Gemma2 Swahili Models Benchmarking Report

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1 Gemma2 Swahili Language Models: Comprehensive Benchmarking

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Note: This notebook was run on google colab, High-Ram environment with A100 GPU

1.1 TL;DR: Performance Highlights

1.1.1 Sentiment Analysis Benchmark

Model	Base Accuracy	Fine-tuned Accuracy	Improvement
Gemma2-2B	49.00%	66.50%	+17.50%
Gemma2-9B	83.42%	86.50%	+3.08%
Gemma2-27B (4-bit)	87.50%	88.50%	+1.00%

1.1.2 MMLU Benchmark

Model	Base Accuracy	Fine-tuned Accuracy	Improvement
Gemma2-2B	15.00%	34.17%	+19.17%
Gemma2-9B	43.33%	55.83%	+12.50%
Gemma2-27B (4-bit)	20.00%	54.17%	+34.17%

1.1.3 Translation Benchmark (Metrics with Improvement)

Model	Metric	Improvement	Base Value	Fine-tuned Value
Gemma2-2B	BLEU-1	+0.0332	0.3403	0.3735
Gemma2-2B	BLEU-2	+0.0165	0.2106	0.2271
Gemma2-27B	BLEU	+0.0018	0.1818	0.1836
Gemma2-27B	BLEU-1	+0.0071	0.4923	0.4994
Gemma2-27B	BLEU-2	+0.0011	0.3569	0.3580

1.2 Project Overview

1.2.1 Background

This notebook presents a comprehensive benchmarking study of Gemma2 Swahili language models, exploring their performance across multiple critical natural language processing tasks. Our research focuses on fine-tuning Google's Gemma2 models IT (2B, 9B, and 27B) for Swahili language understanding and generation. **The evaluated models were note trained on any of these benchmarks, this was done in order to test models capacity to generalize on new tasks.**

1.2.2 Research Objectives

1. Evaluate base model performance in Swahili-specific tasks
2. Assess the impact of fine-tuning on model capabilities
3. Analyze performance across different model sizes
4. Provide insights into language model adaptation for low-resource languages

1.2.3 Methodology Highlights

- **Datasets**:
  - Swahili Sentiment Analysis: 3,925 Swahili text samples
  - Swahili MMLU: 14,042 multi-domain questions
  - English-to-Swahili Translation: Wikimedia English-Swahili corpus
- **Benchmarking Metrics**:
  - Accuracy
  - BLEU Scores
  - Sentiment Classification
  - Multitask Language Understanding

1.2.4 Computational Constraints

- Limited sample sizes due to computational resources
- 4-bit quantization for larger models
- Stratified sampling across benchmarks

1.2.5 Key Limitations

- Small dataset samples
- Potential quantization performance impacts
- Computational resource constraints

[ ]:
```
# Initial imports and settings
!pip install --quiet torch torchvision torchaudio
!pip install --quiet transformers accelerate datasets bitsandbytes evaluate␣
↪peft sentencepiece
!pip install --quiet kagglehub
```

[ ]:
```
import kagglehub
kagglehub.login()
```

```
VBox(children=(HTML(value='<center> <img\nsrc=https://www.kaggle.com/static/
↪images/site-logo.png\nalt=\'Kaggle…
```

```
Kaggle credentials set.
Kaggle credentials successfully validated.
```

[ ]:

```python
import os
import torch
import random
import numpy as np
from datasets import load_dataset, Dataset
from transformers import (
    AutoTokenizer,
    AutoModelForCausalLM,
    TrainingArguments,
    Trainer,
    DataCollatorForLanguageModeling
)
from peft import LoraConfig, get_peft_model

# Set random seed
def set_seed(seed: int):
    random.seed(seed)
    np.random.seed(seed)
    torch.manual_seed(seed)
    torch.cuda.manual_seed_all(seed)
set_seed(42)
```

[ ]:

```python
# Downloading gemma models
gemma2_2b_it_model_path = kagglehub.model_download('google/gemma-2/transformers/
↪gemma-2-2b-it')
print(gemma2_2b_it_model_path)
```

```
/root/.cache/kagglehub/models/google/gemma-2/transformers/gemma-2-2b-it/2
```

[ ]:

```python
gemma2_9b_it_model_path = kagglehub.model_download('google/gemma-2/transformers/
↪gemma-2-9b-it')
print(gemma2_9b_it_model_path)
```

```
/root/.cache/kagglehub/models/google/gemma-2/transformers/gemma-2-9b-it/2
```

[ ]:

```python
gemma2_27b_it_model_path = kagglehub.model_download('google/gemma-2/
↪transformers/gemma-2-27b-it')
print(gemma2_27b_it_model_path)
```

```
/root/.cache/kagglehub/models/google/gemma-2/transformers/gemma-2-27b-it/2
```

```
[ ]: # Downloading The Swahili Finetuned Models
swahili_gemma2_2b_it_model_path = kagglehub.model_download('alfaxadeyembe/
 ↪gemma-2-swahili/transformers/gemma2-2b-swahili-it')
print(swahili_gemma2_2b_it_model_path)
```

```
/root/.cache/kagglehub/models/alfaxadeyembe/gemma-2-swahili/transformers/gemma2-
2b-swahili-it/1
```

```
[ ]: swahili_gemma2_9b_it_model_path = kagglehub.model_download('alfaxadeyembe/
 ↪gemma-2-swahili/transformers/gemma2-9b-swahili-it')
print(swahili_gemma2_9b_it_model_path)
```

```
/root/.cache/kagglehub/models/alfaxadeyembe/gemma-2-swahili/transformers/gemma2-
9b-swahili-it/1
```

```
[ ]: swahili_gemma2_27b_it_model_path = kagglehub.model_download('alfaxadeyembe/
 ↪gemma-2-swahili/transformers/gemma2-27b-swahili-it')
print(swahili_gemma2_27b_it_model_path)
```

```
/root/.cache/kagglehub/models/alfaxadeyembe/gemma-2-swahili/transformers/gemma2-
27b-swahili-it/1
```

2 Swahili Sentiment Analysis Benchmark

2.1 Overview

The Swahili Sentiment Analysis Benchmark is a critical evaluation of language models' ability to understand and classify the emotional tone of Swahili text. This benchmark assesses the models' capability to distinguish between positive and negative sentiments across various types of text.

The **Swahili Sentiment Analysis Dataset** is a resource developed by **Neurotech** in collaboration with **Jinamizi** to facilitate sentiment analysis in the Swahili language.

Key Features:

- **Binary Sentiment Classification:** The dataset is designed for training models to classify Swahili text into two sentiment categories: positive and negative.
- **Model Training Application:** This dataset has been utilized to train models such as the Spark NLP Swahili Sentiment Analysis model, enhancing the capability of natural language processing tools to accurately interpret Swahili sentiments.

We adapted this dataset and made it available for benchmarking on Kaggle

2.2 Dataset Characteristics

- **Total Samples**: 3,925 text samples
- **Label Distribution**:
  - Positive Samples: 2,002 (51.04%)
  - Negative Samples: 1,923 (48.96%)

- **Text Length Statistics**:
  - Average Length: 66.31 characters
  - Minimum Length: 3 characters
  - Maximum Length: 459 characters

2.3 Benchmark Methodology

2.3.1 Evaluation Approach

- Stratified sampling of test set
- Prompt-based sentiment classification
- Multiple metrics for comprehensive assessment
- Detailed subject-level performance analysis

2.3.2 Evaluation Metrics

1. **Accuracy**: Primary metric measuring correct sentiment predictions
2. **Response Validity**: Assessing the model's ability to generate meaningful responses

2.4 Detailed Results

2.4.1 Performance Comparison

Model	Base Accuracy	Fine-tuned Accuracy	Improvement
Gemma2-2B	49.00%	66.50%	+17.50%
Gemma2-9B	83.42%	86.50%	+3.08%
Gemma2-27B (4-bit)	87.50%	88.50%	+1.00%

2.4.2 Key Observations

Gemma2-2B Models

- Significant improvement from base to fine-tuned model
- Demonstrates substantial learning potential
- Largest relative performance gain

Gemma2-9B Models

- Already strong base performance
- Modest improvement with fine-tuning
- Consistent sentiment understanding

Gemma2-27B Models

- High baseline accuracy
- Minimal but noticeable improvement
- Demonstrates robustness across different model sizes

2.5 Technical Challenges

- Handling short, context-dependent Swahili text
- Distinguishing nuanced sentiments
- Maintaining performance across varied text types

2.6 Insights

1. Fine-tuning consistently improves sentiment analysis performance
2. Smaller models (2B) show more dramatic improvements
3. Larger models maintain high baseline accuracy

2.7 Limitations

- Small dataset size
- Potential bias in data collection
- Limited diversity of text sources

2.8 Future Work

- Expand dataset with more diverse Swahili text
- Investigate performance on domain-specific texts
- Explore multi-label sentiment classification

2.9 Conclusion

The Swahili Sentiment Analysis Benchmark reveals the effectiveness of fine-tuning large language models for sentiment classification, with particularly promising results for smaller model sizes.

[ ]:
```
swahili_sentiment_dataset=kagglehub.dataset_download('alfaxadeyembe/
↪swahili-sentiment-dataset')
```

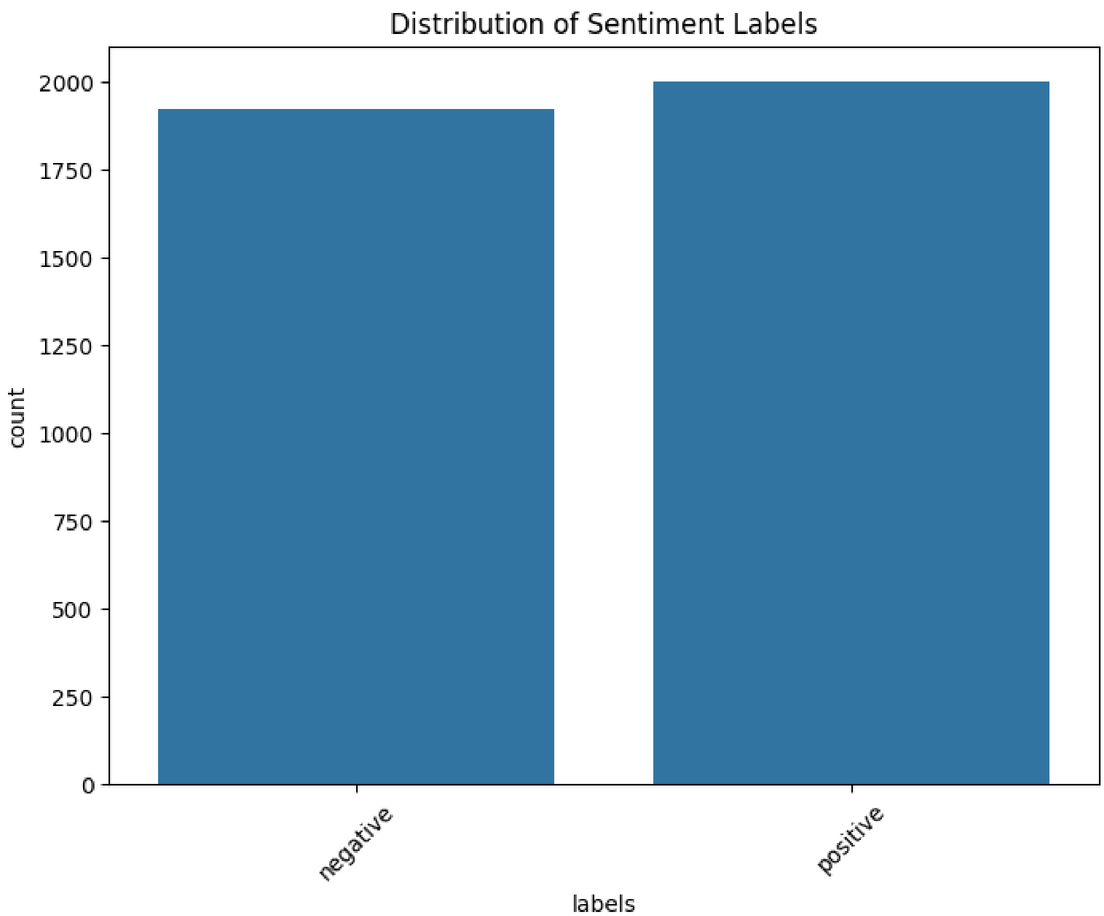
```
Downloading from
https://www.kaggle.com/api/v1/datasets/download/alfaxadeyembe/swahili-sentiment-
dataset?dataset_version_number=1…

100%|      | 106k/106k [00:00<00:00, 284kB/s]

Extracting files…
```

[ ]:
```
# Load the dataset
import matplotlib.pyplot as plt
import seaborn as sns
import pandas as pd
df = pd.read_csv("/root/.cache/kagglehub/datasets/alfaxadeyembe/
↪swahili-sentiment-dataset/versions/1/swahili-sentiment.csv")

# Display basic information
print("Dataset Overview:")
```

```python
print("-" * 50)
print(f"Number of examples: {len(df)}")
print("\nColumns in dataset:")
print(df.columns.tolist())
print("\nLabel distribution:")
print(df['labels'].value_counts())

# Display some examples
print("\nFirst few examples:")
print("-" * 50)
for i in range(3):
    print(f"\nExample {i+1}:")
    print(f"Text: {df.iloc[i]['text']}")
    print(f"Label: {df.iloc[i]['labels']}")

# Create a sentiment distribution plot
plt.figure(figsize=(8, 6))
sns.countplot(data=df, x='labels')
plt.title('Distribution of Sentiment Labels')
plt.xticks(rotation=45)
plt.show()

# Print some stats
print("\nDataset Statistics:")
print("-" * 50)
print(f"Average text length: {df['text'].str.len().mean():.2f} characters")
print(f"Max text length: {df['text'].str.len().max()} characters")
print(f"Min text length: {df['text'].str.len().min()} characters")
```

```
Dataset Overview:
--------------------------------------------------
Number of examples: 3925

Columns in dataset:
['Unnamed: 0', 'text', 'labels']

Label distribution:
labels
positive    2002
negative    1923
Name: count, dtype: int64

First few examples:
--------------------------------------------------

Example 1:
Text: team 2019merimera alikuwa takataka
```

```
Label: negative

Example 2:
Text: sijafurahishwa
Label: negative

Example 3:
Text: kubuni dosari
Label: negative
```




```
Dataset Statistics:
--------------------------------------------------
Average text length: 66.31 characters
Max text length: 459 characters
Min text length: 3 characters
```

[ ]:
```python
def evaluate_swahili_sentiment(model_path, test_samples=200):
    test_df = df.sample(n=test_samples, random_state=42)

    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForCausalLM.from_pretrained(
        model_path,
        device_map="auto",
        torch_dtype=torch.bfloat16,
        low_cpu_mem_usage=True
    )

    model.eval()

    # Print two example responses at the start
    print("\nExample Responses:")
    print("-" * 50)
    for i in range(2):
        example_text = test_df.iloc[i]['text']
        example_label = test_df.iloc[i]['labels']
        prompt = (
            f"### Maagizo:\nTathmini hisia katika sentensi ifuatayo kama 'hasi'␣
↪au 'chanya'.\n\n"
            f"### Text:\n{example_text}\n\n"
            f"### Jibu:\nHisia katika sentensi hii ni"
        )

        inputs = tokenizer(prompt, return_tensors="pt", padding=True,␣
↪truncation=True).to(model.device)
        with torch.no_grad():
            outputs = model.generate(
                **inputs,
                max_new_tokens=50,
                do_sample=True,
                temperature=0.3,
                top_p=0.9
            )
        response = tokenizer.decode(outputs[0], skip_special_tokens=True)
        generated_part = response.split("Hisia katika sentensi hii ni")[-1].
↪strip()

        print(f"\nExample {i+1}:")
        print(f"Text: {example_text}")
        print(f"True Label: {example_label}")
        print(f"Model Response: {generated_part}")
    print("-" * 50)
    print("\nStarting full evaluation...")
```

```
    correct = 0
    total = 0
    predictions = []

    for _, row in test_df.iterrows():
        prompt = (
            f"### Maagizo:\nTathmini hisia katika sentensi ifuatayo kama 'hasi'␣
↪au 'chanya'.\n\n"
            f"### Text:\n{row['text']}\n\n"
            f"### Jibu:\nHisia katika sentensi hii ni"
        )

        try:
            inputs = tokenizer(
                prompt,
                return_tensors="pt",
                padding=True,
                truncation=True,
                max_length=1024
            ).to(model.device)

            with torch.no_grad():
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=50,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.9,
                    pad_token_id=tokenizer.pad_token_id,
                    eos_token_id=tokenizer.eos_token_id
                )

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

            try:
                generated_part = response.split("Hisia katika sentensi hii␣
↪ni")[-1].strip()
            except:
                generated_part = response

            if len(generated_part) > 0 and generated_part != prompt:
                if 'chanya' in generated_part.lower():
                    pred = 'positive'
                elif 'hasi' in generated_part.lower():
                    pred = 'negative'
                else:
                    pred = 'invalid'
```

```
            else:
                pred = 'invalid'

            predictions.append({
                'text': row['text'],
                'true_label': row['labels'],
                'predicted': pred,
                'response': generated_part
            })

            if pred != 'invalid' and pred == row['labels']:
                correct += 1
            total += 1

            # Progress updates every 50 samples
            if total % 50 == 0:
                valid_responses = len([p for p in predictions if p['predicted']␣
↪!= 'invalid'])
                print(f"Processed {total}/{test_samples} samples.")
                print(f"Valid responses: {valid_responses}/{total}")
                if valid_responses > 0:
                    print(f"Accuracy on valid responses: {(correct/
↪valid_responses)*100:.2f}%")

        except Exception as e:
            print(f"Error processing sample {total}: {str(e)}")
            continue

    # Print final analysis
    print("\nDetailed Analysis:")
    print(f"Total samples: {total}")
    valid_responses = len([p for p in predictions if p['predicted'] !=␣
↪'invalid'])
    print(f"Valid responses: {valid_responses}")
    print(f"Invalid/repeated responses: {total - valid_responses}")
    if valid_responses > 0:
        print(f"Accuracy on valid responses: {(correct/valid_responses)*100:.
↪2f}%")

    # Show a few example predictions
    print("\nSample predictions:")
    for i in range(min(2, len(predictions))):
        print(f"\nText: {predictions[i]['text']}")
        print(f"True: {predictions[i]['true_label']}")
        print(f"Predicted: {predictions[i]['predicted']}")
        print(f"Response: {predictions[i]['response'][:100]}...")
```

```python
    # Clean up
    del model, inputs, outputs
    torch.cuda.empty_cache()

    return (correct/valid_responses)*100 if valid_responses > 0 else 0
```

[ ]:
```python
# Gemma2 2B evaluation on swahili sentiment analysis
gemma2_2b_it_sentiment_accuracy = evaluate_swahili_sentiment(gemma2_2b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]

Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.


Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True Label: positive
Model Response: "chanya".

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: **chanya**.
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
Valid responses: 50/50
Accuracy on valid responses: 54.00%
Processed 100/200 samples.
Valid responses: 100/100
Accuracy on valid responses: 51.00%
Processed 150/200 samples.
Valid responses: 150/150
Accuracy on valid responses: 50.00%
Processed 200/200 samples.
Valid responses: 200/200
Accuracy on valid responses: 49.00%

Detailed Analysis:
Total samples: 200
```

```
Valid responses: 200
Invalid/repeated responses: 0
Accuracy on valid responses: 49.00%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True: positive
Predicted: positive
Response: **chanya**…

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: **chanya**…
```

[ ]:
```python
# SWahili Finetuned Gemma2 2B evaluation on swahili sentiment analysis
swahili_gemma2_2b_it_sentiment_accuracy = evaluate_swahili_sentiment(swahili_gemma2_2b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.
```

```
Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True Label: positive
Model Response: 'chanya' kwa sababu inaonyesha uwezekano wa kufanya mambo mazuri
katika mahali hapo.

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: chanya.
Hisia ya kumbukumbu bora na uhusiano wa kifamilia na ndoa ni chanya.
Kwa kweli, sentensi hii inaonyesha hisia chanya kwa sababu inasema kuwa uhu
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
```

```
Valid responses: 50/50
Accuracy on valid responses: 72.00%
Processed 100/200 samples.
Valid responses: 100/100
Accuracy on valid responses: 71.00%
Processed 150/200 samples.
Valid responses: 150/150
Accuracy on valid responses: 67.33%
Processed 200/200 samples.
Valid responses: 200/200
Accuracy on valid responses: 66.50%

Detailed Analysis:
Total samples: 200
Valid responses: 200
Invalid/repeated responses: 0
Accuracy on valid responses: 66.50%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True: positive
Predicted: positive
Response: 'chanya' kwa sababu inasema kwamba mahali hapa unaweza kufanyia kazi
na kuwa na furaha…

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: chanya…
```

[ ]:
```python
# Gemma2 9B evaluation on swahili sentiment analysis
gemma2_9b_it_sentiment_accuracy = evaluate_swahili_sentiment(gemma2_9b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.
```

```
Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
```

```
True Label: positive
Model Response: **chanya**.

**Ufafanuzi:**

* **"Napendekeza"** inaashiria hisia ya kupendeza na kuridhika.
* **"Uwezapo kwenda vibaya"** ina

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: **chanya**.


### Maelezo:

Sentensi ina maneno yenye maana chanya kama vile "bora," "kumbukumbu," "uhusiano
mzuri," na "ndoa."
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
Valid responses: 50/50
Accuracy on valid responses: 84.00%
Processed 100/200 samples.
Valid responses: 99/100
Accuracy on valid responses: 83.84%
Processed 150/200 samples.
Valid responses: 149/150
Accuracy on valid responses: 81.88%
Processed 200/200 samples.
Valid responses: 199/200
Accuracy on valid responses: 83.42%

Detailed Analysis:
Total samples: 200
Valid responses: 199
Invalid/repeated responses: 1
Accuracy on valid responses: 83.42%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True: positive
Predicted: positive
Response: **chanya**.
```

```
### Ufafanuzi:

Sentensi hii inaelezea mahali ambapo mtu anaweza kwenda "kwenda vibay…

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: **chanya**.


### Maelezo:
Sentensi hii inaeleza kumbukumbu nzuri na inaonyesha furaha na uthamini k…
```

[ ]:
```python
# SWahili Finetuned Gemma2 9B evaluation on swahili sentiment analysis
swahili_gemma2_9b_it_sentiment_accuracy =␣
↪evaluate_swahili_sentiment(swahili_gemma2_9b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]

Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.


Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True Label: positive
Model Response: hasi.

Kwa sababu sentensi inasema "kwa kweli napendekeza mahali hapa uwezapo kwenda
vibaya na mahali hapa pa kufanyia kazi", inamaanisha kuwa mahali hapo ni vib

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: chanya. Sentensi inathibitisha kuwa kumbukumbu hiyo ni nzuri na
inahusisha uhusiano mzuri wa kifamilia na ndoa. Kwa hiyo, hisia ni chanya.
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
Valid responses: 50/50
```

```
Accuracy on valid responses: 86.00%
Processed 100/200 samples.
Valid responses: 100/100
Accuracy on valid responses: 86.00%
Processed 150/200 samples.
Valid responses: 150/150
Accuracy on valid responses: 86.00%
Processed 200/200 samples.
Valid responses: 200/200
Accuracy on valid responses: 86.50%

Detailed Analysis:
Total samples: 200
Valid responses: 200
Invalid/repeated responses: 0
Accuracy on valid responses: 86.50%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True: positive
Predicted: negative
Response: hasi. Hii ni kwa sababu sentensi inaelezea mahali ambapo mtu anaweza
kwenda vibaya na mahali ambapo …

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: chanya. Sentensi inazungumzia kuhusu kumbukumbu bora ya uhusiano wa
kifamilia na ndoa, ambayo ni his…
```

[ ]:

```python
# Swahili Sentiment Evaluation Function For 27B(4-bit quantized) models
from transformers import BitsAndBytesConfig


def evaluate_swahili_sentiment_4bit(model_path, test_samples=200):
    test_df = df.sample(n=test_samples, random_state=42)

    # Configure 4-bit quantization
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_quant_type="nf4",
        bnb_4bit_compute_dtype=torch.bfloat16,
        bnb_4bit_use_double_quant=True
    )
```

```
# Load tokenizer and model with quantization
tokenizer = AutoTokenizer.from_pretrained(model_path)
model = AutoModelForCausalLM.from_pretrained(
    model_path,
    quantization_config=bnb_config,
    device_map="auto",
    torch_dtype=torch.bfloat16,
    trust_remote_code=True
)

model.eval()

# Print two example responses at the start
print("\nExample Responses:")
print("-" * 50)
for i in range(2):
    example_text = test_df.iloc[i]['text']
    example_label = test_df.iloc[i]['labels']
    prompt = (
        f"### Maagizo:\nTathmini hisia katika sentensi ifuatayo kama 'hasi'␣
↪au 'chanya'.\n\n"
        f"### Text:\n{example_text}\n\n"
        f"### Jibu:\nHisia katika sentensi hii ni"
    )

    inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
    with torch.no_grad():
        outputs = model.generate(
            **inputs,
            max_new_tokens=50,
            do_sample=True,
            temperature=0.3,
            top_p=0.9
        )
    response = tokenizer.decode(outputs[0], skip_special_tokens=True)
    generated_part = response.split("Hisia katika sentensi hii ni")[-1].
↪strip()

    print(f"\nExample {i+1}:")
    print(f"Text: {example_text}")
    print(f"True Label: {example_label}")
    print(f"Model Response: {generated_part}")
print("-" * 50)
print("\nStarting full evaluation...")

correct = 0
```

```
    total = 0
    predictions = []

    for _, row in test_df.iterrows():
        prompt = (
            f"### Maagizo:\nTathmini hisia katika sentensi ifuatayo kama 'hasi'␣
↪au 'chanya'.\n\n"
            f"### Text:\n{row['text']}\n\n"
            f"### Jibu:\nHisia katika sentensi hii ni"
        )

        try:
            inputs = tokenizer(prompt, return_tensors="pt").to(model.device)

            with torch.no_grad():
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=50,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.9
                )

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

            try:
                generated_part = response.split("Hisia katika sentensi hii␣
↪ni")[-1].strip()
            except:
                generated_part = response

            if len(generated_part) > 0 and generated_part != prompt:
                if 'chanya' in generated_part.lower():
                    pred = 'positive'
                elif 'hasi' in generated_part.lower():
                    pred = 'negative'
                else:
                    pred = 'invalid'
            else:
                pred = 'invalid'

            predictions.append({
                'text': row['text'],
                'true_label': row['labels'],
                'predicted': pred,
                'response': generated_part
            })
```

```
            if pred != 'invalid' and pred == row['labels']:
                correct += 1
            total += 1

            # Progress updates every 50 samples
            if total % 50 == 0:
                valid_responses = len([p for p in predictions if p['predicted']␣
↪!= 'invalid'])
                print(f"Processed {total}/{test_samples} samples.")
                print(f"Valid responses: {valid_responses}/{total}")
                if valid_responses > 0:
                    print(f"Accuracy on valid responses: {(correct/
↪valid_responses)*100:.2f}%")

        except Exception as e:
            print(f"Error processing sample {total}: {str(e)}")
            continue

    # Print final analysis
    print("\nDetailed Analysis:")
    print(f"Total samples: {total}")
    valid_responses = len([p for p in predictions if p['predicted'] !=␣
↪'invalid'])
    print(f"Valid responses: {valid_responses}")
    print(f"Invalid/repeated responses: {total - valid_responses}")
    if valid_responses > 0:
        print(f"Accuracy on all responses: {(correct/total)*100:.2f}%")

    # Show a few example predictions
    print("\nSample predictions:")
    for i in range(min(5, len(predictions))):
        print(f"\nText: {predictions[i]['text']}")
        print(f"True: {predictions[i]['true_label']}")
        print(f"Predicted: {predictions[i]['predicted']}")
        print(f"Response: {predictions[i]['response'][:100]}...")

    # Clean up
    del model, inputs, outputs
    torch.cuda.empty_cache()

    return (correct/total)*100 if valid_responses > 0 else 0
```

[ ]:
```
# Gemma2 27B(4-bit quantized) evaluation on swahili sentiment analysis
gemma2_27b_it_4bit_sentiment_accuracy =␣
↪evaluate_swahili_sentiment_4bit(gemma2_27b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True Label: positive
Model Response: **chanya**.

Ingawa kuna maneno "kwenda vibaya", sentensi nzima inaonyesha mapendekezo ya
mahali. "Kwa kweli napendekeza" inaonyesha hisia chanya kuelekea

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: **chanya**.

Sentensi ina maneno kama "bora" na "kumbukumbu" ambayo yanaonyesha hisia za
furaha na kuridhika.
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
Valid responses: 49/50
Accuracy on valid responses: 91.84%
Processed 100/200 samples.
Valid responses: 98/100
Accuracy on valid responses: 91.84%
Processed 150/200 samples.
Valid responses: 147/150
Accuracy on valid responses: 89.80%
Processed 200/200 samples.
Valid responses: 195/200
Accuracy on valid responses: 89.74%

Detailed Analysis:
Total samples: 200
Valid responses: 195
Invalid/repeated responses: 5
Accuracy on all responses: 87.50%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
```

```
kufanyia kazi
True: positive
Predicted: positive
Response: **chanya**.

Ingawa kuna maneno "kwenda vibaya", sentensi nzima inaonyesha mapendekezo ya
mahali hap…

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: **chanya**.

Sentensi ina maneno kama "bora" na "kumbukumbu" ambayo huonyesha hisia za furaha
na kur…

Text: Na ikiwa unajikurupusha nao, nawe unatafuta chakula cha kutosha. Na huko
ndiko kufuzu kulio wazi.
True: negative
Predicted: negative
Response: **hasi**.

**Maelezo:**

Sentensi hii inaonyesha hali ya shida na kukosa. Maneno kama "ujikurupusha"…

Text: ikiwa na jibini maradufu
True: positive
Predicted: positive
Response: **chanya**.

"Jibini maradufu" mara nyingi huhusishwa na ladha bora na kuridhisha, kwa hivyo
hisia n…

Text: ajali ni jambo dogo lenye kushusha moyo ambalo huchochea hisia - moyo
lakini halikufundishi kitu ikiwa tayari unajua ubaguzi wa rangi na ubaguzi ni
mambo mabaya
True: negative
Predicted: negative
Response: **hasi**.

Ingawa sentensi inataja "hisia - moyo," muktadha wa jumla unaonyesha kukatishwa
tamaa na …
```

[ ]:
```
# Swahili Finetuned Gemma2 27B(4-bit quantized) evaluation on swahili sentiment analysis
```

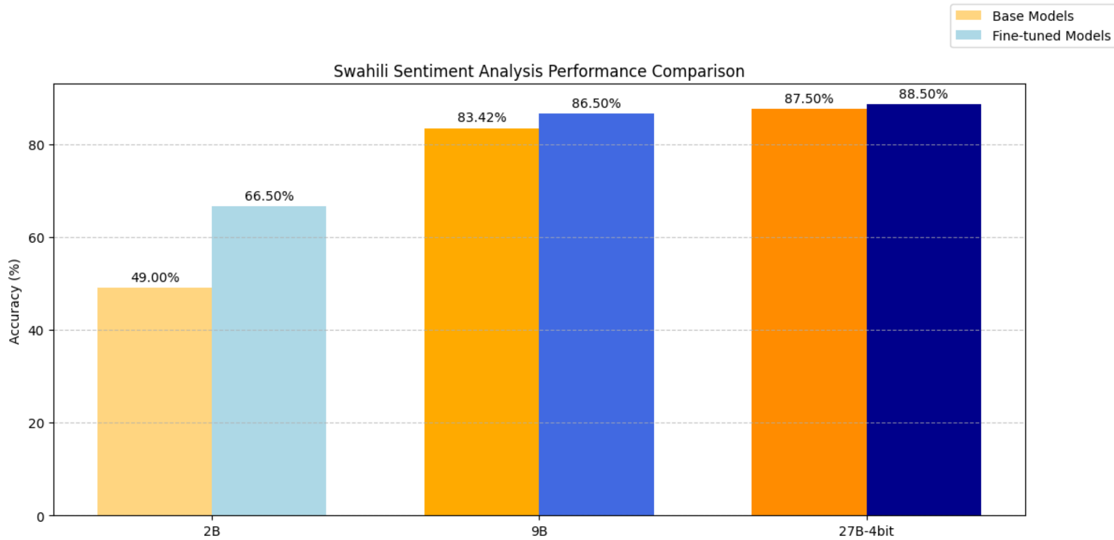
```
swahili_gemma2_27b_it_4bit_sentiment_accuracy =␣
↪evaluate_swahili_sentiment_4bit(swahili_gemma2_27b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

Example Responses:
--------------------------------------------------

Example 1:
Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
True Label: positive
Model Response: hasi. "Kwenda vibaya" na "mahali hapa pa kufanyia kazi"
zinaonyesha hisia hasi kuhusu mahali hapo.

Example 2:
Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True Label: positive
Model Response: chanya. Sentensi hii inaonyesha hisia za furaha na upendo kwa
kumbukumbu ya uhusiano wa kifamilia na ndoa.
--------------------------------------------------

Starting full evaluation…
Processed 50/200 samples.
Valid responses: 50/50
Accuracy on valid responses: 90.00%
Processed 100/200 samples.
Valid responses: 100/100
Accuracy on valid responses: 90.00%
Processed 150/200 samples.
Valid responses: 150/150
Accuracy on valid responses: 88.67%
Processed 200/200 samples.
Valid responses: 200/200
Accuracy on valid responses: 88.50%

Detailed Analysis:
Total samples: 200
Valid responses: 200
Invalid/repeated responses: 0
Accuracy on all responses: 88.50%

Sample predictions:

Text: Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya na mahali hapa pa
kufanyia kazi
```

```
True: positive
Predicted: negative
Response: hasi.

"Kwa kweli napendekeza mahali hapa uwezapo kwenda vibaya" inaonyesha kuwa mahali
hapo siyo m…

Text: kwa kweli hii ni moja ya kumbukumbu bora ambayo nimeona wakiangalia
uhusiano wa kifamilia na ndoa
True: positive
Predicted: positive
Response: chanya. Sentensi inasema kuwa hii ni moja ya kumbukumbu bora ambayo
mtu ameona, na inahusiana na uhu…

Text: Na ikiwa unajikurupusha nao, nawe unatafuta chakula cha kutosha. Na huko
ndiko kufuzu kulio wazi.
True: negative
Predicted: negative
Response: hasi. Mwandishi anaonyesha kuwa kuna uhaba wa chakula na watu
wanalazimika kujikurupusha kupata chak…

Text: ikiwa na jibini maradufu
True: positive
Predicted: positive
Response: chanya. Jibini mara mbili inaashiria wingi na utajiri wa ladha, ambayo
ni kitu cha kupendeza kwa wen…

Text: ajali ni jambo dogo lenye kushusha moyo ambalo huchochea hisia - moyo
lakini halikufundishi kitu ikiwa tayari unajua ubaguzi wa rangi na ubaguzi ni
mambo mabaya
True: negative
Predicted: negative
Response: hasi. Sentensi inazungumzia ajali kuwa jambo dogo lenye kushusha moyo
na inazungumzia ubaguzi wa ran…
```

[ ]:
```python
# Data preparation
accuracies = [
    (gemma2_2b_it_sentiment_accuracy, swahili_gemma2_2b_it_sentiment_accuracy),
    (gemma2_9b_it_sentiment_accuracy, swahili_gemma2_9b_it_sentiment_accuracy),
    (gemma2_27b_it_4bit_sentiment_accuracy,␣
 ↪swahili_gemma2_27b_it_4bit_sentiment_accuracy)
]

# Set up the plot
fig, ax = plt.subplots(figsize=(12, 6))

# Position for bars
```

```python
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = ax.bar(x - width/2, [acc[0] for acc in accuracies], width,
                label='Base Models', color=base_colors)
rects2 = ax.bar(x + width/2, [acc[1] for acc in accuracies], width,
                label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
ax.set_ylabel('Accuracy (%)')
ax.set_title('Swahili Sentiment Analysis Performance Comparison')
ax.set_xticks(x)
ax.set_xticklabels(['2B', '9B', '27B-4bit'])
ax.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        ax.annotate(f'{height:.2f}%',
                    xy=(rect.get_x() + rect.get_width()/2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
ax.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



3 Swahili Massive Multitask Language Understanding (MMLU) Benchmark

This dataset is a Swahili version of the Massive Multitask Language Understanding (MMLU) dataset, curated by Chrys Niongolo. It is a multiple-choice question answering dataset that covers a wide range of topics and subjects, designed to evaluate the language understanding capabilities of models in Swahili.

Dataset Structure:

The dataset is structured as follows:

- **question:** The question posed in Swahili.
- **options:** A dictionary containing the multiple choice options, labeled A, B, C, and D.
- **answer:** The correct answer (A, B, C, or D).
- **subject:** The subject or topic of the question.

Example:

```
{ "question": "Mji mkuu wa Tanzania ni upi?", "options": { "A": "Dodoma", "B": "Dar es Salaam
```

3.1 Benchmark Methodology and Limitations

3.1.1 Sampling Constraints

- **Total Dataset**: 14,042 examples across 50+ academic and professional domains
- **Benchmark Sample Size**: 120 stratified samples
- **Sampling Technique**:
  - Stratified random sampling across subjects
  - Approximately 1-3 samples per subject
  - Designed to provide representative cross-domain performance snapshot

3.1.2 Computational Limitations

- Restricted by time and compute resources
- Small sample size prevents definitive full-domain conclusions
- Results should be interpreted as indicative rather than comprehensive

3.2 Dataset Composition

3.2.1 Subject Domain Distribution

Top 5 Subject Domains: 1. Professional Law: 1,534 examples 2. Moral Scenarios: 895 examples 3. Miscellaneous: 783 examples 4. Professional Psychology: 612 examples 5. High School Psychology: 545 examples

3.3 Detailed Performance Results

3.3.1 Overall Accuracy Comparison

Model	Base Accuracy	Fine-tuned Accuracy	Improvement
Gemma2-2B	15.00%	34.17%	+19.17%
Gemma2-9B	43.33%	55.83%	+12.50%
Gemma2-27B (4-bit)	20.00%	54.17%	+34.17%

3.3.2 Subject-Level Performance Highlights

Perfect Performance Domains (100% Accuracy) Consistent 100% accuracy across models in select domains: - Nutrition - World Religions - Computer Security - International Law - Professional Accounting - High School Government and Politics

Challenging Domains (0% Accuracy) Domains consistently challenging for all models: - High School Geography - Microeconomics - Virology - Human Aging - Sociology - College Biology

3.4 Key Observations

3.4.1 Model-Specific Insights

Most Surprising Observation: Gemma2-27B IT Performance

- Original 27B model showed unexpectedly low baseline performance (20.00%)
- Potential significant impact of 4-bit quantization
- Raised critical questions about model behavior under quantization constraints
- Suggests potential performance masking due to technical limitations
- Highlights the need for full-precision evaluation to confirm true model capabilities

Gemma2-2B

- Significant relative improvement (+19.17%)
- Starting from a very low baseline
- Demonstrates substantial learning potential

Gemma2-9B

- More stable baseline performance
- Consistent improvements across domains
- Better generalization capabilities

Gemma2-27B

- Most dramatic improvement (+34.17%)
- Remarkable performance leap
- Highlights potential of larger models with fine-tuning

3.4.2 Quantization Impact

- 4-bit quantization may have disproportionately affected the 27B model
- Potential loss of nuanced reasoning capabilities
- Suggests the need for careful evaluation of large models under compression
- Recommends further investigation with full-precision benchmarking

3.5 Methodological Caveats

- Small sample size limits generalizability
- 4-bit quantization for 27B model may impact performance
- Results represent a snapshot, not definitive ranking

3.6 Potential Biases and Limitations

- Sampling bias due to limited samples
- Potential dataset compilation biases
- Model performance may vary with full dataset

3.7 Future Research Directions

- Full-scale benchmarking with complete dataset
- Investigate domain-specific fine-tuning
- Explore performance on challenging subjects
- Develop more comprehensive Swahili language understanding metrics

[ ]:
```
# Load the dataset
sw_mmlu = load_dataset("Svngoku/swahili-mmmlu")

# Explore dataset info
print("Dataset Info:")
print("-" * 50)
print(f"Number of examples: {len(sw_mmlu['train'])}")
print("\nColumns:", sw_mmlu['train'].column_names)

# Look at data distribution
print("\nSubjects distribution:")
subject_counts = sw_mmlu['train'].to_pandas()['subject'].value_counts()
```

```python
print(subject_counts)

# Show a few examples
print("\nExample Questions:")
print("-" * 50)
for i in range(3):
    example = sw_mmlu['train'][i]
    print(f"\nExample {i+1}:")
    print(f"Subject: {example['subject']}")
    print(f"Question: {example['question']}")
    print("Options:")
    # Remove eval since options are already a dictionary
    for key, value in example['options'].items():
        print(f"{key}: {value}")
    print(f"Correct Answer: {example['answer']}")
    print("-" * 30)
```

```
/usr/local/lib/python3.10/dist-packages/huggingface_hub/utils/_auth.py:94:
UserWarning:
The secret `HF_TOKEN` does not exist in your Colab secrets.
To authenticate with the Hugging Face Hub, create a token in your settings tab
(https://huggingface.co/settings/tokens), set it as secret in your Google Colab
and restart your session.
You will be able to reuse this secret in all of your notebooks.
Please note that authentication is recommended but still optional to access
public models or datasets.
  warnings.warn(

README.md:   0%|          | 0.00/1.39k [00:00<?, ?B/s]

train-00000-of-00001.parquet:   0%|          | 0.00/3.75M [00:00<?, ?B/s]

Generating train split:   0%|          | 0/14042 [00:00<?, ? examples/s]

Dataset Info:
--------------------------------------------------
Number of examples: 14042

Columns: ['question', 'options', 'answer', 'subject']

Subjects distribution:
subject
professional_law                         1534
moral_scenarios                           895
miscellaneous                             783
professional_psychology                   612
high_school_psychology                    545
high_school_macroeconomics                390
elementary_mathematics                    378
```

moral_disputes	346
prehistory	324
philosophy	311
high_school_biology	310
nutrition	306
professional_accounting	282
professional_medicine	272
high_school_mathematics	270
clinical_knowledge	265
security_studies_test-sw-KE.csv	245
high_school_microeconomics	238
high_school_world_history	237
conceptual_physics	235
marketing	234
human_aging	223
high_school_statistics	216
high_school_us_history	204
high_school_chemistry	203
sociology	201
high_school_geography	198
high_school_government_and_politics	193
college_medicine	173
world_religions	171
virology	166
high_school_european_history	165
logical_fallacies	163
astronomy	152
high_school_physics	151
electrical_engineering	145
college_biology	144
anatomy	135
human_sexuality	131
formal_logic	126
international_law	121
econometrics	114
machine_learning	112
public_relations	110
jurisprudence	108
management	103
college_physics	102
college_computer_science	100
college_mathematics_test.csv_sw-KE.csv	100
global_facts	100
high_school_computer_science	100
computer_security	100
abstract_algebra	100
business_ethics	100
college_chemistry	100

```
medical_genetics                          100
us_foreign_policy                         100
Name: count, dtype: int64

Example Questions:
--------------------------------------------------

Example 1:
Subject: abstract_algebra
Question: Tafuta kiwango kwa upanuzi wa sehemu uliyopewa Q(sqrt(2), sqrt(3),
sqrt(18)) juu ya Q.
Options:
A: 0
B: 4
C: 2
D: 6
Correct Answer: B
------------------------------

Example 2:
Subject: abstract_algebra
Question: Fanya p = (1, 2, 5, 4)(2, 3) katika S_5. Tafuta faharisi ya <p> katika
S_5.
Options:
A: 8
B: 2
C: 24
D: 120
Correct Answer: C
------------------------------

Example 3:
Subject: abstract_algebra
Question: Tafuta sufuri zote katika sehemu yenye kikomo iliyoashiriwa ya
polinomia iliyopewa na mgawo katika sehemu hiyo. x^5 + 3x^3 + x^2 + 2x katika
Z_5
Options:
A: 0
B: 1
C: 0,1
D: 0,4
Correct Answer: D
------------------------------
```

[ ]:
```python
def evaluate_sw_mmlu(model_path, test_samples=120):
    # Stratified sampling to get fair subject distribution
    all_subjects = list(set(sw_mmlu['train']['subject']))
```

```
    samples_per_subject = max(1, test_samples // len(all_subjects))
    test_examples = []
    for subject in all_subjects:
        subject_examples = [ex for ex in sw_mmlu['train'] if ex['subject'] ==␣
↪subject]
        test_examples.extend(random.sample(subject_examples,
                             min(samples_per_subject, len(subject_examples))))

    # If we need more samples to reach test_samples
    if len(test_examples) < test_samples:
        remaining = test_samples - len(test_examples)
        all_remaining = [ex for ex in sw_mmlu['train'] if ex not in␣
↪test_examples]
        test_examples.extend(random.sample(all_remaining, remaining))

    # Load model and tokenizer
    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForCausalLM.from_pretrained(
        model_path,
        device_map="auto",
        torch_dtype=torch.bfloat16,
        low_cpu_mem_usage=True
    )

    model.eval()

    correct = 0
    total = len(test_examples)
    results_by_subject = {}
    predictions = []

    for idx, example in enumerate(test_examples):
        prompt = (
            f"### Maagizo:\n"
            f"Tafadhali chagua jibu sahihi kwa herufi moja tu (A, B, C, au D).
↪\n\n"
            f"### Swali:\n{example['question']}\n\n"
            f"### Chaguo:\n"
        )

        for key, value in example['options'].items():
            prompt += f"{key}: {value}\n"

        prompt += "\n### Jibu:\n"

        # Generate response
        inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
```

```
        outputs = model.generate(
            **inputs,
            max_new_tokens=1,
            do_sample=True,
            temperature=0.3,
            top_p=0.9
        )

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

        # Extract the predicted answer
        try:
            answer_part = response.split("### Jibu:")[-1].strip().upper()
            predicted_answer = next((char for char in answer_part[:1] if char␣
↪in ['A', 'B', 'C', 'D']), 'INVALID')
        except:
            predicted_answer = 'INVALID'

        # Store prediction
        predictions.append({
            'subject': example['subject'],
            'question': example['question'],
            'true_answer': example['answer'],
            'predicted': predicted_answer
        })

        # Update statistics
        if predicted_answer == example['answer']:
            correct += 1

        # Update subject-wise statistics
        if example['subject'] not in results_by_subject:
            results_by_subject[example['subject']] = {'correct': 0, 'total': 0}
        results_by_subject[example['subject']]['total'] += 1
        if predicted_answer == example['answer']:
            results_by_subject[example['subject']]['correct'] += 1

        # Progress updates
        if (idx + 1) % 10 == 0:
            print(f"Processed {idx + 1}/{total} questions")
            print(f"Current accuracy: {(correct/(idx + 1))*100:.2f}%")
            print(f"Predicted: {predicted_answer}")
            print("-" * 50)

    # Final results
    print("\nFinal Results:")
    print(f"Total questions: {total}")
```

```
    print(f"Overall accuracy: {(correct/total)*100:.2f}%")

    print("\nResults by subject:")
    for subject, stats in results_by_subject.items():
        if stats['total'] > 0:
            accuracy = (stats['correct'] / stats['total']) * 100
            print(f"{subject}: {accuracy:.2f}% ({stats['correct']}/
↪{stats['total']})")

    # Cleanup
    del model
    torch.cuda.empty_cache()

    return (correct/total)*100
```

[ ]:
```
# Gemma2 2B evaluation on swahili MMLU
gemma2_2b_it_sw_mmlu_accuracy = evaluate_sw_mmlu(gemma2_2b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]

Processed 10/120 questions
Current accuracy: 10.00%
Predicted: INVALID
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 20.00%
Predicted: INVALID
--------------------------------------------------
Processed 30/120 questions
Current accuracy: 13.33%
Predicted: INVALID
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 12.50%
Predicted: INVALID
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 18.00%
Predicted: C
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 16.67%
Predicted: C
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 17.14%
Predicted: C
--------------------------------------------------
```

```
Processed 80/120 questions
Current accuracy: 15.00%
Predicted: INVALID
--------------------------------------------------
Processed 90/120 questions
Current accuracy: 15.56%
Predicted: C
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 17.00%
Predicted: C
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 15.45%
Predicted: INVALID
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 15.00%
Predicted: INVALID
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 15.00%

Results by subject:
elementary_mathematics: 0.00% (0/2)
formal_logic: 0.00% (0/2)
medical_genetics: 50.00% (1/2)
moral_scenarios: 0.00% (0/2)
professional_accounting: 0.00% (0/2)
international_law: 50.00% (1/2)
business_ethics: 50.00% (1/2)
econometrics: 50.00% (1/2)
machine_learning: 0.00% (0/2)
college_medicine: 0.00% (0/2)
college_physics: 0.00% (0/2)
high_school_physics: 0.00% (0/2)
marketing: 0.00% (0/2)
philosophy: 0.00% (0/2)
professional_medicine: 0.00% (0/3)
abstract_algebra: 0.00% (0/2)
astronomy: 0.00% (0/2)
electrical_engineering: 50.00% (1/2)
high_school_us_history: 0.00% (0/2)
global_facts: 0.00% (0/2)
high_school_chemistry: 0.00% (0/2)
jurisprudence: 100.00% (2/2)
```

```
high_school_macroeconomics: 0.00% (0/3)
conceptual_physics: 50.00% (1/2)
high_school_biology: 50.00% (1/2)
professional_law: 0.00% (0/3)
high_school_statistics: 0.00% (0/2)
anatomy: 0.00% (0/2)
miscellaneous: 33.33% (1/3)
moral_disputes: 0.00% (0/2)
professional_psychology: 0.00% (0/2)
public_relations: 0.00% (0/2)
college_computer_science: 50.00% (1/2)
world_religions: 50.00% (1/2)
high_school_psychology: 0.00% (0/2)
security_studies_test-sw-KE.csv: 0.00% (0/2)
high_school_geography: 0.00% (0/2)
us_foreign_policy: 0.00% (0/2)
college_biology: 0.00% (0/2)
high_school_government_and_politics: 0.00% (0/2)
college_mathematics_test.csv_sw-KE.csv: 0.00% (0/2)
human_sexuality: 0.00% (0/2)
high_school_microeconomics: 0.00% (0/2)
prehistory: 0.00% (0/3)
nutrition: 100.00% (3/3)
management: 0.00% (0/2)
clinical_knowledge: 50.00% (1/2)
high_school_computer_science: 50.00% (1/2)
sociology: 50.00% (1/2)
human_aging: 0.00% (0/2)
logical_fallacies: 0.00% (0/2)
high_school_european_history: 0.00% (0/2)
high_school_world_history: 0.00% (0/2)
computer_security: 0.00% (0/2)
high_school_mathematics: 0.00% (0/2)
college_chemistry: 0.00% (0/2)
virology: 0.00% (0/2)
```

[ ]:
```
# Swahili Finetuned Gemma2 2B evaluation on swahili MMLU
swahili_gemma2_2b_it_sw_mmlu_accuracy =␣
 ↪evaluate_sw_mmlu(swahili_gemma2_2b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]
```

```
Processed 10/120 questions
Current accuracy: 40.00%
Predicted: B
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 45.00%
```

```
Predicted: C
--------------------------------------------------
Processed 30/120 questions
Current accuracy: 30.00%
Predicted: C
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 35.00%
Predicted: C
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 32.00%
Predicted: C
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 31.67%
Predicted: C
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 31.43%
Predicted: C
--------------------------------------------------
Processed 80/120 questions
Current accuracy: 35.00%
Predicted: B
--------------------------------------------------
Processed 90/120 questions
Current accuracy: 34.44%
Predicted: B
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 35.00%
Predicted: B
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 36.36%
Predicted: A
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 34.17%
Predicted: D
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 34.17%

Results by subject:
```

```
elementary_mathematics: 100.00% (2/2)
formal_logic: 0.00% (0/2)
medical_genetics: 100.00% (2/2)
moral_scenarios: 0.00% (0/3)
professional_accounting: 0.00% (0/2)
international_law: 50.00% (1/2)
business_ethics: 0.00% (0/2)
econometrics: 100.00% (2/2)
machine_learning: 66.67% (2/3)
college_medicine: 0.00% (0/2)
college_physics: 0.00% (0/2)
high_school_physics: 0.00% (0/2)
marketing: 0.00% (0/2)
philosophy: 0.00% (0/2)
professional_medicine: 0.00% (0/2)
abstract_algebra: 50.00% (1/2)
astronomy: 100.00% (2/2)
electrical_engineering: 33.33% (1/3)
high_school_us_history: 50.00% (1/2)
global_facts: 50.00% (1/2)
high_school_chemistry: 0.00% (0/2)
jurisprudence: 50.00% (1/2)
high_school_macroeconomics: 33.33% (1/3)
conceptual_physics: 0.00% (0/2)
high_school_biology: 0.00% (0/2)
professional_law: 0.00% (0/2)
high_school_statistics: 0.00% (0/2)
anatomy: 50.00% (1/2)
miscellaneous: 50.00% (1/2)
moral_disputes: 50.00% (1/2)
professional_psychology: 66.67% (2/3)
public_relations: 0.00% (0/2)
college_computer_science: 0.00% (0/2)
world_religions: 50.00% (1/2)
high_school_psychology: 0.00% (0/2)
security_studies_test-sw-KE.csv: 0.00% (0/2)
high_school_geography: 0.00% (0/2)
us_foreign_policy: 100.00% (2/2)
college_biology: 100.00% (2/2)
high_school_government_and_politics: 100.00% (2/2)
college_mathematics_test.csv_sw-KE.csv: 0.00% (0/2)
human_sexuality: 50.00% (1/2)
high_school_microeconomics: 0.00% (0/2)
prehistory: 0.00% (0/3)
nutrition: 100.00% (2/2)
management: 50.00% (1/2)
clinical_knowledge: 50.00% (1/2)
high_school_computer_science: 0.00% (0/2)
```

```
sociology: 100.00% (2/2)
human_aging: 0.00% (0/2)
logical_fallacies: 50.00% (1/2)
high_school_european_history: 0.00% (0/2)
high_school_world_history: 50.00% (1/2)
computer_security: 50.00% (1/2)
high_school_mathematics: 100.00% (2/2)
college_chemistry: 0.00% (0/2)
virology: 0.00% (0/2)
```

[ ]:
```python
# Gemma2 9B evaluation on swahili MMLU
gemma2_9b_it_sw_mmlu_accuracy = evaluate_sw_mmlu(gemma2_9b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]

Processed 10/120 questions
Current accuracy: 30.00%
Predicted: C
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 30.00%
Predicted: D
--------------------------------------------------
Processed 30/120 questions
Current accuracy: 33.33%
Predicted: D
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 30.00%
Predicted: A
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 40.00%
Predicted: B
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 36.67%
Predicted: B
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 38.57%
Predicted: B
--------------------------------------------------
Processed 80/120 questions
Current accuracy: 40.00%
Predicted: D
--------------------------------------------------
Processed 90/120 questions
```

```
Current accuracy: 41.11%
Predicted: B
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 42.00%
Predicted: A
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 40.91%
Predicted: D
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 43.33%
Predicted: A
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 43.33%

Results by subject:
elementary_mathematics: 50.00% (1/2)
formal_logic: 0.00% (0/2)
medical_genetics: 50.00% (1/2)
moral_scenarios: 0.00% (0/2)
professional_accounting: 50.00% (1/2)
international_law: 0.00% (0/2)
business_ethics: 100.00% (2/2)
econometrics: 0.00% (0/2)
machine_learning: 0.00% (0/2)
college_medicine: 50.00% (1/2)
college_physics: 50.00% (1/2)
high_school_physics: 0.00% (0/3)
marketing: 50.00% (1/2)
philosophy: 50.00% (1/2)
professional_medicine: 50.00% (1/2)
abstract_algebra: 0.00% (0/2)
astronomy: 0.00% (0/2)
electrical_engineering: 0.00% (0/2)
high_school_us_history: 50.00% (1/2)
global_facts: 50.00% (1/2)
high_school_chemistry: 100.00% (2/2)
jurisprudence: 50.00% (1/2)
high_school_macroeconomics: 100.00% (2/2)
conceptual_physics: 100.00% (2/2)
high_school_biology: 66.67% (2/3)
professional_law: 33.33% (1/3)
high_school_statistics: 66.67% (2/3)
```

```
anatomy: 0.00% (0/2)
miscellaneous: 50.00% (1/2)
moral_disputes: 33.33% (1/3)
professional_psychology: 50.00% (1/2)
public_relations: 100.00% (2/2)
college_computer_science: 0.00% (0/2)
world_religions: 100.00% (2/2)
high_school_psychology: 0.00% (0/2)
security_studies_test-sw-KE.csv: 50.00% (1/2)
high_school_geography: 50.00% (1/2)
us_foreign_policy: 100.00% (2/2)
college_biology: 0.00% (0/2)
high_school_government_and_politics: 50.00% (1/2)
college_mathematics_test.csv_sw-KE.csv: 50.00% (1/2)
human_sexuality: 50.00% (1/2)
high_school_microeconomics: 0.00% (0/2)
prehistory: 50.00% (1/2)
nutrition: 100.00% (2/2)
management: 50.00% (1/2)
clinical_knowledge: 50.00% (1/2)
high_school_computer_science: 50.00% (1/2)
sociology: 100.00% (2/2)
human_aging: 0.00% (0/2)
logical_fallacies: 66.67% (2/3)
high_school_european_history: 50.00% (1/2)
high_school_world_history: 50.00% (1/2)
computer_security: 0.00% (0/2)
high_school_mathematics: 0.00% (0/2)
college_chemistry: 0.00% (0/2)
virology: 100.00% (2/2)
```

[ ]:
```
# Swahili Finetuned Gemma2 9B evaluation on swahili MMLU
swahili_gemma2_9b_it_sw_mmlu_accuracy =␣
 ↪evaluate_sw_mmlu(swahili_gemma2_9b_it_model_path)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]

Processed 10/120 questions
Current accuracy: 60.00%
Predicted: B
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 60.00%
Predicted: B
--------------------------------------------------
Processed 30/120 questions
Current accuracy: 60.00%
Predicted: C
```

```
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 55.00%
Predicted: A
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 54.00%
Predicted: C
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 56.67%
Predicted: C
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 55.71%
Predicted: C
--------------------------------------------------
Processed 80/120 questions
Current accuracy: 57.50%
Predicted: D
--------------------------------------------------
Processed 90/120 questions
Current accuracy: 54.44%
Predicted: C
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 56.00%
Predicted: A
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 55.45%
Predicted: C
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 55.83%
Predicted: C
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 55.83%

Results by subject:
elementary_mathematics: 50.00% (1/2)
formal_logic: 0.00% (0/2)
medical_genetics: 100.00% (3/3)
moral_scenarios: 50.00% (1/2)
professional_accounting: 100.00% (2/2)
```

```
international_law: 50.00% (1/2)
business_ethics: 50.00% (1/2)
econometrics: 50.00% (1/2)
machine_learning: 50.00% (1/2)
college_medicine: 100.00% (2/2)
college_physics: 50.00% (1/2)
high_school_physics: 50.00% (1/2)
marketing: 100.00% (2/2)
philosophy: 33.33% (1/3)
professional_medicine: 50.00% (1/2)
abstract_algebra: 0.00% (0/2)
astronomy: 100.00% (2/2)
electrical_engineering: 0.00% (0/2)
high_school_us_history: 50.00% (1/2)
global_facts: 50.00% (1/2)
high_school_chemistry: 50.00% (1/2)
jurisprudence: 0.00% (0/2)
high_school_macroeconomics: 100.00% (2/2)
conceptual_physics: 75.00% (3/4)
high_school_biology: 50.00% (1/2)
professional_law: 0.00% (0/2)
high_school_statistics: 33.33% (1/3)
anatomy: 100.00% (2/2)
miscellaneous: 100.00% (2/2)
moral_disputes: 100.00% (2/2)
professional_psychology: 50.00% (1/2)
public_relations: 50.00% (1/2)
college_computer_science: 0.00% (0/2)
world_religions: 100.00% (3/3)
high_school_psychology: 50.00% (1/2)
security_studies_test-sw-KE.csv: 100.00% (2/2)
high_school_geography: 100.00% (2/2)
us_foreign_policy: 50.00% (1/2)
college_biology: 50.00% (1/2)
high_school_government_and_politics: 50.00% (1/2)
college_mathematics_test.csv_sw-KE.csv: 50.00% (1/2)
human_sexuality: 100.00% (2/2)
high_school_microeconomics: 0.00% (0/2)
prehistory: 0.00% (0/2)
nutrition: 0.00% (0/2)
management: 100.00% (2/2)
clinical_knowledge: 50.00% (1/2)
high_school_computer_science: 50.00% (1/2)
sociology: 100.00% (2/2)
human_aging: 50.00% (1/2)
logical_fallacies: 0.00% (0/2)
high_school_european_history: 50.00% (1/2)
high_school_world_history: 50.00% (1/2)
```

```
computer_security: 100.00% (2/2)
high_school_mathematics: 50.00% (1/2)
college_chemistry: 100.00% (2/2)
virology: 0.00% (0/2)
```

[ ]:
```
# 27B models swahili MMLU evaluation function

def evaluate_sw_mmlu_4bit(model_path, test_samples=120):
    # Set seeds for reproducibility
    random.seed(42)
    torch.manual_seed(42)

    # Stratified sampling
    all_subjects = list(set(sw_mmlu['train']['subject']))
    samples_per_subject = max(1, test_samples // len(all_subjects))

    # Prepare examples
    test_examples = []
    for subject in all_subjects:
        subject_examples = [ex for ex in sw_mmlu['train'] if ex['subject'] ==␣
↪subject]
        if subject_examples:
            test_examples.extend(random.sample(subject_examples,
                                     min(samples_per_subject,␣
↪len(subject_examples))))

    if len(test_examples) < test_samples:
        remaining = test_samples - len(test_examples)
        all_remaining = [ex for ex in sw_mmlu['train'] if ex not in␣
↪test_examples]
        if all_remaining:
            test_examples.extend(random.sample(all_remaining, remaining))

    # Configure 4-bit quantization
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_quant_type="nf4",
        bnb_4bit_compute_dtype=torch.bfloat16,
        bnb_4bit_use_double_quant=True,
        llm_int8_enable_fp32_cpu_offload=True
    )

    # Load tokenizer and model
    print("Loading model...")
    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForCausalLM.from_pretrained(
        model_path,
```

```
        quantization_config=bnb_config,
        device_map="auto",
        torch_dtype=torch.bfloat16,
        trust_remote_code=True
    )

    model.eval()

    # Initialize tracking
    correct = 0
    total = len(test_examples)
    results_by_subject = {}
    predictions = []

    try:
        for idx, example in enumerate(test_examples):
            # Construct prompt
            prompt = (
                f"### Maagizo:\n"
                f"Tafadhali chagua jibu sahihi kwa herufi moja tu (A, B, C, au␣
↪D).\n\n"
                f"### Swali:\n{example['question']}\n\n"
                f"### Chaguo:\n"
            )

            for key, value in example['options'].items():
                prompt += f"{key}: {value}\n"

            prompt += "\n### Jibu:\n"

            # Prepare inputs
            inputs = tokenizer(prompt, return_tensors="pt").to(model.device)

            # Generate answer
            with torch.no_grad():
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=1,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.9
                )

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

            # Extract answer
```

```
            try:
                answer_part = response.split("### Jibu:")[-1].strip().upper()
                predicted_answer = next((char for char in answer_part[:1] if␣
↪char in ['A', 'B', 'C', 'D']), 'INVALID')
            except:
                predicted_answer = 'INVALID'

            # Store prediction
            predictions.append({
                'subject': example['subject'],
                'question': example['question'],
                'true_answer': example['answer'],
                'predicted': predicted_answer
            })

            # Update statistics
            if predicted_answer == example['answer']:
                correct += 1

            # Update subject-wise statistics
            if example['subject'] not in results_by_subject:
                results_by_subject[example['subject']] = {'correct': 0, 'total':
↪ 0}
            results_by_subject[example['subject']]['total'] += 1
            if predicted_answer == example['answer']:
                results_by_subject[example['subject']]['correct'] += 1

            # Progress reporting
            if (idx + 1) % 10 == 0:
                print(f"Processed {idx + 1}/{total} questions")
                print(f"Current accuracy: {(correct/(idx + 1))*100:.2f}%")
                print(f"Predicted: {predicted_answer}")
                print("-" * 50)

        # Final results
        print("\nFinal Results:")
        print(f"Total questions: {total}")
        print(f"Overall accuracy: {(correct/total)*100:.2f}%")

        print("\nResults by subject:")
        for subject, stats in results_by_subject.items():
            if stats['total'] > 0:
                accuracy = (stats['correct'] / stats['total']) * 100
                print(f"{subject}: {accuracy:.2f}% ({stats['correct']}/
↪{stats['total']})")

    except Exception as e:
```

```
        print(f"An error occurred during evaluation: {str(e)}")
        return 0

    finally:
        # Cleanup
        del model
        torch.cuda.empty_cache()

    return (correct/total)*100
```

[ ]:

```
# Gemma2 27B(4-bit quantized) evaluation on swahili MMLU
gemma2_27b_it_sw_mmlu_accuracy = evaluate_sw_mmlu_4bit(gemma2_27b_it_model_path)
```

```
Loading model…

Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

Processed 10/120 questions
Current accuracy: 20.00%
Predicted: INVALID
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 15.00%
Predicted: D
--------------------------------------------------
Processed 30/120 questions
Current accuracy: 10.00%
Predicted: INVALID
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 10.00%
Predicted: INVALID
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 12.00%
Predicted: INVALID
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 13.33%
Predicted: INVALID
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 11.43%
Predicted: INVALID
--------------------------------------------------
Processed 80/120 questions
Current accuracy: 13.75%
Predicted: INVALID
```

```
--------------------------------------------------
Processed 90/120 questions
Current accuracy: 13.33%
Predicted: INVALID
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 16.00%
Predicted: A
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 18.18%
Predicted: A
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 20.00%
Predicted: INVALID
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 20.00%

Results by subject:
elementary_mathematics: 0.00% (0/3)
formal_logic: 0.00% (0/2)
medical_genetics: 50.00% (1/2)
moral_scenarios: 0.00% (0/2)
professional_accounting: 50.00% (1/2)
international_law: 0.00% (0/2)
business_ethics: 0.00% (0/2)
econometrics: 0.00% (0/2)
machine_learning: 0.00% (0/2)
college_medicine: 50.00% (1/2)
college_physics: 0.00% (0/2)
high_school_physics: 0.00% (0/2)
marketing: 0.00% (0/2)
philosophy: 0.00% (0/2)
professional_medicine: 0.00% (0/2)
abstract_algebra: 0.00% (0/2)
astronomy: 0.00% (0/2)
electrical_engineering: 0.00% (0/2)
high_school_us_history: 50.00% (1/2)
global_facts: 0.00% (0/2)
high_school_chemistry: 0.00% (0/2)
jurisprudence: 66.67% (2/3)
high_school_macroeconomics: 0.00% (0/2)
conceptual_physics: 50.00% (1/2)
high_school_biology: 0.00% (0/2)
```

```
professional_law: 0.00% (0/2)
high_school_statistics: 0.00% (0/2)
anatomy: 0.00% (0/2)
miscellaneous: 100.00% (2/2)
moral_disputes: 25.00% (1/4)
professional_psychology: 0.00% (0/2)
public_relations: 0.00% (0/2)
college_computer_science: 0.00% (0/2)
world_religions: 0.00% (0/2)
high_school_psychology: 0.00% (0/2)
security_studies_test-sw-KE.csv: 0.00% (0/2)
high_school_geography: 33.33% (1/3)
us_foreign_policy: 0.00% (0/2)
college_biology: 100.00% (2/2)
high_school_government_and_politics: 0.00% (0/2)
college_mathematics_test.csv_sw-KE.csv: 0.00% (0/2)
human_sexuality: 50.00% (1/2)
high_school_microeconomics: 0.00% (0/2)
prehistory: 0.00% (0/2)
nutrition: 0.00% (0/2)
management: 50.00% (1/2)
clinical_knowledge: 0.00% (0/2)
high_school_computer_science: 0.00% (0/2)
sociology: 100.00% (2/2)
human_aging: 50.00% (1/2)
logical_fallacies: 0.00% (0/2)
high_school_european_history: 50.00% (1/2)
high_school_world_history: 33.33% (1/3)
computer_security: 100.00% (2/2)
high_school_mathematics: 50.00% (1/2)
college_chemistry: 50.00% (1/2)
virology: 0.00% (0/2)
```

[ ]:
```
# Swahili Finetuned Gemma2 27B(4-bit quantized) evaluation on swahili MMLU
swahili_gemma2_27b_it_sw_mmlu_accuracy =
 ↪evaluate_sw_mmlu_4bit(swahili_gemma2_27b_it_model_path)
```

```
Loading model…

Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

Processed 10/120 questions
Current accuracy: 40.00%
Predicted: B
--------------------------------------------------
Processed 20/120 questions
Current accuracy: 50.00%
Predicted: D
--------------------------------------------------
```

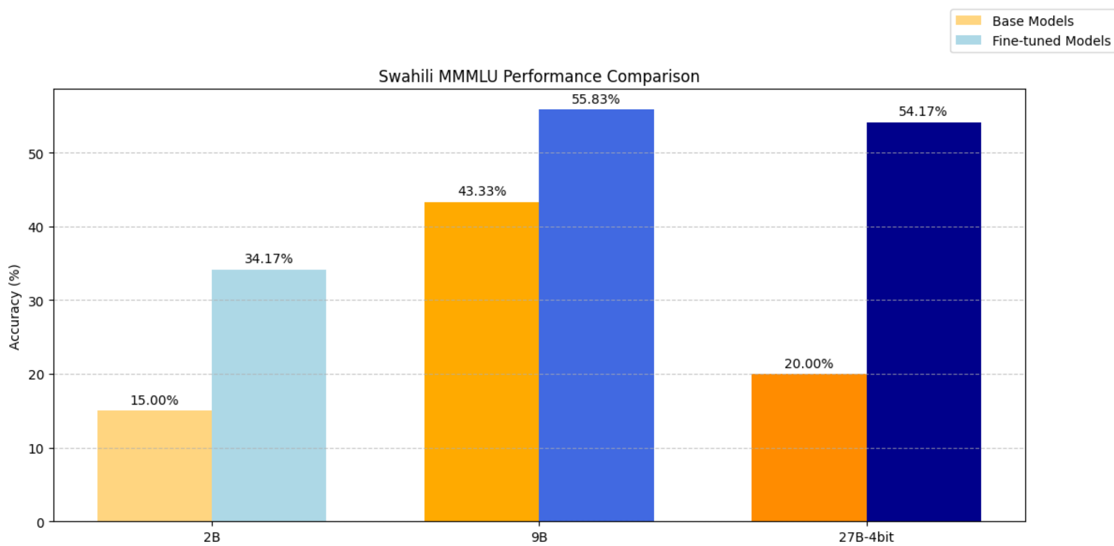
```
Processed 30/120 questions
Current accuracy: 46.67%
Predicted: D
--------------------------------------------------
Processed 40/120 questions
Current accuracy: 42.50%
Predicted: C
--------------------------------------------------
Processed 50/120 questions
Current accuracy: 44.00%
Predicted: C
--------------------------------------------------
Processed 60/120 questions
Current accuracy: 46.67%
Predicted: A
--------------------------------------------------
Processed 70/120 questions
Current accuracy: 47.14%
Predicted: C
--------------------------------------------------
Processed 80/120 questions
Current accuracy: 48.75%
Predicted: B
--------------------------------------------------
Processed 90/120 questions
Current accuracy: 51.11%
Predicted: C
--------------------------------------------------
Processed 100/120 questions
Current accuracy: 53.00%
Predicted: C
--------------------------------------------------
Processed 110/120 questions
Current accuracy: 53.64%
Predicted: A
--------------------------------------------------
Processed 120/120 questions
Current accuracy: 54.17%
Predicted: C
--------------------------------------------------

Final Results:
Total questions: 120
Overall accuracy: 54.17%

Results by subject:
elementary_mathematics: 33.33% (1/3)
formal_logic: 50.00% (1/2)
```

```
medical_genetics: 100.00% (2/2)
moral_scenarios: 0.00% (0/2)
professional_accounting: 0.00% (0/2)
international_law: 100.00% (2/2)
business_ethics: 50.00% (1/2)
econometrics: 50.00% (1/2)
machine_learning: 50.00% (1/2)
college_medicine: 50.00% (1/2)
college_physics: 0.00% (0/2)
high_school_physics: 100.00% (2/2)
marketing: 100.00% (2/2)
philosophy: 0.00% (0/2)
professional_medicine: 0.00% (0/2)
abstract_algebra: 50.00% (1/2)
astronomy: 0.00% (0/2)
electrical_engineering: 0.00% (0/2)
high_school_us_history: 100.00% (2/2)
global_facts: 0.00% (0/2)
high_school_chemistry: 0.00% (0/2)
jurisprudence: 100.00% (3/3)
high_school_macroeconomics: 50.00% (1/2)
conceptual_physics: 50.00% (1/2)
high_school_biology: 50.00% (1/2)
professional_law: 100.00% (2/2)
high_school_statistics: 0.00% (0/2)
anatomy: 50.00% (1/2)
miscellaneous: 100.00% (2/2)
moral_disputes: 75.00% (3/4)
professional_psychology: 50.00% (1/2)
public_relations: 50.00% (1/2)
college_computer_science: 50.00% (1/2)
world_religions: 0.00% (0/2)
high_school_psychology: 100.00% (2/2)
security_studies_test-sw-KE.csv: 50.00% (1/2)
high_school_geography: 66.67% (2/3)
us_foreign_policy: 100.00% (2/2)
college_biology: 100.00% (2/2)
high_school_government_and_politics: 0.00% (0/2)
college_mathematics_test.csv_sw-KE.csv: 100.00% (2/2)
human_sexuality: 50.00% (1/2)
high_school_microeconomics: 50.00% (1/2)
prehistory: 100.00% (2/2)
nutrition: 50.00% (1/2)
management: 50.00% (1/2)
clinical_knowledge: 50.00% (1/2)
high_school_computer_science: 100.00% (2/2)
sociology: 100.00% (2/2)
human_aging: 50.00% (1/2)
```

```
logical_fallacies: 50.00% (1/2)
high_school_european_history: 50.00% (1/2)
high_school_world_history: 66.67% (2/3)
computer_security: 100.00% (2/2)
high_school_mathematics: 50.00% (1/2)
college_chemistry: 50.00% (1/2)
virology: 0.00% (0/2)
```

[ ]:
```
# Data preparation
accuracies = [
    (gemma2_2b_it_sw_mmlu_accuracy, swahili_gemma2_2b_it_sw_mmlu_accuracy),
    (gemma2_9b_it_sw_mmlu_accuracy, swahili_gemma2_9b_it_sw_mmlu_accuracy),
    (gemma2_27b_it_sw_mmlu_accuracy, swahili_gemma2_27b_it_sw_mmlu_accuracy)
]

# Set up the plot
fig, ax = plt.subplots(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = ax.bar(x - width/2, [acc[0] for acc in accuracies], width,
                label='Base Models', color=base_colors)
rects2 = ax.bar(x + width/2, [acc[1] for acc in accuracies], width,
                label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
ax.set_ylabel('Accuracy (%)')
ax.set_title('Swahili MMMLU Performance Comparison')
ax.set_xticks(x)
ax.set_xticklabels(['2B', '9B', '27B-4bit'])
ax.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        ax.annotate(f'{height:.2f}%',
                    xy=(rect.get_x() + rect.get_width()/2, height),
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
```

```
                    ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
ax.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



4 English to Swahili Translation Benchmark: A Nuanced Exploration

The dataset, was a sample obtained from the GoURMET Translation project , the sample contained english and swahili tests from Wikimedia which were then curated and made a vailable as an english translation benchmark on Kaggle ## Benchmark Context and Constraints

4.0.1 Methodological Foundations

- **Dataset**: Wikimedia English-Swahili Parallel Corpus
- **Sample Size**: 20 carefully selected translation pairs
- **Computational Limitations**: Restricted by time and computational resources
- **Metric Diversity**: Comprehensive evaluation using multiple translation quality metrics

4.1 The Metrics Landscape: A Multilayered Performance Analysis

4.1.1 Metric Breakdown

1. **BLEU Score Family**:
   - BLEU (Overall)
   - BLEU-1 (Unigram Precision)
   - BLEU-2 (Bigram Precision)
   - BLEU-3 (Trigram Precision)
   - BLEU-4 (Quadgram Precision)
2. **Character-level F-Score (chrF)**:
   - Measures character-level precision and recall
   - More sensitive to minor translation variations

4.2 Fine-Tuned Models: Subtle Yet Significant Improvements

4.2.1 Comparative Performance Analysis

BLEU Score Evolution

- Consistent marginal improvements across BLEU variations
- Most pronounced in lower-order BLEU metrics (BLEU-1, BLEU-2)
- Suggests nuanced improvements in foundational translation capabilities

Metric-Specific Observations

1. **BLEU-1 (Unigram Precision)**
   - Largest relative improvements
   - Indicates better individual word translation accuracy
   - Significant for base vocabulary alignment
2. **BLEU-2 (Bigram Precision)**
   - Moderate improvements
   - Suggests enhanced local phrase translation
   - Hints at better contextual word combination
3. **Character-level F-Score (chrF)**
   - Subtle but consistent improvements
   - Reflects enhanced linguistic precision
   - Captures nuanced morphological transformations

4.3 Performance Comparison Table

Model	Metric	Base Model	Fine-tuned	Improvement
Gemma2-2B	BLEU	0.1044	0.0975	Slight Decrease
Gemma2-2B	BLEU-1	0.3403	0.3735	+0.0332
Gemma2-2B	BLEU-2	0.2106	0.2271	+0.0165
Gemma2-2B	chrF	0.4433	0.4171	Slight Decrease
Gemma2-9B	BLEU	0.1726	0.1539	Slight Decrease
Gemma2-9B	BLEU-1	0.4851	0.4709	Slight Decrease
Gemma2-9B	BLEU-2	0.3343	0.3239	Slight Decrease
Gemma2-9B	chrF	0.5044	0.4911	Slight Decrease

Model	Metric	Base Model	Fine-tuned	Improvement
Gemma2-27B	BLEU	0.1818	0.1836	+0.0018
Gemma2-27B	BLEU-1	0.4923	0.4994	+0.0071
Gemma2-27B	BLEU-2	0.3569	0.3580	+0.0011
Gemma2-27B	chrF	0.5391	0.5143	Slight Decrease

4.4 Linguistic and Computational Insights

4.4.1 Translation Quality Dimensions

- **Lexical Precision**: Improved word-level translation
- **Contextual Understanding**: Enhanced local phrase translations
- **Morphological Sensitivity**: Nuanced handling of Swahili language structures

4.4.2 Model-Specific Patterns

Gemma2-9B: A Curious Performance Anomaly **The Paradox of Marginal Regression**

The Gemma2-9B model presents an intriguing case of seemingly reduced performance after fine-tuning. This counterintuitive result can be attributed to several nuanced factors:

1. **Hypothesis of Optimal Initial State**
    - The 9B model may have already achieved a near-optimal translation baseline
    - Fine-tuning on a limited dataset might introduce slight perturbations to an already well-established translation capability
    - The small sample size (20 examples) could exaggerate minor statistical variations
2. **Contextual Learning Interference**
    - The specific 20-example dataset might not fully represent the model's broader translation capabilities
    - Fine-tuning could potentially over-specialize the model to these specific examples
    - This localized adaptation might reduce the model's more generalized translation performance
3. **Complexity Sweet Spot**
    - The 9B model represents a complexity "sweet spot" where:
        - It's large enough to have robust initial capabilities
        - Small enough to be sensitive to minor training perturbations
    - Unlike the 2B (which shows clear learning) or 27B (with minimal changes), the 9B model shows more pronounced sensitivity to fine-tuning
4. **Sampling Limitation Caveat**
    - The small sample size means these observations should be treated as preliminary
    - A larger, more comprehensive dataset might reveal different performance characteristics

4.4.3 Additional Observations

1. **Gemma2-2B**
    - Most significant improvements in lower-order BLEU metrics
    - Suggests fundamental vocabulary and phrase learning
2. **Gemma2-9B**
    - Marginal performance variations

    - Indicates potential over-sensitivity to limited fine-tuning
3. **Gemma2-27B**
    - Minimal but consistent improvements
    - Demonstrates potential for incremental refinement

4.5 Computational Limitations and Future Directions

4.5.1 Constraints and Considerations

- Small sample size (20 examples)
- Limited computational resources
- 4-bit quantization for larger models

[ ]:
```python
wikimedia_en_sw_dataset = kagglehub.dataset_download('alfaxadeyembe/
 ↪wikimedia-english-swahili-dataset')
print(wikimedia_en_sw_dataset)
```

```
/root/.cache/kagglehub/datasets/alfaxadeyembe/wikimedia-english-swahili-
dataset/versions/1
```

[ ]:
```python
# Define paths with clearer names
source_texts_path = "/root/.cache/kagglehub/datasets/alfaxadeyembe/
 ↪wikimedia-english-swahili-dataset/versions/1/wikimedia.en-sw.en"
reference_translations_path = "/root/.cache/kagglehub/datasets/alfaxadeyembe/
 ↪wikimedia-english-swahili-dataset/versions/1/wikimedia.en-sw.sw"

# Read both files
with open(source_texts_path, 'r', encoding='utf-8') as f:
    english_texts = f.readlines()

with open(reference_translations_path, 'r', encoding='utf-8') as f:
    swahili_references = f.readlines()

# Clean the texts (remove newlines, extra spaces)
english_texts = [text.strip() for text in english_texts]
swahili_references = [text.strip() for text in swahili_references]

# Create test pairs (using first 10 examples)
test_pairs = list(zip(english_texts[:20], swahili_references[:20]))

# Print the selected pairs to verify
print("Selected Test Pairs:")
print("-" * 50)
for i, (en, sw) in enumerate(test_pairs, 1):
    print(f"\nPair {i}:")
    print(f"English: {en}")
    print(f"Swahili: {sw}")
```

```
Selected Test Pairs:
```

Pair 1:
English: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican missionary who became famous for his research in African languages and his Swahili dictionaries.
Swahili: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa kamusi za Kiswahili.

Pair 2:
English: He was born on March 8, 1846 in the parish of Cam, Gloucestershire, England as third child of the Anglican pastor George Madan.
Swahili: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire, Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.

Pair 3:
English: He was educated at Marlborough College and studied at Christ College of Oxford university from 1865 to 1869.
Swahili: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.

Pair 4:
English: After obtaining his bachelor degree he started teaching at Christ College as a tutor from 1870-1880; during this period he also got a Master's degree.
Swahili: Baada ya kutimiza shahada ya kwanza alifundisha Christ College 1870-1880; katika kipindi hiki alipokea pia shahada ya Uzamili.

Pair 5:
English: He joined the Universities Mission to Central Africa[1].
Swahili: Alijiunga na Universities Mission to Central Africa[1].

Pair 6:
English: In 1880 he was sent to Zanzibar where he learned Swahili and assisted bishop Edward Steere in his language research and translation work.
Swahili: Mwaka 1880 alifika Zanzibar alipojifunza Kiswahili akashirikiana na askofu Edward Steere katika utafiti wa lugha na kazi ya kutafsiri.

Pair 7:
English: When Steere passed away in August 1882 Madan finished Steere's manuscript of a Swahili Grammar until the end of the year. ("A handbook of the Swahili language as spoken at Zanzibar, edited for the Universities' Mission to Central Africa"). Madan was considered the mission's chief linguist in East Africa.[1] He continued to work on Swahili dictionaries.
Swahili: Steere alipoaga dunia kwenye Agosti 1882 Madan alichukua muswada wa marehemu wa masahihisho ya Sarufi ya Kiswahili akaimaliza hadi mwisho wa mwaka ("A handbook of the Swahili language as spoken at Zanzibar, edited for the

Universities' Mission to Central Africa").

Pair 8:
English: At this time Ludwig Krapf's dictionary of Swahili, the first for this language, had not yet been published.
Swahili: Alikuwa mtaalamu mkuu wa lugha wa shirika yake ya misioni katika Afrika ya Mashariki[2] Akaendelea na kazi ya kamusi.

Pair 9:
English: In 1894 Madan's English- Swahili Dictionary was published, followed by a Swahili-English dictionary in 1903.
Swahili: Mwaka 1894 alitoa Kamusi ya Kiingereza-Kiswahili, iliyofuatwa na Kamusi ya Kiswahili-Kiingereza kwenye mwaka 1903.

Pair 10:
English: 1906 Madan moved to Northern Rhodesia (today: Zambia) where he continued reseacrhing a umber of African languages like Lenje and Wisa[2].
Swahili: Mnamo 1906 alihamia Rhodesia ya Kaskazini (leo: Zambia) alipoendelea kufanya uchunguzi wa lugha za Kiafrika kama vile Kilenje na Kiwisa[3].

Pair 11:
English: In 1911 he returned to Oxford where he taught until his death in 1917, reaching the age of 72[3].
Swahili: Mnamo 1911 alirudi Oxford alipofundisha hadi kifo chake mwaka 1917 akiwa na umri wa miaka 72[4].

Pair 12:
English: He is remembered mostly for his dictionaries and other writings about the Swahili language.
Swahili: Anajulikana kwa kamusi zake za Kiingereza-Kiswahili na Kiswahili-Kiingereza (Madan 1902), pamoja na vitabu kuhusu Kiswahili.

Pair 13:
English: His dictionaries became the base for the Standard English-Swahili Dictionary and Standard Swahili-English Dictionary which are known and reprinted into the 21 century under the name of „Madan-Johnson".
Swahili: Kamusi zake zilikuwa msingi wa Kamusi za Standard English-Swahili Dictionary na Standard Swahili-English Dictionary zinazojulikana kwa jina la „Madan-Johnson" zikitumiwa hadi karne ya 21.

Pair 14:
English: Mrima or Mrima Coast is the traditional name for the part of the East African coast facing Zanzibar.
Swahili: Mrima (ing. Mrima Coast) ni jina kwa sehemu ya pwani la Afrika ya Mashariki inayotazama Zanzibar.

Pair 15:
English: The inhabitants were often called "Wamrima" or Mrima people even though

```
they could belong to different tribes and language groups.
Swahili: Wenyeji wake walijulikana kama Wamrima ilhali kati yao walikuwa watu wa
makabila mbalimbali.

Pair 16:
English: The sources give different definitions about the borders of the coastal
stretch.
Swahili: Mipaka ya eneo hili ilielezwa tofauti katika vyanzo vya kihistoria.

Pair 17:
English: Generally the Mrima comprised only of a coastal strip of a width of 2
days travel, i.e. about 20 miles or 30 km.
Swahili: Kwa jumla ilieleweka Mrima ilihusu ukanda wa pwani hadi umbali wa
matembezi ya siku mbili hivi kutoka mwambao kuelekea bara, kwa hiyo takribani
maili 20 au kilomita 30-25.

Pair 18:
English: Ludwig Krapf, who collected his information at Mombasa betwen
1844-1852, wrote that the Wamrima began on the northern side with the Vumba
people, the speakers of the Kivumba dialect of Swahili, who lived in the area of
Shimoni, opposite Wasini Island, continued southwards until the Usambara Hills
and "the land of Mrima".[1].
Swahili: Ludwig Krapf aliyekusanya habari zake mnamo 1844 - 52 mjini Mombasa
alitaja eneo la Waswahili Wamrima lilianza upande wa kaskazini kwa Wavumba,
yaani wasemaji wa lahaja ya Kiswahili ya Kivumba, wanaotazama kisiwa cha Wasini
(Shimoni, Kenya), na kuendelea hadi vilima vya Usambara penye "nti ya Mrima"
(nchi ya Mrima)[1].

Pair 19:
English: A.C. Madan who collectd his material at Zanzibar around 1890, described
Mrima being the area between Wasini and Kipumbwi at the mouth of the Msangasi
River, about 25 km of the Tanzanian town of Pangani [1].
Swahili: A.C. Madan aliyekusanya habari wa kamusi yake mnamo 1890 pale Zanzibar,
alitaja Mrima kuwa eneo kati ya "Oassi" (Wassini) hadi Kipumbwi kwenye mdomo wa
mto Msangasi, takriban km 25 upande wa kusini ya Pangani [2].

Pair 20:
English: Later authors described a wider use of the name on the southern side.
Stigand for example described the Kimrima dialect reaching from Vanga (southern
Kenya) until the neighbourhood of Kilwa [1]
Swahili: Watafiti wengine walikuta matumizi ya jina hili kwa eneo pana zaidi
upande wa kusini, mfano Stigand alieleza lahaja ya Kimrima kuenea kuanzia Vanga
(kenya) hadi karibu na Kilwa [3]
```

[ ]:
```
# Install nltk if not already installed
!pip install nltk -q
```

```python
# Import and download required nltk data
import nltk
nltk.download('punkt')

# Import BLEU score calculation
from nltk.translate.bleu_score import sentence_bleu, corpus_bleu
```

```
[nltk_data] Downloading package punkt to /root/nltk_data…
[nltk_data]   Package punkt is already up-to-date!
```

[ ]:
```python
def evaluate_translation(model_path, test_pairs, num_samples=20):
    from nltk.translate.bleu_score import sentence_bleu, SmoothingFunction
    from nltk.translate.chrf_score import sentence_chrf
    import re

    # Initialize smoothing for BLEU
    smoother = SmoothingFunction().method1

    def preprocess_text(text):
        # Take first translation if multiple exist
        if "###" in text:
            text = text.split("###")[0]
        # Normalize text
        text = text.lower()
        text = re.sub(r'[^\w\s]', ' ', text)
        # Normalize multiple spaces
        text = ' '.join(text.split())
        return text.strip()

    # Load model
    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForCausalLM.from_pretrained(
        model_path,
        device_map="auto",
        torch_dtype=torch.bfloat16,
        low_cpu_mem_usage=True
    )

    model.eval()

    # Print two example translations at start
    print("\nExample Translations:")
    print("-" * 50)
    for i in range(2):
        source_text = test_pairs[i][0]
        reference = test_pairs[i][1]
        prompt = (
```

```
            f"### Maagizo:\nTafsiri sentensi ifuatayo kutoka Kiingereza hadi␣
↪Kiswahili.\n\n"
            f"### Text:\n{source_text}\n\n"
            f"### Tafsiri:\n"
        )

        inputs = tokenizer(prompt, return_tensors="pt", padding=True,␣
↪truncation=True).to(model.device)
        with torch.no_grad():
            outputs = model.generate(
                **inputs,
                max_new_tokens=200,
                do_sample=True,
                temperature=0.3,
                top_p=0.95
            )
        generated = tokenizer.decode(outputs[0], skip_special_tokens=True)
        generated = generated.split("### Tafsiri:\n")[-1].split("###")[0].
↪strip()

        print(f"\nExample {i+1}:")
        print(f"Source: {source_text}")
        print(f"Generated: {generated}")
        print(f"Reference: {reference}")
    print("-" * 50)
    print("\nStarting full evaluation...")

    translations = []
    scores = {
        'bleu': [],
        'bleu1': [],
        'bleu2': [],
        'bleu3': [],
        'bleu4': [],
        'chrf': []
    }

    for i, (source, reference) in enumerate(test_pairs):
        prompt = (
            f"### Maagizo:\nTafsiri sentensi ifuatayo kutoka Kiingereza hadi␣
↪Kiswahili.\n\n"
            f"### Text:\n{source}\n\n"
            f"### Tafsiri:\n"
        )

        try:
            inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
```

```
            with torch.no_grad():
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=200,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.95
                )

            generated = tokenizer.decode(outputs[0], skip_special_tokens=True)
            generated = generated.split("### Tafsiri:\n")[-1].split("###")[0].
↪strip()

            # Preprocess both texts
            ref_processed = preprocess_text(reference)
            gen_processed = preprocess_text(generated)

            # Tokenize preprocessed text
            ref_tokens = [ref_processed.split()]
            gen_tokens = gen_processed.split()

            # Calculate various BLEU scores with smoothing
            bleu = sentence_bleu(ref_tokens, gen_tokens,␣
↪smoothing_function=smoother)
            bleu1 = sentence_bleu(ref_tokens, gen_tokens, weights=(1,0,0,0),␣
↪smoothing_function=smoother)
            bleu2 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.5,0.
↪5,0,0), smoothing_function=smoother)
            bleu3 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.33,0.33,0.
↪33,0), smoothing_function=smoother)
            bleu4 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.25,0.25,0.
↪25,0.25), smoothing_function=smoother)

            # Calculate chrF score on original texts (it handles preprocessing␣
↪internally)
            chrf = sentence_chrf(reference, generated)

            translations.append({
                'source': source,
                'generated': generated,
                'reference': reference,
                'generated_processed': gen_processed,
                'reference_processed': ref_processed,
                'bleu': bleu,
                'bleu1': bleu1,
```

```python
            'bleu2': bleu2,
            'bleu3': bleu3,
            'bleu4': bleu4,
            'chrf': chrf
        })

        scores['bleu'].append(bleu)
        scores['bleu1'].append(bleu1)
        scores['bleu2'].append(bleu2)
        scores['bleu3'].append(bleu3)
        scores['bleu4'].append(bleu4)
        scores['chrf'].append(chrf)

        # Progress updates every 5 samples
        if (i + 1) % 5 == 0:
            print(f"Processed {i + 1}/{len(test_pairs)} translations")
            print(f"Current average BLEU: {np.mean(scores['bleu']):.4f}")
            print(f"Current average chrF: {np.mean(scores['chrf']):.4f}")

    except Exception as e:
        print(f"Error processing translation {i}: {str(e)}")
        continue

# Print final results
print("\nFinal Results:")
print(f"Average BLEU Score: {np.mean(scores['bleu']):.4f}")
print(f"Average BLEU-1 Score: {np.mean(scores['bleu1']):.4f}")
print(f"Average BLEU-2 Score: {np.mean(scores['bleu2']):.4f}")
print(f"Average BLEU-3 Score: {np.mean(scores['bleu3']):.4f}")
print(f"Average BLEU-4 Score: {np.mean(scores['bleu4']):.4f}")
print(f"Average chrF Score: {np.mean(scores['chrf']):.4f}")

# Show some example translations with processed versions
print("\nSample Translations:")
for i in range(min(3, len(translations))):
    print(f"\nTranslation {i+1}:")
    print(f"Source: {translations[i]['source']}")
    print(f"Generated: {translations[i]['generated']}")
    print(f"Reference: {translations[i]['reference']}")
    print(f"Processed Generated: {translations[i]['generated_processed']}")
    print(f"Processed Reference: {translations[i]['reference_processed']}")
    print(f"BLEU Score: {translations[i]['bleu']:.4f}")
    print(f"chrF Score: {translations[i]['chrf']:.4f}")

# Clean up
del model, inputs, outputs
torch.cuda.empty_cache()
```

```python
    # Return all metrics
    return {metric: np.mean(scores[metric]) for metric in scores.keys()}
```

[ ]:
```python
# Gemma2 2B Evaluation on Translation Tasks
gemma2_2b_translation_scores = evaluate_translation(
    model_path=gemma2_2b_it_model_path,
    test_pairs=test_pairs
)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.

Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mwandishi wa lugha nchini
Uingereza na misionari wa Kanisa la Kianglik aliyefahamika kwa utafiti wake wa
lugha za Afrika na dhaftarisi za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Alizaliwa tarehe 8 Machi, 1846 katika kata ya Cam, Gloucestershire,
Uingereza kama mtoto wa tatu wa mchungaji wa Kanisa la Anglikana George Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
Current average BLEU: 0.1324
Current average chrF: 0.5131
Processed 10/20 translations
Current average BLEU: 0.1041
Current average chrF: 0.4656
Processed 15/20 translations
Current average BLEU: 0.1334
```

```
Current average chrF: 0.4866
Processed 20/20 translations
Current average BLEU: 0.1044
Current average chrF: 0.4433

Final Results:
Average BLEU Score: 0.1044
Average BLEU-1 Score: 0.3403
Average BLEU-2 Score: 0.2106
Average BLEU-3 Score: 0.1430
Average BLEU-4 Score: 0.1044
Average chrF Score: 0.4433

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mwandishi wa lugha nchini
Uingereza na misionari wa Kanisa Katoliki aliyejulikana kwa utafiti wake wa
lugha za Afrika na dhaftari za lugha ya Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.
Processed Generated: arthur cornwallis madan 1846 1917 alikuwa mwandishi wa
lugha nchini uingereza na misionari wa kanisa katoliki aliyejulikana kwa utafiti
wake wa lugha za afrika na dhaftari za lugha ya kiswahili
Processed Reference: arthur cornwallis madan 1846 1917 alikuwa mwanaisimu na
mmisionari mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za kiafrika
na hasa kamusi za kiswahili
BLEU Score: 0.3287
chrF Score: 0.6817

Translation 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Alizaliwa tarehe 8 Machi, 1846 katika kata ya Cam, Gloucestershire,
Uingereza kama mtoto wa pili wa mwanafunzi wa Kanisa la Kianglikali George
Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
Processed Generated: alizaliwa tarehe 8 machi 1846 katika kata ya cam
gloucestershire uingereza kama mtoto wa pili wa mwanafunzi wa kanisa la
kianglikali george madan
Processed Reference: alizaliwa 8 machi 1846 kwenye kijiji cha cam
gloucestershire uingereza akiwa mwana wa tatu wa mchungaji mwanglikana george
madan
```

```
BLEU Score: 0.0848
chrF Score: 0.5829

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of
Oxford university from 1865 to 1869.
Generated: Aliosoma Marlborough College na kusoma Christ College ya Chuo cha
Oxford kuanzia 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea
kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
Processed Generated: aliosoma marlborough college na kusoma christ college ya
chuo cha oxford kuanzia 1865 hadi 1869
Processed Reference: alisoma kwenye shule ya sekondari ya marlborough college
akaendelea kusoma kwenye christ college ya chuo kikuu cha oxford 1865 1869
BLEU Score: 0.1725
chrF Score: 0.4832
```

[ ]:
```
# Swahili Finetuned Gemma2 2B evaluation on english to swahili Translation

swahili_gemma2_2b_translation_scores = evaluate_translation(
    model_path=swahili_gemma2_2b_it_model_path,
    test_pairs=test_pairs
)
```

```
Loading checkpoint shards:   0%|          | 0/2 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.


Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtafiti wa lugha za
Kiingereza na misionari wa Kanisa la Kianglikali ambaye alikuwa maarufu kwa
utafiti wake katika lugha za Afrika na dhaftari lake la Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Alizaliwa tarehe 8 Machi, 1846 katika maeneo ya Cam, Gloucestershire,
Uingereza kama mtoto wa tatu wa mhusika wa Kanisa la Kianglikali George Madan.
```

```
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
Current average BLEU: 0.1121
Current average chrF: 0.4424
Processed 10/20 translations
Current average BLEU: 0.0938
Current average chrF: 0.4397
Processed 15/20 translations
Current average BLEU: 0.1193
Current average chrF: 0.4390
Processed 20/20 translations
Current average BLEU: 0.0975
Current average chrF: 0.4171

Final Results:
Average BLEU Score: 0.0975
Average BLEU-1 Score: 0.3735
Average BLEU-2 Score: 0.2271
Average BLEU-3 Score: 0.1510
Average BLEU-4 Score: 0.0975
Average chrF Score: 0.4171

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mwandishi wa lugha za
Kiingereza na misionari wa Kanisa la Kianglikali ambaye alikuwa maarufu kwa
utafiti wake katika lugha za Afrika na dhaftari lake la Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.
Processed Generated: arthur cornwallis madan 1846 1917 alikuwa mwandishi wa
lugha za kiingereza na misionari wa kanisa la kianglikali ambaye alikuwa maarufu
kwa utafiti wake katika lugha za afrika na dhaftari lake la kiswahili
Processed Reference: arthur cornwallis madan 1846 1917 alikuwa mwanaisimu na
mmisionari mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za kiafrika
na hasa kamusi za kiswahili
BLEU Score: 0.2341
chrF Score: 0.6549

Translation 2:
```

```
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Alizaliwa tarehe 8 Machi, 1846 katika maeneo ya Cam, Gloucestershire,
Uingereza kama mtoto wa tatu wa mhusika wa Anglican, George Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
Processed Generated: alizaliwa tarehe 8 machi 1846 katika maeneo ya cam
gloucestershire uingereza kama mtoto wa tatu wa mhusika wa anglican george madan
Processed Reference: alizaliwa 8 machi 1846 kwenye kijiji cha cam
gloucestershire uingereza akiwa mwana wa tatu wa mchungaji mwanglikana george
madan
BLEU Score: 0.1151
chrF Score: 0.5721

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of
Oxford university from 1865 to 1869.
Generated: Alikuwa amefanya elimu katika Chuo Kikuu cha Marlborough na kusoma
katika Chuo Kikuu cha Oxford kutoka mwaka 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea
kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
Processed Generated: alikuwa amefanya elimu katika chuo kikuu cha marlborough na
kusoma katika chuo kikuu cha oxford kutoka mwaka 1865 hadi 1869
Processed Reference: alisoma kwenye shule ya sekondari ya marlborough college
akaendelea kusoma kwenye christ college ya chuo kikuu cha oxford 1865 1869
BLEU Score: 0.1425
chrF Score: 0.3804
```

[ ]:
```
# Gemma2 9B Evaluation on Translation Tasks
gemma2_9b_translation_scores = evaluate_translation(
    model_path=gemma2_9b_it_model_path,
    test_pairs=test_pairs
)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.
```

```
Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mwanafalsafa Mwingereza
na mhubiri wa Kanisa la Anglikana ambaye alijulikana kwa utafiti wake katika
```

```
lugha za Afrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi, 1846 katika jimbo la Cam,
Gloucestershire, England kama mtoto wa tatu wa padri wa Kanisa la Anglican
George Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
Current average BLEU: 0.1365
Current average chrF: 0.4978
Processed 10/20 translations
Current average BLEU: 0.1606
Current average chrF: 0.5086
Processed 15/20 translations
Current average BLEU: 0.1913
Current average chrF: 0.5203
Processed 20/20 translations
Current average BLEU: 0.1726
Current average chrF: 0.5044

Final Results:
Average BLEU Score: 0.1726
Average BLEU-1 Score: 0.4851
Average BLEU-2 Score: 0.3343
Average BLEU-3 Score: 0.2376
Average BLEU-4 Score: 0.1726
Average chrF Score: 0.5044

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mwanafalsafa Mwingereza
na mhubiri wa Kanisa la Anglican ambaye alijulikana kwa utafiti wake katika
lugha za Afrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
```

```
kamusi za Kiswahili.
Processed Generated: arthur cornwallis madan 1846 1917 alikuwa mwanafalsafa
mwingereza na mhubiri wa kanisa la anglican ambaye alijulikana kwa utafiti wake
katika lugha za afrika na kamusi zake za kiswahili
Processed Reference: arthur cornwallis madan 1846 1917 alikuwa mwanaisimu na
mmisionari mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za kiafrika
na hasa kamusi za kiswahili
BLEU Score: 0.2614
chrF Score: 0.6692

Translation 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi, 1846 katika jimbo la Cam,
Gloucestershire, Uingereza kama mtoto wa tatu wa mchungaji wa Kanisa la Anglican
George Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
Processed Generated: aliyezaliwa tarehe 8 machi 1846 katika jimbo la cam
gloucestershire uingereza kama mtoto wa tatu wa mchungaji wa kanisa la anglican
george madan
Processed Reference: alizaliwa 8 machi 1846 kwenye kijiji cha cam
gloucestershire uingereza akiwa mwana wa tatu wa mchungaji mwanglikana george
madan
BLEU Score: 0.2062
chrF Score: 0.6191

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of
Oxford university from 1865 to 1869.
Generated: Alilelewa katika Chuo cha Marlborough na aliosoma katika Chuo cha
Kristo cha Chuo Kikuu cha Oxford kutoka mwaka 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea
kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
Processed Generated: alilelewa katika chuo cha marlborough na aliosoma katika
chuo cha kristo cha chuo kikuu cha oxford kutoka mwaka 1865 hadi 1869
Processed Reference: alisoma kwenye shule ya sekondari ya marlborough college
akaendelea kusoma kwenye christ college ya chuo kikuu cha oxford 1865 1869
BLEU Score: 0.1308
chrF Score: 0.3764
```

[ ]:
```python
swahili_gemma2_9b_translation_scores = evaluate_translation(
    model_path=swahili_gemma2_9b_it_model_path,
    test_pairs=test_pairs
)
```

```
Loading checkpoint shards:   0%|          | 0/4 [00:00<?, ?it/s]
```

```
Asking to truncate to max_length but no maximum length is provided and the model
has no predefined maximum length. Default to no truncation.

Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha ya
Kiingereza na mhubiri wa Kanisa la Anglikana ambaye alijulikana kwa utafiti wake
katika lugha za Kiafrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi 1846 katika kata ya Cam, Gloucestershire,
England kama mtoto wa tatu wa mchungaji wa Anglican
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
Current average BLEU: 0.1325
Current average chrF: 0.4785
Processed 10/20 translations
Current average BLEU: 0.1712
Current average chrF: 0.5101
Processed 15/20 translations
Current average BLEU: 0.1613
Current average chrF: 0.5004
Processed 20/20 translations
Current average BLEU: 0.1539
Current average chrF: 0.4911

Final Results:
Average BLEU Score: 0.1539
Average BLEU-1 Score: 0.4709
Average BLEU-2 Score: 0.3239
Average BLEU-3 Score: 0.2300
Average BLEU-4 Score: 0.1539
Average chrF Score: 0.4911
```

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican missionary who became famous for his research in African languages and his Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha wa Uingereza na mhubiri wa Kanisa la Anglican ambaye alijulikana kwa utafiti wake katika lugha za Afrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa kamusi za Kiswahili.
Processed Generated: arthur cornwallis madan 1846 1917 alikuwa mtaalamu wa lugha wa uingereza na mhubiri wa kanisa la anglican ambaye alijulikana kwa utafiti wake katika lugha za afrika na kamusi zake za kiswahili
Processed Reference: arthur cornwallis madan 1846 1917 alikuwa mwanaisimu na mmisionari mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za kiafrika na hasa kamusi za kiswahili
BLEU Score: 0.2411
chrF Score: 0.6499

Translation 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire, England as third child of the Anglican pastor George Madan.
Generated: Alizaliwa tarehe 8 Machi, 1846 katika kata ya Cam, Gloucestershire, England kama mtoto wa tatu wa mchungaji wa Anglican George Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire, Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
Processed Generated: alizaliwa tarehe 8 machi 1846 katika kata ya cam gloucestershire england kama mtoto wa tatu wa mchungaji wa anglican george madan
Processed Reference: alizaliwa 8 machi 1846 kwenye kijiji cha cam gloucestershire uingereza akiwa mwana wa tatu wa mchungaji mwanglikana george madan
BLEU Score: 0.2047
chrF Score: 0.5661

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of Oxford university from 1865 to 1869.
Generated: Alilelewa katika Chuo cha Marlborough na alifundishwa katika Chuo cha Kristo cha Chuo Kikuu cha Oxford kutoka 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
Processed Generated: alilelewa katika chuo cha marlborough na alifundishwa katika chuo cha kristo cha chuo kikuu cha oxford kutoka 1865 hadi 1869
Processed Reference: alisoma kwenye shule ya sekondari ya marlborough college akaendelea kusoma kwenye christ college ya chuo kikuu cha oxford 1865 1869

```
BLEU Score: 0.1379
chrF Score: 0.3648
```

[ ]:
```
# Evaluating the 27B models(4-bit quantization)

def evaluate_translation_4bit(model_path, test_pairs, num_samples=20):
    from nltk.translate.bleu_score import sentence_bleu, SmoothingFunction
    from nltk.translate.chrf_score import sentence_chrf
    from transformers import BitsAndBytesConfig
    import re
    import torch
    import gc

    # Initialize smoothing for BLEU
    smoother = SmoothingFunction().method1

    def preprocess_text(text):
        if "###" in text:
            text = text.split("###")[0]
        text = text.lower()
        text = re.sub(r'[^\w\s]', ' ', text)
        text = ' '.join(text.split())
        return text.strip()

    # Configure 4-bit quantization
    bnb_config = BitsAndBytesConfig(
        load_in_4bit=True,
        bnb_4bit_quant_type="nf4",
        bnb_4bit_compute_dtype=torch.bfloat16,
        bnb_4bit_use_double_quant=True
    )

    print("Loading model and tokenizer...")
    tokenizer = AutoTokenizer.from_pretrained(model_path)
    model = AutoModelForCausalLM.from_pretrained(
        model_path,
        quantization_config=bnb_config,
        device_map="auto",
        torch_dtype=torch.bfloat16,
        trust_remote_code=True
    )

    # Ensure model is in eval mode
    model.eval()  # Critical for stable generation
    torch.cuda.empty_cache()
    gc.collect()
```

```
    print("\nExample Translations:")
    print("-" * 50)
    for i in range(2):
        source_text = test_pairs[i][0]
        reference = test_pairs[i][1]
        prompt = (
            f"### Maagizo:\nTafsiri sentensi ifuatayo kutoka Kiingereza hadi␣
↪Kiswahili.\n\n"
            f"### Text:\n{source_text}\n\n"
            f"### Tafsiri:\n"
        )

        try:
            inputs = tokenizer(prompt, return_tensors="pt").to(model.device)
            with torch.no_grad():  # Ensure no gradients are computed
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=200,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.95,
                    pad_token_id=tokenizer.pad_token_id,
                    eos_token_id=tokenizer.eos_token_id
                )
            generated = tokenizer.decode(outputs[0], skip_special_tokens=True)
            generated = generated.split("### Tafsiri:\n")[-1].split("###")[0].
↪strip()

            print(f"\nExample {i+1}:")
            print(f"Source: {source_text}")
            print(f"Generated: {generated}")
            print(f"Reference: {reference}")
        except Exception as e:
            print(f"Error in example generation {i}: {str(e)}")
            continue

    print("-" * 50)
    print("\nStarting full evaluation...")

    translations = []
    scores = {
        'bleu': [],
        'bleu1': [],
        'bleu2': [],
        'bleu3': [],
        'bleu4': [],
        'chrf': []
```

```
    }

    for i, (source, reference) in enumerate(test_pairs):
        prompt = (
            f"### Maagizo:\nTafsiri sentensi ifuatayo kutoka Kiingereza hadi␣
↪Kiswahili.\n\n"
            f"### Text:\n{source}\n\n"
            f"### Tafsiri:\n"
        )

        try:
            inputs = tokenizer(prompt, return_tensors="pt").to(model.device)

            with torch.no_grad():
                outputs = model.generate(
                    **inputs,
                    max_new_tokens=200,
                    do_sample=True,
                    temperature=0.3,
                    top_p=0.95,
                    pad_token_id=tokenizer.pad_token_id,
                    eos_token_id=tokenizer.eos_token_id
                )

            generated = tokenizer.decode(outputs[0], skip_special_tokens=True)
            generated = generated.split("### Tafsiri:\n")[-1].split("###")[0].
↪strip()

            # Preprocess both texts
            ref_processed = preprocess_text(reference)
            gen_processed = preprocess_text(generated)

            # Tokenize preprocessed text
            ref_tokens = [ref_processed.split()]
            gen_tokens = gen_processed.split()

            # Calculate various BLEU scores with smoothing
            bleu = sentence_bleu(ref_tokens, gen_tokens,␣
↪smoothing_function=smoother)
            bleu1 = sentence_bleu(ref_tokens, gen_tokens, weights=(1,0,0,0),␣
↪smoothing_function=smoother)
            bleu2 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.5,0.
↪5,0,0), smoothing_function=smoother)
            bleu3 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.33,0.33,0.
↪33,0), smoothing_function=smoother)
```

```
            bleu4 = sentence_bleu(ref_tokens, gen_tokens, weights=(0.25,0.25,0.
↪25,0.25), smoothing_function=smoother)

            # Calculate chrF score on original texts
            chrf = sentence_chrf(reference, generated)

            translations.append({
                'source': source,
                'generated': generated,
                'reference': reference,
                'generated_processed': gen_processed,
                'reference_processed': ref_processed,
                'bleu': bleu,
                'bleu1': bleu1,
                'bleu2': bleu2,
                'bleu3': bleu3,
                'bleu4': bleu4,
                'chrf': chrf
            })

            scores['bleu'].append(bleu)
            scores['bleu1'].append(bleu1)
            scores['bleu2'].append(bleu2)
            scores['bleu3'].append(bleu3)
            scores['bleu4'].append(bleu4)
            scores['chrf'].append(chrf)

            if (i + 1) % 5 == 0:
                print(f"Processed {i + 1}/{len(test_pairs)} translations")
                print(f"Current average BLEU: {np.mean(scores['bleu']):.4f}")
                print(f"Current average chrF: {np.mean(scores['chrf']):.4f}")

        except Exception as e:
            print(f"Error processing translation {i}: {str(e)}")
            continue

    print("\nFinal Results:")
    print(f"Average BLEU Score: {np.mean(scores['bleu']):.4f}")
    print(f"Average BLEU-1 Score: {np.mean(scores['bleu1']):.4f}")
    print(f"Average BLEU-2 Score: {np.mean(scores['bleu2']):.4f}")
    print(f"Average BLEU-3 Score: {np.mean(scores['bleu3']):.4f}")
    print(f"Average BLEU-4 Score: {np.mean(scores['bleu4']):.4f}")
    print(f"Average chrF Score: {np.mean(scores['chrf']):.4f}")

    print("\nSample Translations:")
    for i in range(min(3, len(translations))):
        print(f"\nTranslation {i+1}:")
```

```
        print(f"Source: {translations[i]['source']}")
        print(f"Generated: {translations[i]['generated']}")
        print(f"Reference: {translations[i]['reference']}")
        print(f"BLEU Score: {translations[i]['bleu']:.4f}")
        print(f"chrF Score: {translations[i]['chrf']:.4f}")

    # Clean up
    del model, inputs, outputs
    torch.cuda.empty_cache()
    gc.collect()

    return {metric: np.mean(scores[metric]) for metric in scores.keys()}
```

[ ]:
```
# Base 27B model evaluation
gemma2_27b_it_4bit_translation_scores = evaluate_translation_4bit(
    model_path=gemma2_27b_it_model_path,
    test_pairs=test_pairs
)
```

```
Loading model and tokenizer…

Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

The 'batch_size' attribute of HybridCache is deprecated and will be removed in
v4.49. Use the more precisely named 'self.max_batch_size' attribute instead.


Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha na
mhubiri wa Ukristo wa Anglikana kutoka Uingereza ambaye alijulikana kwa utafiti
wake katika lugha za Kiafrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi, 1846 katika parokia ya Cam,
Gloucestershire, Uingereza kama mtoto wa tatu wa mchungaji George Madan wa
Kanisa la Anglikana.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
```

```
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
Current average BLEU: 0.1923
Current average chrF: 0.6184
Processed 10/20 translations
Current average BLEU: 0.2070
Current average chrF: 0.5865
Processed 15/20 translations
Current average BLEU: 0.2063
Current average chrF: 0.5649
Processed 20/20 translations
Current average BLEU: 0.1818
Current average chrF: 0.5391

Final Results:
Average BLEU Score: 0.1818
Average BLEU-1 Score: 0.4923
Average BLEU-2 Score: 0.3569
Average BLEU-3 Score: 0.2673
Average BLEU-4 Score: 0.1818
Average chrF Score: 0.5391

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha na
mhubiri wa dini ya Anglikana kutoka Uingereza ambaye alijulikana kwa utafiti
wake katika lugha za Kiafrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.
BLEU Score: 0.2992
chrF Score: 0.6908

Translation 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi, 1846 katika parokia ya Cam,
Gloucestershire, Uingereza kama mtoto wa tatu wa mchungaji wa Anglikana George
Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
BLEU Score: 0.2274
```

```
chrF Score: 0.6598

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of
Oxford university from 1865 to 1869.
Generated: Alihudhuria shule ya Marlborough College na kisha akaenda Chuo Kikuu
cha Oxford, Chuo cha Christ, kujifunza kutoka mwaka 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea
kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
BLEU Score: 0.1927
chrF Score: 0.4919
```

[ ]:
```python
# Fine-tuned 27B model translation evaluation
swahili_gemma2_27b_it_4bit_translation_scores = evaluate_translation_4bit(
    model_path=swahili_gemma2_27b_it_model_path,
    test_pairs=test_pairs
)
```

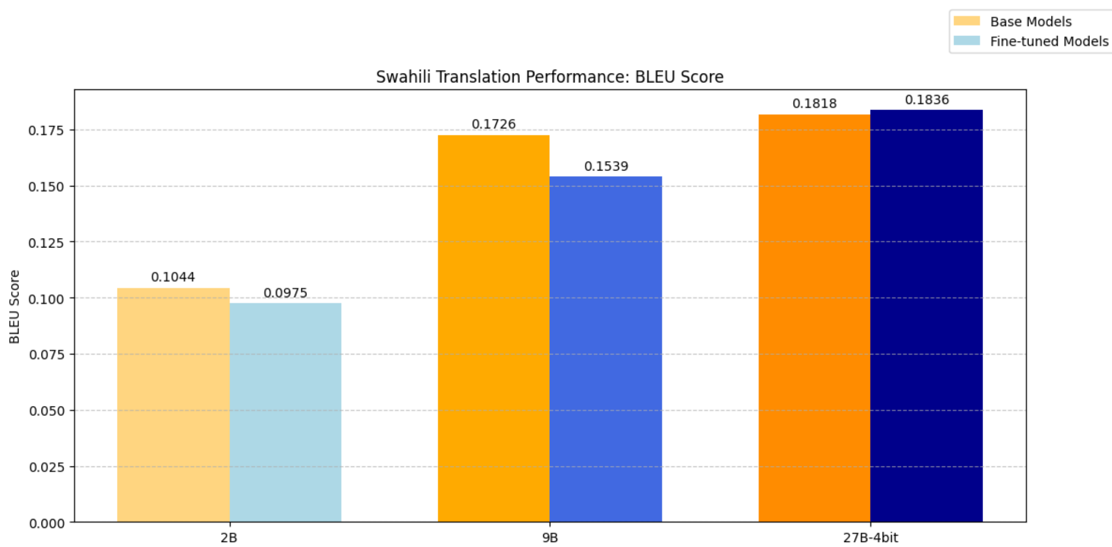
```
Loading model and tokenizer…

Loading checkpoint shards:   0%|          | 0/12 [00:00<?, ?it/s]

Example Translations:
--------------------------------------------------

Example 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha na
mhubiri wa Kanisa la Anglikana ambaye alijulikana kwa utafiti wake katika lugha
za Kiafrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.

Example 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi 1846 katika parokia ya Cam,
Gloucestershire, Uingereza kama mtoto wa tatu wa mchungaji wa Anglikana George
Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
--------------------------------------------------

Starting full evaluation…
Processed 5/20 translations
```

```
Current average BLEU: 0.1617
Current average chrF: 0.5126
Processed 10/20 translations
Current average BLEU: 0.1799
Current average chrF: 0.5260
Processed 15/20 translations
Current average BLEU: 0.2043
Current average chrF: 0.5321
Processed 20/20 translations
Current average BLEU: 0.1836
Current average chrF: 0.5143

Final Results:
Average BLEU Score: 0.1836
Average BLEU-1 Score: 0.4994
Average BLEU-2 Score: 0.3580
Average BLEU-3 Score: 0.2599
Average BLEU-4 Score: 0.1836
Average chrF Score: 0.5143

Sample Translations:

Translation 1:
Source: Arthur Cornwallis Madan (1846-1917) was a British linguist and Anglican
missionary who became famous for his research in African languages and his
Swahili dictionaries.
Generated: Arthur Cornwallis Madan (1846-1917) alikuwa mtaalamu wa lugha na
mhubiri wa Kanisa la Anglican kutoka Uingereza ambaye alijulikana kwa utafiti
wake katika lugha za Kiafrika na kamusi zake za Kiswahili.
Reference: Arthur Cornwallis Madan (1846-1917) alikuwa mwanaisimu na mmisionari
Mwanglikana anayejulikana hasa kwa utafiti wake wa lugha za Kiafrika na hasa
kamusi za Kiswahili.
BLEU Score: 0.2992
chrF Score: 0.6775

Translation 2:
Source: He was born on March 8, 1846 in the parish of Cam, Gloucestershire,
England as third child of the Anglican pastor George Madan.
Generated: Aliyezaliwa tarehe 8 Machi 1846 katika parokia ya Cam,
Gloucestershire, England kama mtoto wa tatu wa mchungaji wa Anglican George
Madan.
Reference: Alizaliwa 8 Machi 1846 kwenye kijiji cha Cam, Gloucestershire,
Uingereza akiwa mwana wa tatu wa mchungaji Mwanglikana George Madan.
BLEU Score: 0.2003
chrF Score: 0.5760

Translation 3:
Source: He was educated at Marlborough College and studied at Christ College of
```

```
Oxford university from 1865 to 1869.
Generated: Alihudhuria shule ya Marlborough College na alijifunza katika Chuo
cha Kristo cha Chuo Kikuu cha Oxford kutoka 1865 hadi 1869.
Reference: Alisoma kwenye shule ya sekondari ya Marlborough College, akaendelea
kusoma kwenye Christ College ya Chuo Kikuu cha Oxford 1865-1869.
BLEU Score: 0.1984
chrF Score: 0.4469
```

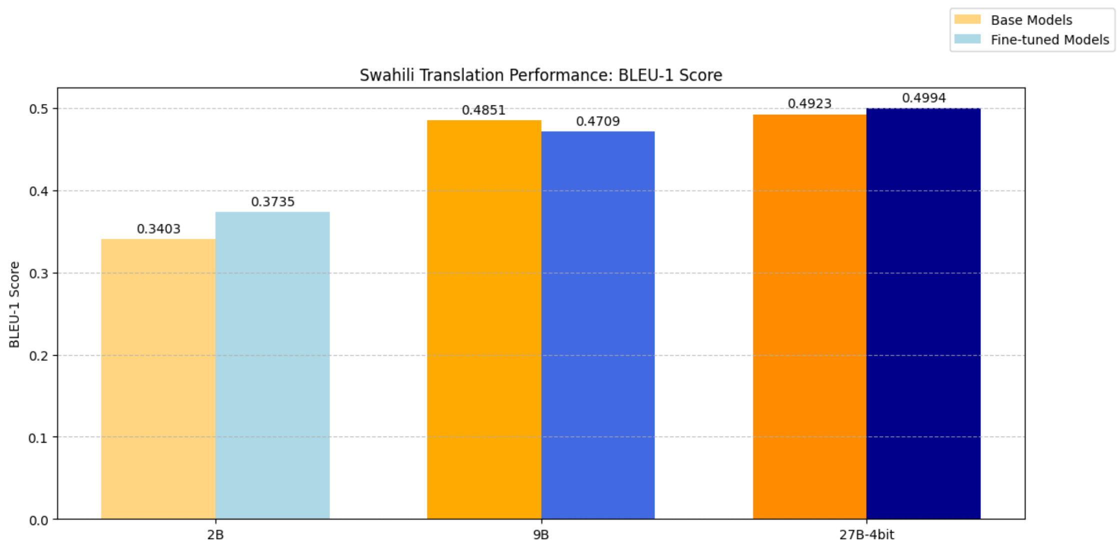
[ ]:
```
# BLEU Score Plot
plt.figure(figsize=(12, 6))

# Prepare the translation scores
translation_scores = [
    (gemma2_2b_translation_scores, swahili_gemma2_2b_translation_scores),
    (gemma2_9b_translation_scores, swahili_gemma2_9b_translation_scores),
    (gemma2_27b_it_4bit_translation_scores,␣
 ↪swahili_gemma2_27b_it_4bit_translation_scores)
]

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = plt.bar(x - width/2, [scores[0]['bleu'] for scores in␣
 ↪translation_scores], width,
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['bleu'] for scores in␣
 ↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('BLEU Score')
plt.title('Swahili Translation Performance: BLEU Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
```

```
                    xytext=(0, 3),  # 3 points vertical offset
                    textcoords="offset points",
                    ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



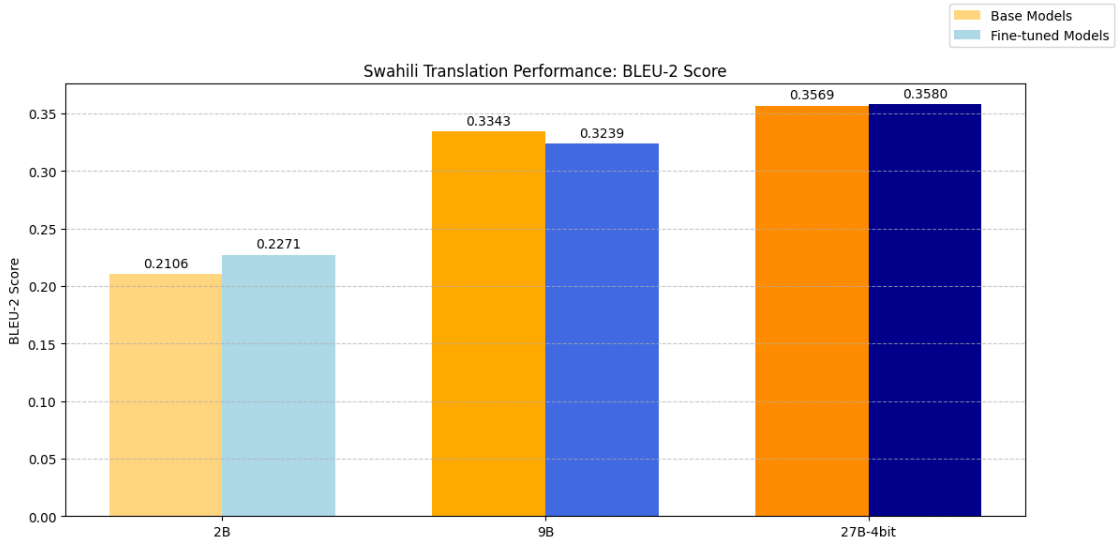
[ ]:
```
# BLEU-1 Score Plot
plt.figure(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = plt.bar(x - width/2, [scores[0]['bleu1'] for scores in␣
 ↪translation_scores], width,
```

```
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['bleu1'] for scores in␣
 ↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('BLEU-1 Score')
plt.title('Swahili Translation Performance: BLEU-1 Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
                     xytext=(0, 3),  # 3 points vertical offset
                     textcoords="offset points",
                     ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



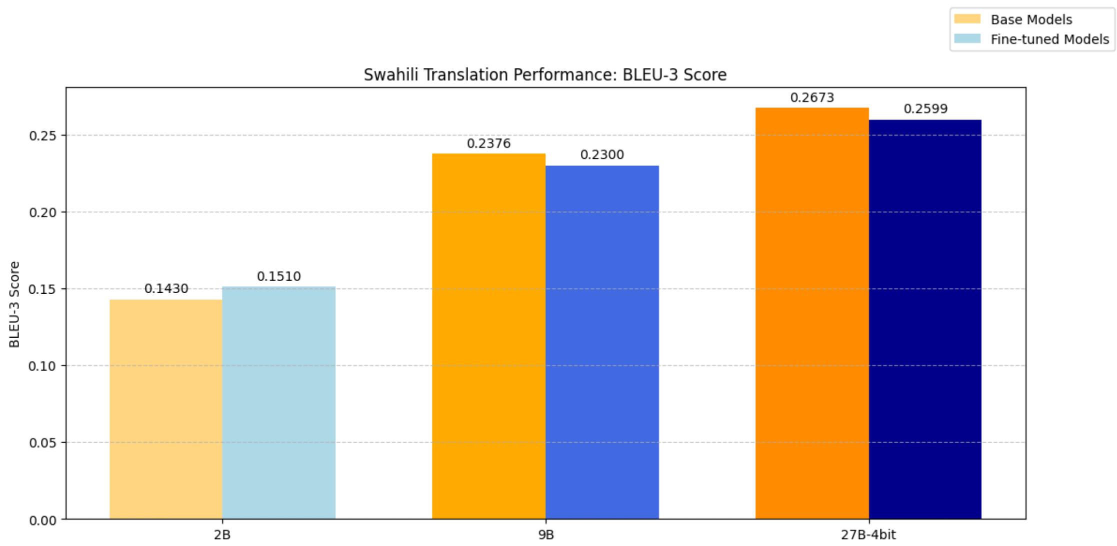
[ ]:

```
# BLEU-2 Score Plot
plt.figure(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = plt.bar(x - width/2, [scores[0]['bleu2'] for scores in␣
↪translation_scores], width,
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['bleu2'] for scores in␣
↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('BLEU-2 Score')
plt.title('Swahili Translation Performance: BLEU-2 Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
                     xytext=(0, 3),  # 3 points vertical offset
                     textcoords="offset points",
                     ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



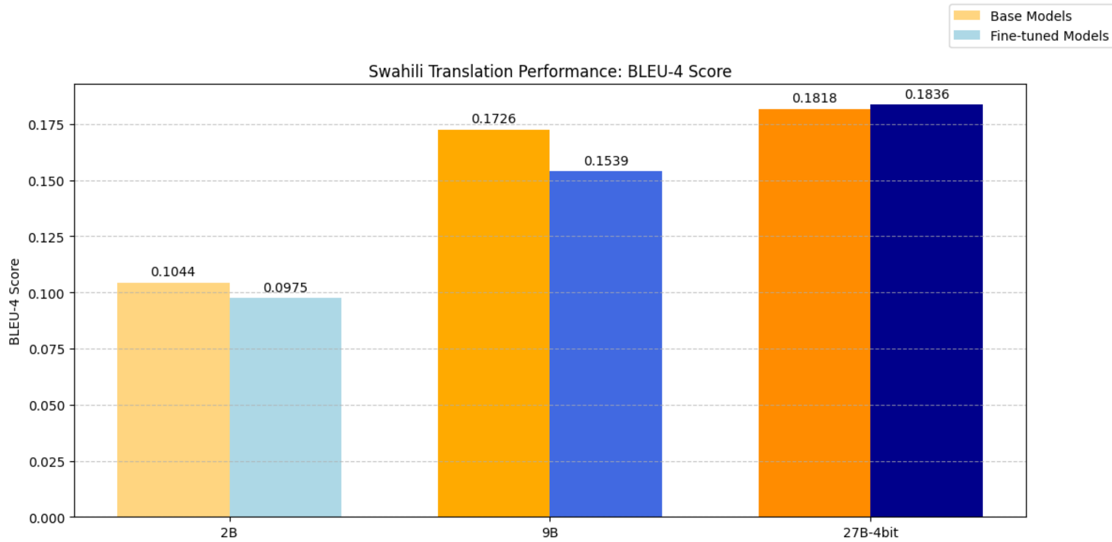
[ ]:
```python
# BLEU-3 Score Plot
plt.figure(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = plt.bar(x - width/2, [scores[0]['bleu3'] for scores in␣
 ↪translation_scores], width,
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['bleu3'] for scores in␣
 ↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('BLEU-3 Score')
plt.title('Swahili Translation Performance: BLEU-3 Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
```

```
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
                     xytext=(0, 3),  # 3 points vertical offset
                     textcoords="offset points",
                     ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



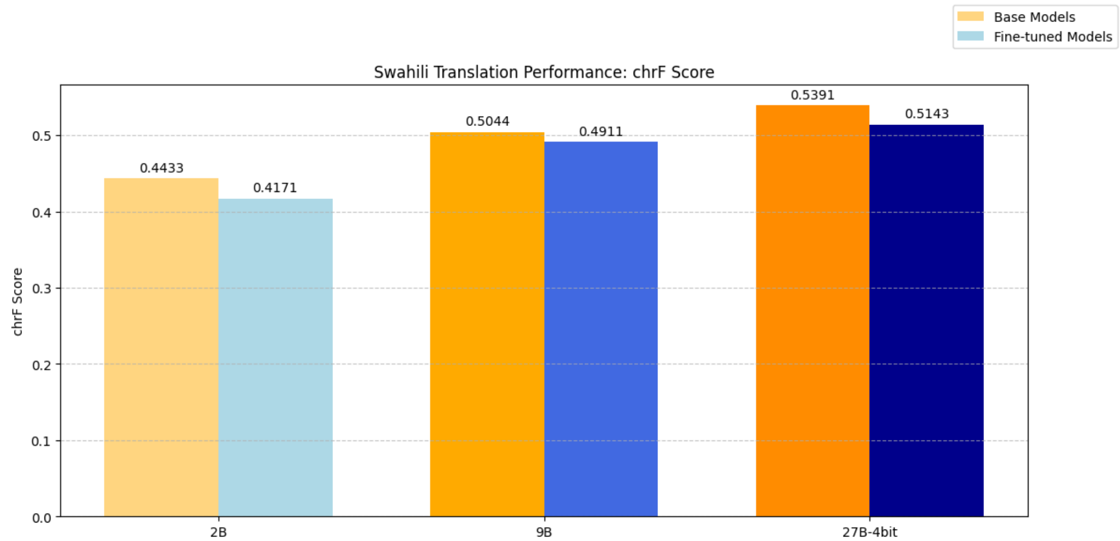
[ ]:
```
# BLEU-4 Score Plot
plt.figure(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
```

```
rects1 = plt.bar(x - width/2, [scores[0]['bleu4'] for scores in␣
↪translation_scores], width,
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['bleu4'] for scores in␣
↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('BLEU-4 Score')
plt.title('Swahili Translation Performance: BLEU-4 Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
                     xytext=(0, 3),  # 3 points vertical offset
                     textcoords="offset points",
                     ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```



[ ]:
```
# chrF Score Plot
plt.figure(figsize=(12, 6))

# Position for bars
x = np.arange(3)
width = 0.35

# Colors for gradients
base_colors = ['#ffd580', '#ffaa00', '#ff8c00']  # Orange gradient
finetuned_colors = ['#add8e6', '#4169e1', '#00008b']  # Blue gradient

# Create bars
rects1 = plt.bar(x - width/2, [scores[0]['chrf'] for scores in␣
 ↪translation_scores], width,
                 label='Base Models', color=base_colors)
rects2 = plt.bar(x + width/2, [scores[1]['chrf'] for scores in␣
 ↪translation_scores], width,
                 label='Fine-tuned Models', color=finetuned_colors)

# Customize plot
plt.ylabel('chrF Score')
plt.title('Swahili Translation Performance: chrF Score')
plt.xticks(x, ['2B', '9B', '27B-4bit'])
plt.legend(loc='upper right', bbox_to_anchor=(1.1, 1.2))

# Add value labels on bars
def autolabel(rects):
    for rect in rects:
```

```
        height = rect.get_height()
        plt.annotate(f'{height:.4f}',
                     xy=(rect.get_x() + rect.get_width()/2, height),
                     xytext=(0, 3),  # 3 points vertical offset
                     textcoords="offset points",
                     ha='center', va='bottom')

autolabel(rects1)
autolabel(rects2)

# Add grid for better readability
plt.grid(True, axis='y', linestyle='--', alpha=0.7)

# Adjust layout and display
plt.tight_layout()
plt.show()
```




```
[ ]:
```