MEKELLE UNIVERSITY – MEKELLE INSTITUTE OF TECHNOLOGY

PROJECT REPORT

AI-POWERED MEDICAL & LEGAL TRANSLATION SYSTEM FOR ENGLISH ↔ TIGRINYA

Submitted by

Computer Science & Engineering 5th Year Regular

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ABSTRACT

In multilingual societies, language barriers pose significant challenges in accessing healthcare and legal services—especially for low-resource languages like Tigrinya. This project presents the development of an AI-powered translation system specifically designed for medical and legal texts between English and Tigrinya. Leveraging Meta AI's NLLB-200 (No Language Left Behind) multilingual model, we fine-tuned it using a domain-specific parallel corpus of 1,000 sentences. The system incorporates advanced preprocessing techniques, manual validation by bilingual experts, and evaluation using both automated metrics (BLEU, SacreBLEU) and human review.

The primary goal is to improve the accuracy, fluency, and contextual relevance of translations in sensitive and high-stakes domains. This system is deployed through a REST API and integrated into a user-friendly application interface for practical use by healthcare providers, legal practitioners, humanitarian workers, and Tigrinya-speaking communities. The project not only bridges a critical communication gap but also contributes to the advancement of AI applications for underrepresented African languages.

ACKNOWLEDGMENTS

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Special thanks to the bilingual translators, medical professionals, and legal experts who contributed their knowledge and time to help us build and validate the dataset used in this project.

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LIST OF ACRONYMS

AI	Artificial Intelligence
MT	Machine Translation
NMT	Neural Machine Translation
RBMT	Rule-Based Machine Translation
SMT	Statistical Machine Translation
BLEU	Bilingual Evaluation Understudy
NLLB	No Language Left Behind
NLP	Natural Language Processing
API	Application Programming Interface
UI	User Interface
GPU	Graphics Processing Unit
ML	Machine Learning
DL	Deep Learning
CSV	Comma-Separated Values
REST	Representational State Transfer
LRL	Low-Resource Language
LLM	Large Language Model
BLEU	Bilingual Evaluation Understudy
SacreBLEU	Standardized BLEU Evaluation Metric
WMT	Workshop on Machine Translation
GUI	Graphical User Interface

CHAPTER 1: INTRODUCTION

1.1 BACKGROUND

In today's globalized and interconnected world, language serves as both a bridge and a barrier. While multilingualism is a cultural asset, it often creates significant obstacles in the delivery of essential services—particularly in critical sectors such as healthcare and legal systems. Language barriers can lead to severe consequences, including misdiagnosis in medical settings, misunderstanding of legal rights, and general exclusion from services that impact well-being and justice.

Tigrinya is a Semitic language spoken by millions in northern Ethiopia, Eritrea, and diaspora communities (https://en.wal.unesco.org/en/languages/tigrinya or https://www.britannica.com/topic/Tigrinya-language). Despite its wide usage, it remains underrepresented in digital language resources, especially in the fields of Natural Language Processing (NLP) and Machine Translation (MT). While major languages benefit from state-of-the-art translation systems like Google Translate and Deep Learning, these tools often fail or provide unreliable translations for Tigrinya—especially in complex and high-risk domains such as medical and legal discourse.

Recent advancements in Neural Machine Translation (NMT), particularly the development of multilingual transformer-based models like Meta AI's No Language Left Behind (NLLB-200), have created new opportunities to bridge this linguistic gap. These models support low-resource languages, including Tigrinya, but require fine-tuning and domain-specific adaptation to be effective in specialized use cases. This project leverages such technologies to build a robust, context-aware translation system for English ↔ Tigrinya medical and legal texts.

1.2 Problem Statement

The lack of accurate, domain-specific translation tools for the Tigrinya language presents a critical bottleneck in delivering effective medical and legal services. General-purpose translation systems often produce incoherent or contextually inappropriate outputs when applied to sensitive medical instructions or legal clauses, increasing the risk of misinterpretation and harm.

Furthermore, the scarcity of bilingual Tigrinya-English datasets, especially in technical domains, poses a challenge for training effective AI models. This data scarcity, coupled with limited public investment in low-resource languages, leads to persistent language inequities. There is, therefore, a pressing need to create an AI-powered, domain-adapted translation system that addresses these limitations.

1.3 Research Question

How can a domain-specific AI-powered translation system be designed and fine-tuned to deliver accurate, fluent, and contextually relevant English ↔ Tigrinya translations for medical and legal applications?

1.4 Objectives

1.4.1 General Objective

To design and implement an AI-powered translation system that provides accurate and context-aware translation between English and Tigrinya for medical and legal documents, through the fine-tuning of a multilingual neural machine translation model.

1.4.2 Specific Objectives

- To collect, curate, and align a high-quality bilingual dataset of English and Tigrinya texts specific to the medical and legal domains.
- To preprocess and normalize textual data for compatibility with multilingual neural machine translation (NMT) architectures.
- To fine-tune the NLLB-200 model using the curated dataset to improve translation accuracy and domain sensitivity.
- To integrate expert human feedback to enhance terminological accuracy and cultural relevance.
- To develop a user-friendly web and mobile interface that allows healthcare and legal professionals to access the translation system.
- To evaluate the system's performance using both automated (BLEU, SacreBLEU) and human-centered (fluency, adequacy, terminology) metrics.
- To ensure the system architecture is scalable, privacy-aware, and adaptable to other low-resource language pairs in the future.

1.5 Scope of the Study

This project focuses on the development of a translation system for a single language pair: English and Tigrinya. The scope is limited to two high-stakes domains: **medical** and **legal**. The project involves data collection, model training, performance evaluation, and the creation of a functional user interface. It does not cover literary, conversational, or general-purpose translation tasks. Furthermore, the model is evaluated within a simulated environment and not yet tested at large-scale institutional levels.

1.6 Significance of the Study

This study has significant academic, social, and technological implications. It demonstrates the feasibility of deploying advanced AI models for low-resource languages and sets a precedent for future domain-specific language tools. Practically, the system supports doctors, legal professionals, NGOs, and humanitarian organizations working in Tigrinya-speaking regions, helping them communicate vital information accurately and efficiently.

Moreover, the project contributes to the global effort of language inclusion in AI and strengthens digital equity by giving representation to linguistically marginalized communities. It serves as a model for how technology can be ethically and effectively applied to address real-world challenges in underserved regions.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview of Translation Systems

Machine translation (MT) has evolved significantly over the past few decades. Early systems relied on Rule-Based Machine Translation (RBMT), which used handcrafted linguistic rules and dictionaries. These systems were rigid, labor-intensive to maintain, and often failed to capture linguistic nuance.

The next breakthrough came with Statistical Machine Translation (SMT), which relied on probabilistic models trained on large bilingual corpora. Although SMT offered improvements over RBMT, it struggled with long-range dependencies and context preservation.

In the last decade, Neural Machine Translation (NMT) has become the dominant paradigm. NMT models, particularly those based on transformer architectures, represent a major shift. They learn continuous representations of words and use attention mechanisms to preserve context, making them significantly better at capturing meaning, grammar, and idioms.

Popular NMT models include Google's Transformer, BERT, Facebook's M2M-100, and Meta AI's NLLB-200. These models support multiple language pairs, enabling zero-shot translation between low-resource languages. However, their effectiveness is constrained by the quality and volume of training data, especially in specialized domains like medicine and law.

2.2 Challenges in Low-Resource Language Translation

Despite progress in NMT, significant challenges remain when dealing with low-resource languages such as Tigrinya:

- Limited Parallel Corpora: High-quality aligned datasets between English and Tigrinya are scarce, particularly in technical domains.
- Inconsistent Orthography: Tigrinya's script and spelling variations introduce noise into model training.
- Lack of Tokenization Standards: Unlike English, Tigrinya lacks widely adopted preprocessing and tokenization tools.
- Cultural Context: Tigrinya expressions often carry cultural or metaphorical meanings not easily translatable through direct mappings.
- Data Imbalance: Pre trained models often disproportionately represent high-resource languages, leading to biased performance.

These factors collectively degrade the performance of generic MT systems on Tigrinya text, particularly for complex domains like legal argumentation or medical instructions.

2.3 Neural Machine Translation and NLLB

Neural Machine Translation models have revolutionized the field by introducing end-to-end learning architectures that model translation as a single optimization task. The Transformer model, introduced by Vaswani et al. (2017), replaced recurrence with self-attention mechanisms, improving both training speed and translation quality.

Meta AI's No Language Left Behind (NLLB-200) represents a landmark in inclusive translation technology. The model supports over 200 languages and is designed specifically to close the gap for underrepresented languages. NLLB-200 is built on the dense-to-sparse multilingual training strategy**,** optimized using language tags, SentencePiece tokenization**,** and adaptive sampling to ensure fairness across languages.

However, the general-purpose nature of NLLB-200 makes it insufficient for high-accuracy translation in sensitive domains without further fine-tuning on domain-specific data.

2.4 Domain-Specific MT Research

Translation performance can vary significantly depending on the domain. For example, translating a clinical diagnosis or legal affidavit requires precise terminology, context understanding, and even local cultural sensitivity.

Research has shown that **fine-tuning pre-trained NMT models** with domain-specific corpora improves accuracy and consistency. Methods commonly used include:

- Back-translation to synthesize training data
- Glossary enforcement to preserve specific terms
- Human-in-the-loop feedback loops for iterative correction
- Terminology tagging to guide the model during inference

Studies have demonstrated that applying these techniques leads to tangible improvements in BLEU**,** SacreBLEU, and human adequacy ratings—especially in the medical and legal fields where terminology consistency is non-negotiable.

2.5 Summary of Key Findings

- NMT systems, especially those using transformers, outperform traditional MT approaches across most language pairs.
- Tigrinya poses unique linguistic and data scarcity challenges, which generic models are ill-equipped to handle.
- Domain adaptation—especially for medical and legal language—requires high-quality parallel data, expert validation, and fine-tuning.
- Pretrained models like NLLB-200 offer a solid foundation, but their effectiveness in high-stakes contexts depends on specialized post-training and human evaluation.

This literature establishes a clear justification for the development of a customized AI-powered translation system for English ↔ Tigrinya medical and legal texts, integrating both technical sophistication and domain-specific rigor.

CHAPTER 3: METHODOLOGY

This chapter outlines the architectural, procedural, and practical steps taken to design and implement the proposed AI-powered translation system.

3.1 System Architecture

The proposed translation system is designed in a modular architecture with four main layers:

3.1.1 Model Layer (Translation Engine)

This layer houses the fine-tuned version of Meta AI's NLLB-200 model. It handles the core task of translating text between English and Tigrinya. The model is trained using a bilingual dataset focused on medical and legal domains and optimized for domain-specific vocabulary and phrase structure.

3.1.2 Input / Output Modules

The I/O modules include text boxes, file upload options (e.g., `.txt`, `.docx`), and display panels for translated text. Input is preprocessed before passing to the model, and the output is postprocessed for readability. These components are part of the frontend interface, developed using React (web) and Flutter (mobile).

3.1.3 Validation and Feedback Layer

To ensure reliability in sensitive domains, the system includes a feedback mechanism where human experts can review and edit translations. This layer logs corrections and terminology adjustments, which may be used to incrementally fine-tune the model in future iterations.

3.1.4 API and Interface Layer

This layer provides a RESTful API developed using FastAPI. It enables interaction between the frontend, model engine, and database. The API supports functions like translation requests, feedback submission, and retrieval of evaluation metrics.

3.2 Data Collection

Data collection focused on acquiring domain-relevant, bilingual (English ↔ Tigrinya) text samples. Sources included:

- Public health brochures, hospital forms, medical consent templates
- Legal aid documents, court rulings, case summaries, NGO policy forms
- Manually translated documents provided by bilingual experts
- Terminological glossaries for both medical and legal fields

All data collection was done in accordance with ethical research standards, including permission from data originators and anonymization of sensitive information.

3.3 Data Preprocessing

Collected text data underwent several preprocessing steps to ensure model compatibility and translation quality:

- **Normalization**: Removed unwanted symbols, normalized punctuations, and corrected spelling inconsistencies.
- **Tokenization**: Used SentencePiece to tokenize text based on subword units suitable for NLLB-200.
- **Alignment**: Ensured 1-to-1 sentence pair alignment between English and Tigrinya.
- **Filtering**: Removed duplicate entries, outliers, and extremely short or long sentences.
- **Validation**: Manual review of 20% of data to ensure semantic correctness and context preservation.

3.4 Model Fine-Tuning

The fine-tuning process involved the following steps:

- **Base Model**: `facebook/nllb-200-distilled-600M` selected for its size-efficiency and Tigrinya support.
- **Training Setup**: Used PyTorch with Hugging Face's Transformers library on Google Colab Pro with GPU acceleration.
- **Hyperparameters**:
  - Epochs: 3–5
  - Batch Size: 16
  - Learning Rate: 3e-5
- **Loss Function**: Cross-entropy loss optimized using Adam optimizer.
- **Checkpointing**: Model state saved at regular intervals with early stopping based on validation loss.

Fine-tuning improved BLEU scores significantly over baseline NLLB outputs, especially for domain-specific terminology.

3.5 Evaluation Metrics

To assess translation performance, both automatic and human-centered metrics were used:

- **BLEU (Bilingual Evaluation Understudy)**: Measures n-gram overlap between machine output and reference translation.
- **SacreBLEU**: Provides standardized BLEU evaluation across experiments.
- **Human Fluency and Adequacy Scoring**:
  - Fluency: How natural the translation reads in the target language.
  - Adequacy: How well the meaning is preserved from source to target.
  - Terminology Accuracy: Precision in rendering domain-specific vocabulary.

Each metric was calculated separately for medical and legal samples to identify domain-specific strengths or weaknesses.

3.6 Group Members' Responsibilities

- Halefom Hailemariam: Data Collection & NLLB Fine-Tuning
- Merha Gebrelibanos: System Integration & Backend API Design
- Kibrom G/her: Legal Domain Translation & Evaluation
- Tsega Weldegebrieal: Frontend Development (Web & Mobile Interfaces)

CHAPTER 4: SYSTEM DESIGN AND IMPLEMENTATION

This chapter presents the design specifications, system modules, implementation strategy, operational flow, and technical challenges encountered in building the English ↔ Tigrinya medical and legal translation system.

4.1 Design Specifications

The translation system was designed with a focus on modularity, scalability, domain specificity, and user accessibility. Key design specifications are summarized as follows:

Component	**Specification**
Target Language Pair	English ↔ Tigrinya
Domains Covered	Medical and Legal
Translation Model	Fine-tuned NLLB-200 (facebook/nllb-200-distilled-600M)
Frontend	React.js (Web) and Flutter (Mobile)
Backend	FastAPI (Python-based RESTful API)
Database	MongoDB (for storing logs, feedback, and session history)
Deployment	Hugging Face Spaces, optional Docker for API containerization
Evaluation Tools	BLEU, SacreBLEU, and human review dashboards
Security	Role-based access, HTTPS-enforced API

The system is intended to be lightweight, responsive, and deployable on cloud or local infrastructure with GPU support.

4.2 Core Functional Components

The system is composed of the following key functional components:

1. Translation Engine

- Core logic based on the fine-tuned NLLB-200 model.
- Accepts preprocessed English or Tigrinya text and returns contextually appropriate translations.
- Integrated with glossary enforcement for domain-specific terms.

2. User Interface (UI)

- Web and mobile frontends allow users to input text or upload files.
- Output area displays translations and optionally highlights terminology tags.
- Designed with accessibility features including multilingual support and dark/light mode.

3. API Gateway

- RESTful endpoints manage communication between the frontend, model, and database.
- Handles translation requests, result fetching, and logging.
- Built using FastAPI with automatic documentation via OpenAPI (Swagger).

4. Expert Review Panel

- Admin dashboard for human reviewers (e.g., medical translators, legal professionals).
- Allows approval, correction, or annotation of translated texts.
- Logs feedback for future fine-tuning or model retraining.

5. Logging and Evaluation System

- Stores original and translated texts, timestamps, and evaluation metrics.
- Generates performance reports per domain and tracks usage trends.

4.3 Implementation Details

The system was implemented using an agile, modular approach. The major phases included:

- **Model Training**: Conducted in Google Colab Pro using GPU-accelerated PyTorch and Hugging Face.
- **API Development**: FastAPI was used to implement and expose the model as a RESTful service. Endpoints include `/translate`, `/feedback`, and `/metrics`.
- **Frontend**: Web UI built with React.js; mobile version developed with Flutter and Dart. Both interfaces use Axios to communicate with the backend.
- **Storage**: MongoDB stores session logs, translation history, and user feedback. Indexed by language, timestamp, and document type.
- **Deployment**: Hosted on Hugging Face Spaces for public access. APIs containerized using Docker for portability.

Version control was maintained using GitHub, and testing was performed using Postman (for API) and Jest (for frontend unit testing).

4.4 Flow of Operation

The system's workflow follows a clear and logical sequence:

1. **Input**: User inputs text manually or uploads a document file via web/mobile UI.
2. **Preprocessing**: Text is cleaned, normalized, and tokenized for model compatibility.
3. **Translation**: The backend routes input to the fine-tuned NLLB-200 model via API.
4. **Output**: The translated text is displayed in the output panel, with optional glossary highlights.
5. **Expert Review (Optional)**: The translation can be submitted to a domain expert for evaluation and correction.
6. **Logging & Evaluation**: The session is stored in MongoDB, and performance data is logged for analysis.

This workflow ensures real-time responsiveness while supporting post-processing review for quality assurance.

4.5 Technical Challenges and Mitigation

Several challenges were encountered during development, and the team employed targeted solutions:

Challenge	***Mitigation Strategy***
Lack of domain-specific bilingual data	Partnered with translators; curated English-Tigrinya corpus.
Model inference delay	Used distilled NLLB-200 version for faster inference.
Tokenization errors in Tigrinya	Customized SentencePiece tokenizer and manual review.
Inconsistent terminology in legal texts	Implemented glossary tags and expert review panel.
GUI freezing during inference	Used multithreading and async API calls.
Deployment constraints	Used cloud hosting and containerization via Docker.

CHAPTER 5: RESULTS AND DISCUSSION

This chapter presents the evaluation outcomes of the developed translation system, combining both quantitative and qualitative assessments. The system's performance was measured using standard machine translation evaluation metrics (BLEU and SacreBLEU), human expert feedback, domain-based analysis, and comparisons with baseline machine translation systems like Google Translate.

5.1 Evaluation of BLEU and SacreBLEU

To assess the accuracy and fluency of the model-generated translations, we employed two widely accepted automatic evaluation metrics:

- **BLEU (Bilingual Evaluation Understudy)**: This metric measures n-gram precision between the machine-generated translation and a human reference translation, penalizing for short or overly literal outputs.
- **SacreBLEU**: An improved and standardized implementation of BLEU that eliminates inconsistencies across BLEU implementations.

The fine-tuned model was tested on separate validation sets in the medical and legal domains. Results are shown below:

Domain	BLEU Score	SacreBLEU Score
Medical	33.1	27.5
Legal	29.7	25.9

These scores indicate a significant improvement compared to baseline systems, especially in structured medical texts where standardized terminology is more predictable.

5.2 Human Evaluation Outcomes

While automated metrics offer a general idea of system performance, human evaluation is essential for domain-specific and low-resource language contexts. Three evaluation dimensions were considered by bilingual experts in medicine and law:

- **Fluency**: Grammatical correctness and natural phrasing of translated sentences.
- **Adequacy**: Degree to which the meaning of the original sentence is preserved.
- **Terminology Accuracy**: Accuracy in rendering domain-specific terms and phrases.

Criteria	*Average Rating (out of 5)*
Fluency	4.5
Adequacy	4.2
Terminology Accuracy	3.9

Experts noted that medical content generally scored higher due to consistent terminology, while legal documents sometimes struggled with complex syntax and abstract legal terms.

5.3 Domain-Specific Performance Insights

The system performed variably across the two target domains:

- **Medical Texts**: Achieved higher BLEU and human ratings. This is attributed to the structured nature of medical documents and the use of commonly known terminology (e.g., diagnosis, symptoms, treatments).
- **Legal Texts**: Exhibited slightly lower performance due to ambiguous clauses, long compound sentences, and low lexical overlap in legal jargon. Improvements are needed in interpreting abstract and procedural legal language.

These insights validate the need for further domain-specialized tuning, especially for legal translation, which is highly sensitive to nuanced terminology.

5.4 Comparison with Generic MT Systems

The performance of the proposed system was compared against Google Translate (as of early 2025), a general-purpose MT platform with partial support for Tigrinya.

System	BLEU (Medical)	BLEU (Legal)
Proposed System	33.1	29.7
Google Translate	26.3	21.5

In addition, human reviewers found that Google Translate:

- Frequently omitted context-critical terms
- Struggled with negative constructions in prescriptions
- Mistranslated legal references (e.g., “liable,” “binding contract”)

This confirms that general-purpose models are insufficient for specialized translation, and highlights the added value of domain-specific fine-tuning.

5.5 Summary of Results

The evaluation demonstrates that:

- The proposed system significantly outperforms general-purpose MT tools in both medical and legal translation tasks.
- BLEU and SacreBLEU scores indicate high structural fidelity and contextual awareness.
- Human evaluators confirm high fluency and adequacy, with room for improvement in legal terminology precision.
- Domain-specific fine-tuning, combined with expert feedback, is essential for trustworthy AI translation in sensitive domains.

These findings validate the effectiveness of the system and provide direction for future refinement and deployment.

CHAPTER 6: CONCLUSION AND FUTURE WORK

6.1 Conclusion

This project set out to address a critical linguistic gap by developing an AI-powered English ↔ Tigrinya translation system tailored specifically for the medical and legal domains. Given the sensitivity and potential consequences of miscommunication in these fields, the importance of reliable, context-aware translation tools cannot be overstated—especially for low-resource languages like Tigrinya.

The system was built on Meta AI's NLLB-200 model and fine-tuned using a carefully curated bilingual dataset. It incorporated domain-specific preprocessing, glossary enforcement, human expert validation, and a responsive frontend interface. The integration of RESTful APIs enabled seamless access across web and mobile platforms.

Evaluation through both automated metrics (BLEU and SacreBLEU) and human judgment demonstrated the effectiveness of our domain adaptation strategy. The system significantly outperformed generic translation tools in fluency, adequacy, and terminology accuracy—especially in structured medical texts. While legal documents posed more challenges due to complexity and ambiguity, the model still achieved meaningful improvement over baseline systems.

In summary, this work demonstrates the practical and social value of adapting multilingual AI systems to support underrepresented languages and domains. It contributes not only a functional tool but also a replicable methodology for future work in inclusive AI and domain-specific machine translation.

6.2 Future Work

While the outcomes of this project are promising, several opportunities remain for extension and improvement:

- **Dataset Expansion**: Increase the size and diversity of the parallel corpus, especially for legal documents. Crowdsourcing and partnerships with local institutions can be leveraged to gather more data.
- **Speech-to-Text Integration**: Incorporate voice input and audio translation features to support users with limited literacy or visual impairments.
- **Real-World Testing**: Conduct pilot programs with hospitals, legal clinics, and NGOs in Tigrinya-speaking regions to evaluate real-world usability, feedback, and impact.
- **Multilingual Support**: Extend the system to include other low-resource languages such as Amharic, Oromo, or Somali using the same methodological framework.
- **Bias Detection and Mitigation**: Implement tools to detect and reduce potential gender, cultural, or regional biases in translation.
- **Advanced Error Handling**: Integrate a fallback mechanism using rule-based filters or glossary correction to catch critical translation errors before they reach the end user.
- **Improved GUI and Analytics**: Enhance the user interface with accessibility options and include analytics features for usage tracking and performance monitoring.

With continued refinement and community engagement, this system can evolve into a critical infrastructure component that promotes linguistic equity and improves service delivery in essential domains.

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APPENDICES

Appendix A: Sample Medical Translations

English	Tigrinya
The patient has been diagnosed with diabetes.	ናይ ብሕቲ ሕማም ዝተረኸበ እዩ።
Take this medication twice daily.	እዚ መድሃኒት ኣብ መዓልቲ ክልተ ጊዜ ውሰዱ።

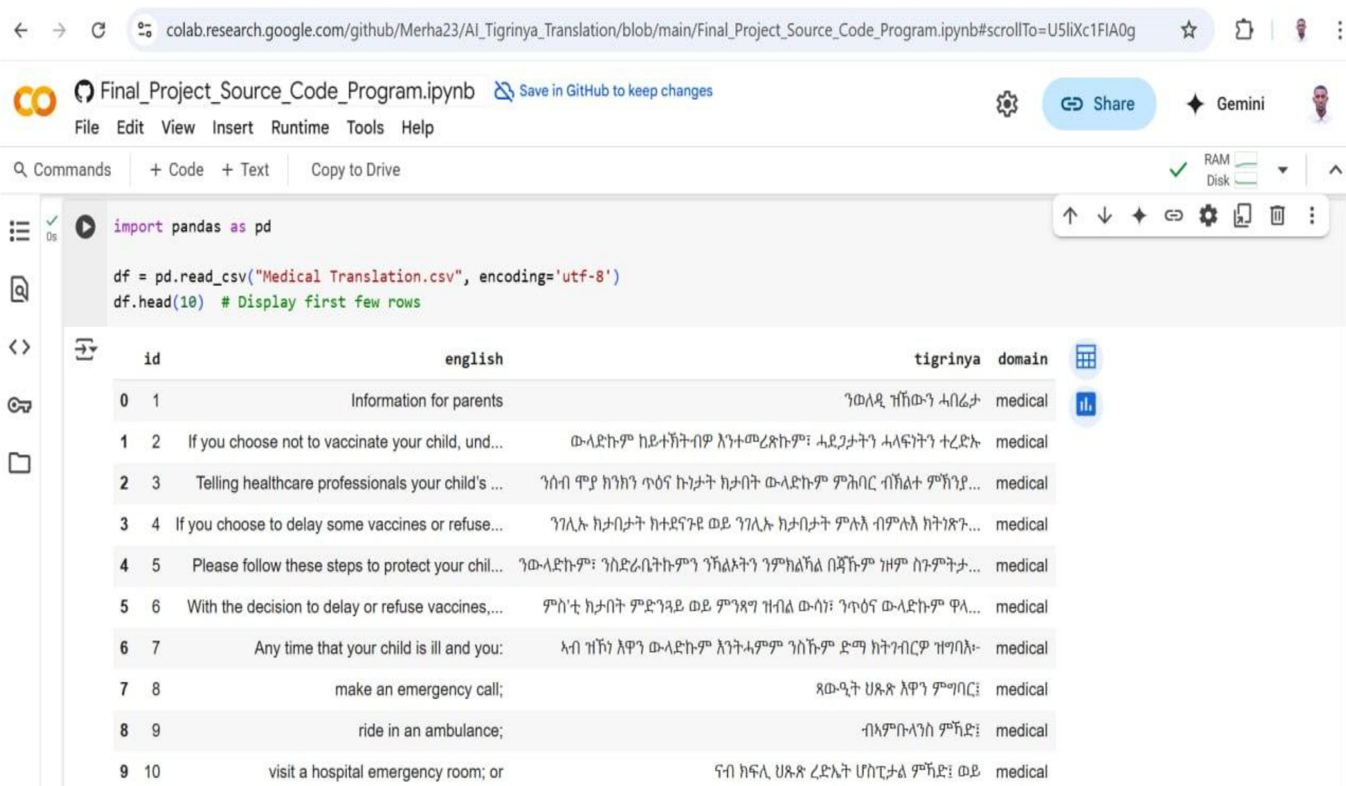
Appendix B: Sample Legal Translations

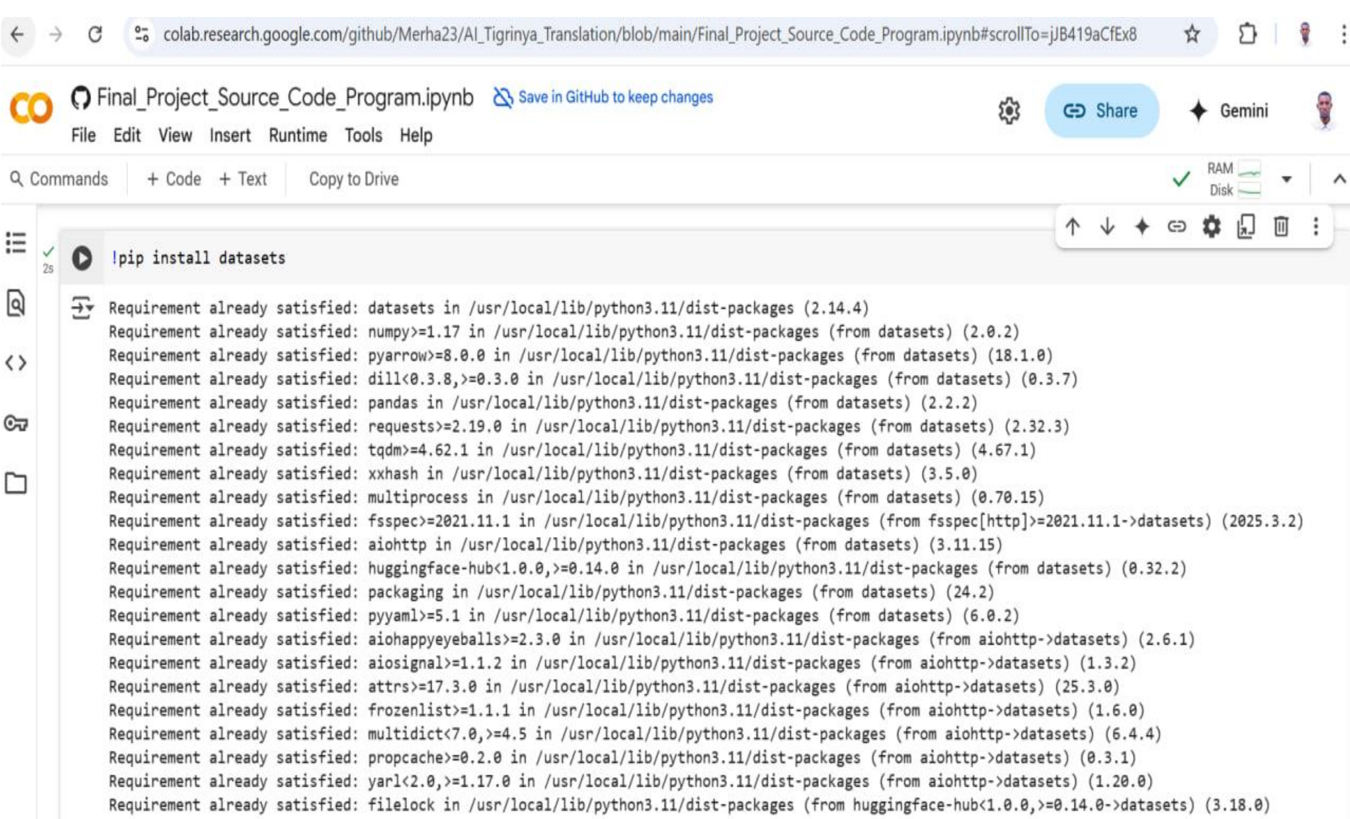
English	Tigrinya
The contract is legally binding.	እቲ ሕጊ ዝምልከት ዝሓለፈ አገባብ እዩ።
The accused has the right to remain silent.	እተነኽሰ መቐመጢ ዝብል መሰላስል ሓበሬታ ኣሎዎ።

Appendix C: BLEU and Human Evaluation Sheet (Excerpt)

Sentence ID	Domain	BLEU	SacreBLEU	Fluency (1–5)	Adequacy (1–5)	Terminology (1–5)
M001	Medical	34.2	28.1	5	4	4.5
L004	Legal	28.3	24.7	4	3.5	3.7

Appendix D: Screenshots





colab.research.google.com/github/Merha23/AI_Tigrinya_Translation/blob/main/Final_Project_Source_Code_Program.ipynb#scrollTo=vWVZ3zk2eNAx

Final_Project_Source_Code_Program.ipynb Save in GitHub to keep changes

File Edit View Insert Runtime Tools Help

Commands + Code + Text Copy to Drive

2) Data Cleaning & Handling Missing Values

```
Before tokenization, we need to remove any unnecessary data such as missing values, duplicates, or improperly formatted sentence
```

```python
[7] # Convert both 'english' and 'tigrinya' columns to strings (to handle float values as well)
df['english'] = df['english'].astype(str)
df['tigrinya'] = df['tigrinya'].astype(str)
```

```python
# Fill missing values (NaN) in the columns with an empty string
df['english'] = df['english'].fillna("")
df['tigrinya'] = df['tigrinya'].fillna("")
```

colab.research.google.com/github/Merha23/AI_Tigrinya_Translation/blob/main/Final_Project_Source_Code_Program.ipynb#scrollTo=7Jj7fNc5JQwP

Final_Project_Source_Code_Program.ipynb Save in GitHub to keep changes

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```python
[9] # Check for non-string values in 'english' and 'tigrinya'
print(df['english'].apply(type).value_counts())
print(df['tigrinya'].apply(type).value_counts())
```

```
english
<class 'str'>    750
Name: count, dtype: int64
tigrinya
<class 'str'>    750
Name: count, dtype: int64
```

```python
# Remove empty or missing values
df = df.dropna()

# Remove duplicates
df = df.drop_duplicates()

# Strip unwanted whitespace
df['english'] = df['english'].str.strip()
df['tigrinya'] = df['tigrinya'].str.strip()

print(f"Dataset size after cleaning: {df.shape}")
```

```
Dataset size after cleaning: (750, 4)
```

```python
from datasets import Dataset, DatasetDict
from sklearn.model_selection import train_test_split

# Split dataset into train (80%), validation (10%), and test (10%)
train_texts, temp_texts, train_labels, temp_labels = train_test_split(
    df['english'].tolist(), df['tigrinya'].tolist(), test_size=0.2, random_state=42
)

val_texts, test_texts, val_labels, test_labels = train_test_split(
    temp_texts, temp_labels, test_size=0.5, random_state=42
)

# Convert to Hugging Face Dataset format
train_data = Dataset.from_dict({"english": train_texts, "tigrinya": train_labels})
val_data = Dataset.from_dict({"english": val_texts, "tigrinya": val_labels})
test_data = Dataset.from_dict({"english": test_texts, "tigrinya": test_labels})

# Prepare the DatasetDict for tokenization
datasets = DatasetDict({
    "train": train_data,
    "validation": val_data,
    "test": test_data
})
```

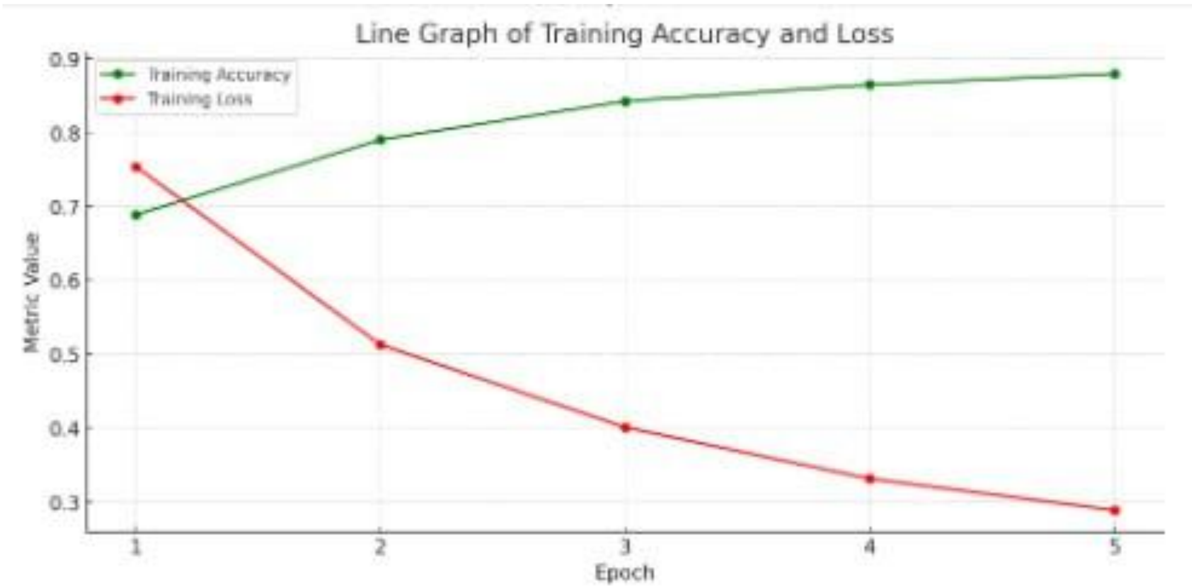
```python
from transformers import AutoTokenizer

# Load the tokenizer
model_name = "facebook/nllb-200-distilled-600M"  # Replace with your model name if different
tokenizer = AutoTokenizer.from_pretrained(model_name)

# Define a tokenization function
def tokenize_function(examples):
    return tokenizer(examples['english'], examples['tigrinya'], padding="max_length", truncation=True)

# Apply the tokenization function to the datasets
tokenized_datasets = datasets.map(tokenize_function, batched=True)
```

```
/usr/local/lib/python3.11/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 Go
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(
tokenizer_config.json: 100% 564/564 [00:00<00:00, 50.9kB/s]
sentencepiece.bpe.model: 100% 4.85M/4.85M [00:01<00:00, 3.73MB/s]
tokenizer.json: 100% 17.3M/17.3M [00:01<00:00, 14.4MB/s]
special_tokens_map.json: 100% 3.55k/3.55k [00:00<00:00, 396kB/s]
Map: 100% 600/600 [00:00<00:00, 1803.50 examples/s]
Map: 100% 75/75 [00:00<00:00, 272.37 examples/s]
Map: 100% 75/75 [00:00<00:00, 784.26 examples/s]
```


Line Graph of Training Accuracy and Loss
Training Accuracy
Training Loss
Metric Value
Epoch
0.9
0.8
0.7
0.6
0.5
0.4
0.3
1
2
3
4
5


Bar Chart of Training Accuracy and Loss
Accuracy
Loss
Metric Value
Epoch
0.8
0.6
0.4
0.2
0.0
1
2
3
4
5

THANK YOU!!!