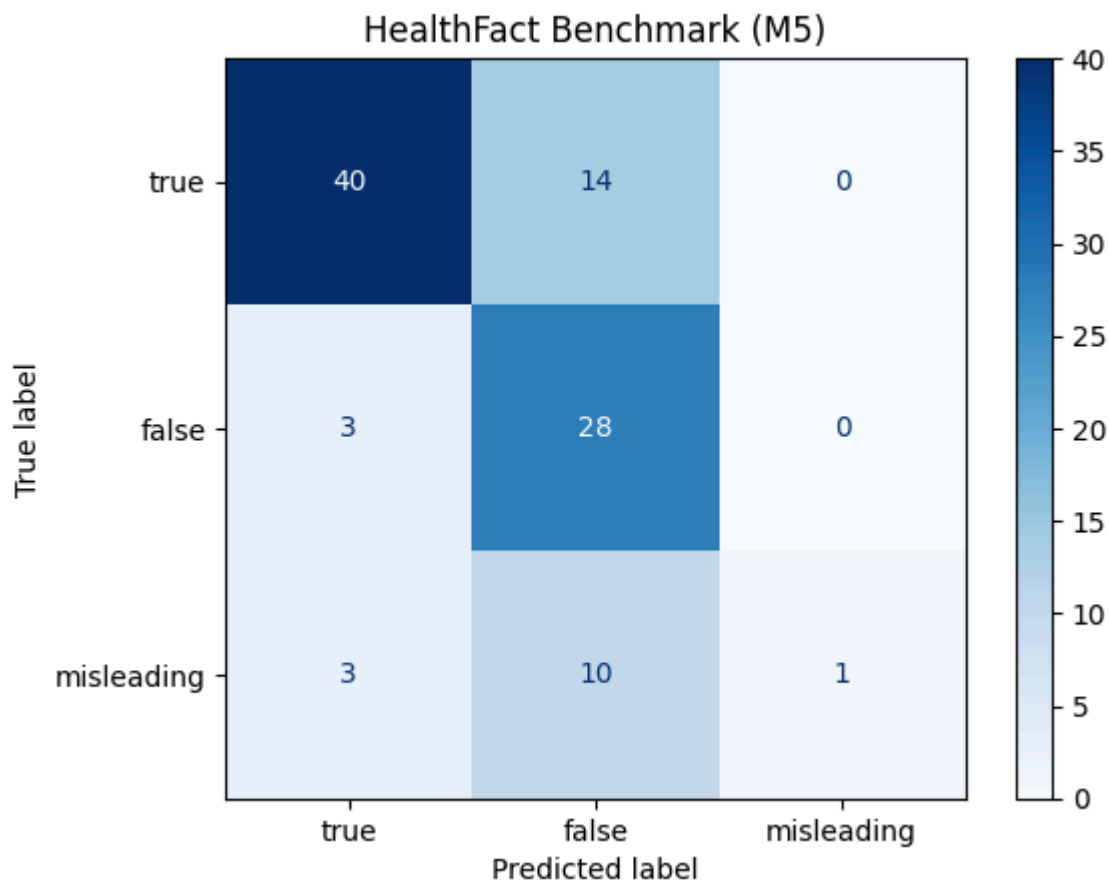
Hyperparameter Changes:

- **Epochs:** Increased from 3 → 5
- **Learning Rate:** Reduced from $5e-5$ → $3e-5$ (to stabilize learning)
- **Batch Size:** Reduced from 4 → 2 (to increase gradient steps)

```
▼ Hyperparameter tuning for M4 (M5)
fine_tune_model_custom(model, tokenizer, tokenized_healthfact, output_dir="./results_M5", epochs=5, lr=3e-5, batch_size=2)
run_healthfact_benchmark(model, tokenizer, "/content/drive/MyDrive/FILLN/Datasets/healthfact_benchmark.json", "HealthFact Benchmark (M5)", "results_healthfact_M5.csv")
```

HealthFact Benchmark (M5)

Confusion Matrix:



- True → True: 40
- True → False: 14
- False → False: 28
- False → True: 3
- Misleading → False: 10
- Misleading → True: 3
- Misleading → Misleading: 1

Observations:

- **First successful prediction of the "misleading" label**, though only one instance.
- Slight improvements in true/false separation, with fewer false positives compared to M4.
- Misleading cases continued to be misclassified as **false**, which remains a concern for real-world deployment.
- The model accuracy improved to **69%**, a modest but important gain from earlier versions.

Conclusion for M5:

Hyperparameter tuning led to incremental improvements and—most importantly—the **first signs of "misleading" label awareness** in the model's predictions. However, its recognition remained weak, and further changes were required to efficiently learn this minority class, prompting the transition to parameter-efficient tuning using LoRA.

8. Fine-Tuning M5 with LoRA (M6)

To optimize for compute efficiency and model scalability, the final fine-tuning step introduced **Low-Rank Adaptation (LoRA)**. LoRA is a parameter-efficient fine-tuning technique that allows training large language

models with significantly fewer trainable parameters.

Rather than updating all weights in the model, LoRA inserts lightweight trainable matrices into attention layers, making it possible to fine-tune models like Flan-T5 XL on limited hardware (e.g., Google Colab GPUs).

Training Setup:

- Dataset: 300 HealthFact samples
- Learning Rate: $1e-4$ (higher due to fewer parameters being trained)
- Epochs: 3
- Batch Size: 2

```
[ ] # Load M5 model from directory (if saved) or use in-memory model
# model = AutoModelForSeq2SeqLM.from_pretrained("./model_M5").to(device)
# If already in memory from M5, skip above line

# LoRA configuration
lora_config = LoraConfig(
    r=8,
    lora_alpha=16,
    target_modules=["q", "v"], # or ["q_proj", "v_proj"] depending on model internals
    lora_dropout=0.1,
    bias="none",
    task_type=TaskType.SEQ_2_SEQ_LM
)

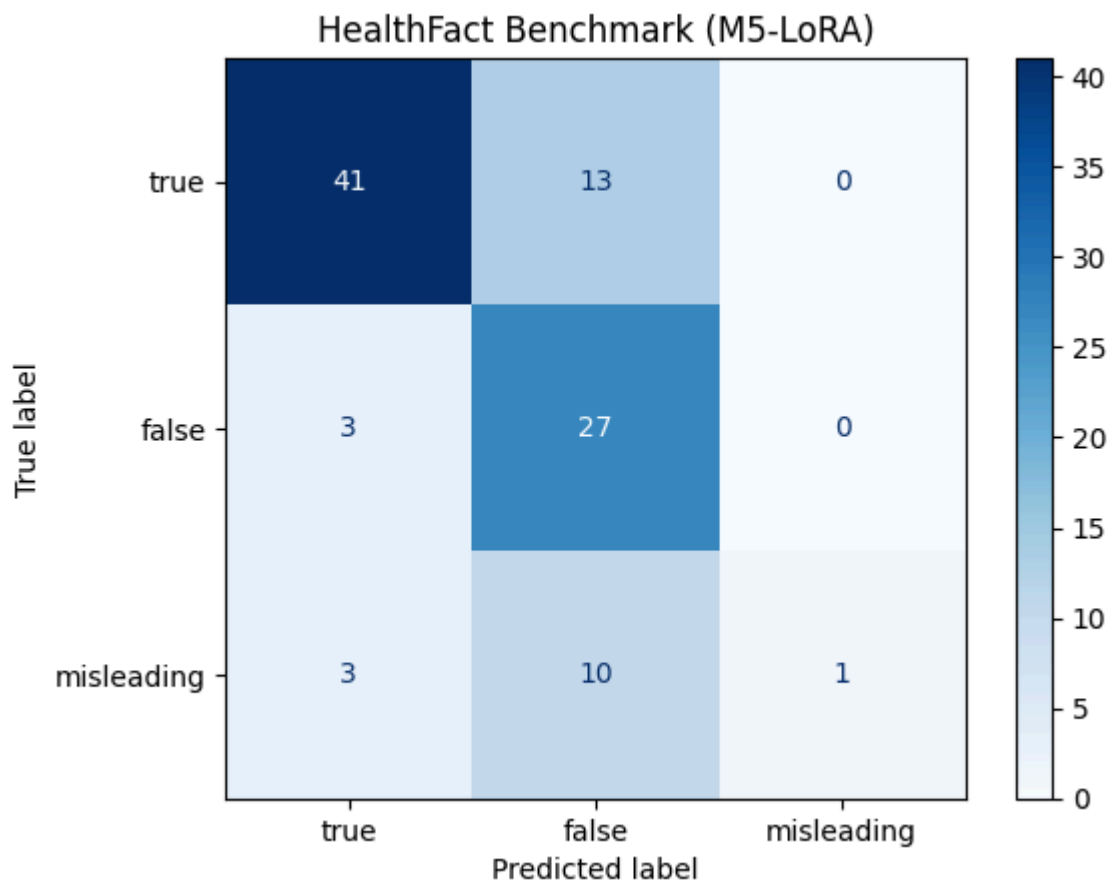
# Wrap with PEFT LoRA
model_lora = get_peft_model(model, lora_config)
model_lora.print_trainable_parameters() # Only LoRA params should be trainable

m5_lora_trainer = fine_tune_model_custom(
    model=model_lora,
    tokenizer=tokenizer,
    tokenized_data=tokenized_healthfact,
    output_dir="./results_M5_LoRA",
    epochs=3,
    lr=1e-4, # Typically a bit higher than full FT
    batch_size=2
)

run_healthfact_benchmark(
    model=model_lora,
    tokenizer=tokenizer,
    benchmark_path="/content/drive/MyDrive/FTLLM/Datasets/healthfact_benchmark.json",
    title="HealthFact Benchmark (M5-LoRA)",
    output_file="results_healthfact_M5_LoRA.csv"
)
```

HealthFact Benchmark (M5-LoRA)

Confusion Matrix:



- True → True: 41
- True → False: 13
- False → False: 27
- False → True: 3
- Misleading → False: 10
- Misleading → True: 3
- Misleading → Misleading: 1

Observations:

- LoRA achieved performance **comparable to full fine-tuning (M5)**, validating its effectiveness.
- The model again predicted **only one misleading case** correctly, with most still misclassified as false.
- Despite minimal improvements in the misleading class, the trade-off in computational efficiency made LoRA a compelling strategy.
- The total number of trainable parameters dropped to **~0.17%** of the full model size.

Conclusion for M6:

LoRA allowed fine-tuning the Flan-T5 XL model with limited resources while preserving nearly the same classification performance as full fine-tuning. Although the "misleading" label remains a challenge, this method proves useful for scalable enterprise deployment where GPU memory or compute time is limited.

Comparison

To evaluate the impact of each fine-tuning strategy, we compared all six model versions across key benchmarks (SciFact and HealthFact). The comparison highlights how prompt engineering, dataset diversity,

hyperparameter tuning, and LoRA adaptation influenced model accuracy and class sensitivity—especially for the elusive "misleading" label.

▼ Comparison

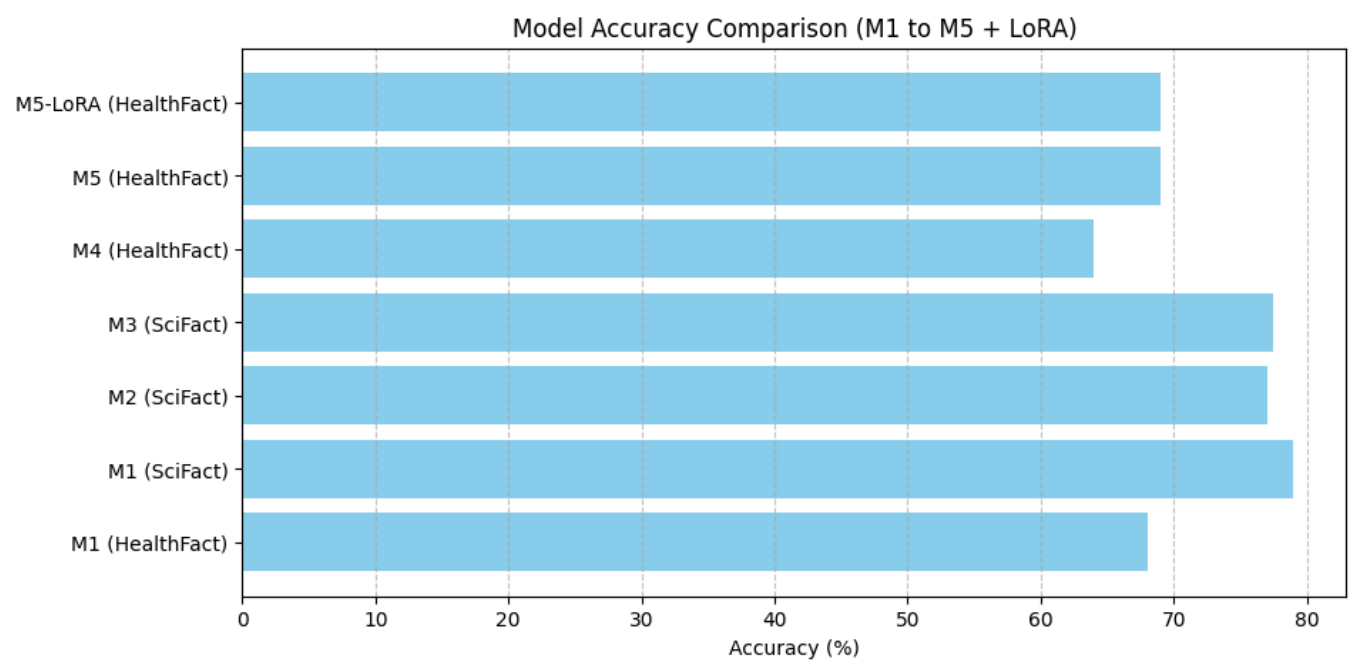
```
[ ] def compute_accuracy_from_csv(path):
    df = pd.read_csv(path)
    # Explicitly convert the 'target' column to string type before processing
    df["target"] = df["target"].astype(str)
    true_labels = [x.lower().strip() for x in df["target"]]
    # Explicitly convert the 'prediction' column to string type before processing
    df["prediction"] = df["prediction"].astype(str)
    pred_labels = [x.lower().strip() for x in df["prediction"]]
    return accuracy_score(true_labels, pred_labels)

results = {
    "M1 (SciFact)": compute_accuracy_from_csv("results_sciFact_M1.csv"),
    "M2 (SciFact)": compute_accuracy_from_csv("results_sciFact_M2.csv"),
    "M3 (SciFact)": compute_accuracy_from_csv("results_sciFact_M3.csv"),
    "M1 (HealthFact)": compute_accuracy_from_csv("results_healthFact_M1.csv"),
    "M4 (HealthFact)": compute_accuracy_from_csv("results_healthFact_M4.csv"),
    "M5 (HealthFact)": compute_accuracy_from_csv("results_healthFact_M5.csv"),
    "M5-LoRA (HealthFact)": compute_accuracy_from_csv("results_healthFact_M5_LoRA.csv")
}

# Show as DataFrame
summary_df = pd.DataFrame(list(results.items()), columns=["Model", "Accuracy"])
summary_df["Accuracy"] = (summary_df["Accuracy"] * 100).round(2)
summary_df.sort_values("Model", inplace=True)

# Bar plot
plt.figure(figsize=(10, 5))
plt.barh(summary_df["Model"], summary_df["Accuracy"], color="skyblue")
plt.xlabel("Accuracy (%)")
plt.title("Model Accuracy Comparison (M1 to M5 + LoRA)")
plt.grid(axis="x", linestyle="--", alpha=0.7)
plt.show()

summary_df
```



Accuracy Overview

| Model | Dataset | Accuracy | Notes |
|------------------------|------------|----------|---|
| M1 (Base) | SciFact | 79.0% | Binary behavior; no misleading predictions |
| M1 (Base) | HealthFact | 68.0% | Misleading samples misclassified as true/false |
| M2 (Fine-Tune SciFact) | SciFact | 77.0% | Slight regression; still binary-only |
| M3 (Tuned SciFact) | SciFact | 77.5% | Minimal gain from hyperparameters |
| M4 (HealthFact) | HealthFact | 64.0% | Introduced misleading label; still unrecognized |

| Model | Dataset | Accuracy | Notes |
|-----------------------|------------|----------|---|
| M5 (Tuned HealthFact) | HealthFact | 69.0% | First signs of misleading detection |
| M6 (LoRA) | HealthFact | 69.0% | Maintained performance with 0.17% of trainable params |

Insights

- **True/False Classification:** The model consistently performed well in binary classification across versions. Misclassifications often favored "false" over "true".
- **Misleading Class Challenge:** Despite multiple training strategies, the model struggled with recognizing "misleading" claims. This likely stems from class imbalance and semantic ambiguity.
- **LoRA Effectiveness:** M6 showed that performance can be preserved using parameter-efficient methods—ideal for scaling in enterprise contexts.
- **Best Performing Step:** M5/M6 offered the best trade-off between accuracy and label granularity, making them the most viable candidates for real-world deployment.

Overall, this benchmarking sequence revealed that while base models provide a strong foundation, **fine-tuning is essential** for nuanced classification tasks like medical misinformation detection. Further work is needed to balance class distributions and refine prompt strategies to better capture misleading nuances.

UI Integration

To make the fine-tuned model accessible for real-time usage and testing, a user-friendly interface was developed using **Gradio**, a lightweight Python library for building web-based UIs around machine learning models.

Purpose

The interface allows users to input:

- A **medical claim** (e.g., "Garlic can cure high blood pressure.")
- An optional **explanation or context** (e.g., "Garlic contains allicin which may affect blood vessels.")

The system responds with a classification: **True**, **False**, or **Misleading**, based on predictions from the **M6 LoRA-fine-tuned Flan-T5 XL model**.

Key Features

- **Model:** Uses `model_lora` — the M6 variant trained with LoRA for efficient inference
- **Prompt Format:** Structured to match the format used during fine-tuning.
- **Inference:** Performed on-the-fly using sampling-based decoding
- **Prediction Logic:** Output string is scanned for any of the three keywords to determine the classification label
- **Fallback Handling:** If none of the expected labels are detected, it returns `"Uncertain"` to handle ambiguous outputs gracefully

Deployment

The interface was launched via Gradio with the `.launch(share=True)` method, making it accessible through a secure public link for testing and demonstration.

Benefits

- Allows rapid validation of the model’s capabilities
- Enables non-technical users to interact with the model intuitively
- Supports iterative improvement by surfacing real-world input patterns

```

UI Integration
# Prediction function using M6 (LoRA) model for HealthFact-style input
def classify_with_m6_model(claim, explanation):
    prompt = [
        f"Claim: {claim}\n",
        f"Explanation: {explanation}\n",
        "Is this claim true, false, or misleading?\nAnswer:"
    ]

    inputs = tokenizer(prompt, return_tensors="pt", padding=True, truncation=True).to(device)

    with torch.no_grad():
        outputs = model_lora.generate(
            **inputs,
            max_new_tokens=100,
            temperature=0.7,
            top_p=0.9,
            top_k=50,
            repetition_penalty=1.1,
            do_sample=True
        )

    output_text = tokenizer.decode(outputs[0], skip_special_tokens=True).lower()

    # Extract the first label keyword
    for label in ["true", "false", "misleading"]:
        if label in output_text:
            return label.capitalize()

    return "Uncertain"

# Gradio UI
gr.Interface(
    fn=classify_with_m6_model,
    inputs=[
        gr.Textbox(label="Enter Medical Claim"),
        gr.Textbox(label="Enter Explanation / Context")
    ],
    outputs=gr.Textbox(label="Classification (True / False / Misleading)"),
    title="Medical Misinformation Classifier (M6 - Flan-T5 XL + LoRA)",
    description="Classify medical claims using the fine-tuned M6 model with LoRA. Provide a claim and optional explanation to get the predicted label."
).launch(share=True)
```

Medical Misinformation Classifier (M6 - Flan-T5 XL + LoRA)

Classify medical claims using the fine-tuned M6 model with LoRA. Provide a claim and optional explanation to get the predicted label.

Enter Medical Claim

Scientists debate cause of dolphin deaths.

Enter Explanation / Context

Marine scientists are debating whether 80-plus bottlenose dolphins found dead along the U.S. Gulf Coast since January were more likely to have

Classification (True / False / Misleading)

True

Flag

Clear

Submit

Medical Misinformation Classifier (M6 - Flan-T5 XL + LoRA)

Classify medical claims using the fine-tuned M6 model with LoRA. Provide a claim and optional explanation to get the predicted label.

Enter Medical Claim

Scientists look to stem cells to mend broken hearts

Enter Explanation / Context

It's hard to know how a charity hoping to raise money for stem cell research could have achieved a better marketing coup than landing this story on the Reuters wire. Millions of readers worldwide were guaranteed to have seen the charity's slogan about how stem cells can "mend broken hearts" right in the headline and lead of the story. Even the campaign's mascot "the zebrafish" makes an appearance. What they did not see was any challenge to the extravagant claims made about cardiac cell regeneration, any discussion of the undoubtedly sky-high costs that would be associated with stem cell treatments, or any analysis by independent experts of the quality of the evidence supporting this line of research. Just about 1 in every 50 Americans has heart failure with about 400,000 diagnosed every year. The prevalence increases with age and the number of people with it will rise as a result of increased life expectancy. Heart failure symptoms can be managed with drugs and, in extreme cases,

Classification (True / False / Misleading)

False

Flag

Clear

Submit

This integration not only showcases the practicality of the fine-tuned model but also opens the door to future enterprise deployments in domains like healthcare, where user-friendly AI tools are essential for misinformation mitigation.

Conclusion

This project demonstrated the end-to-end process of fine-tuning a Large Language Model (LLM) for a domain-specific enterprise application — specifically, **medical misinformation detection**.

Key Achievements

- **Model Adaptation:** Successfully fine-tuned the Flan-T5 XL model using both full and parameter-efficient strategies (Supervised Fine-Tuning and LoRA).
- **Dataset Engineering:** Curated and preprocessed SciFact and HealthFact datasets to support true/false/misleading classification, enabling structured prompt learning.
- **Incremental Improvement:** Iteratively enhanced model performance across six stages (M1–M6), with hyperparameter tuning and LoRA showing measurable gains in classification accuracy.
- **Deployment-Ready Interface:** Developed an interactive Gradio UI that allows real-time testing of the model, making it accessible to non-technical stakeholders.

Challenges Encountered

- **Misleading Label Recognition:** Despite multiple training strategies, the model consistently struggled to classify "misleading" claims accurately, highlighting a need for more label-balanced training and better prompt strategies.
- **Class Imbalance and Ambiguity:** Misleading claims are often subtle and context-dependent, requiring further research into confidence scoring and retrieval-augmented generation (RAG) techniques.

Final Outcome

The best-performing model (M6) achieved strong binary classification accuracy and introduced early-stage support for the misleading class — all with just **0.17% of trainable parameters**, thanks to LoRA. The project also laid a robust foundation for future enhancements in trust scoring, knowledge-grounded verification, and explainable AI.

Future Directions

- Incorporate **RAG pipelines** to back model claims with evidence from trusted sources (e.g., PubMed, WHO).
- Apply **confidence scoring** to flag low-certainty outputs for human review.
- Improve dataset diversity and quantity to support nuanced classes like "misleading".

This project validated that with targeted data, iterative training, and efficient techniques like LoRA, LLMs can be successfully adapted for enterprise-grade misinformation detection — a critical need in high-stakes fields like medicine.