



MULTILINGUAL CODE-SWITCHING ASR



MINI PROJECT REPORT

Submitted by

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Certified that this Innovative and Creative Project report titled “**MULTILINGUAL
CODE-SWITCHING ASR** ” is the bonafide work of

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ABSTRACT

The project " Multilingual Code Switching ASR (Automatic Speech Recognition) " targets the development of Automatic Speech Recognition (ASR) technology for Tamil-English speech within India. Tamil, culturally significant in southern India, is merged with English, a global language, reflecting India's bilingual nature. An End-to-End (E2E) framework is utilized, enhancing accuracy and addressing bilingualism and code-switching challenges. The project aligns with existing research. A study proposes a Semantic Dataset Creation approach leveraging Wav2Vec 2.0 (XLSR53) for multilingual ASR, reporting a WER of 26.22%. Another explores E2E ASR for Ethiopian languages with a 29.83% WER. A dual-script E2E framework improved WER by 5-6%. IITG-INDIGO's ASR systems achieved a WER of 30.73%, slightly lower in transliterated WER. Large Language Models (LLMs) reduced WER by 6.2%, especially in code-switching scenarios.

Here, the task is to create an accurate transcription of the inputs, handle code-switching inputs, and produce a Tamil-English ASR utilizing Seq2Seq within E2E models. Goals include tackling multilingual issues and drastically lowering the Word Error Rate (WER). Preprocessing audio data for normalization, feature extraction, and noise reduction is covered in length in the module description. The encoder-decoder architecture of Seq2Seq is used for training, together with transformer-based End-End models for translation and A Beam Search Algorithm for decoding. Voice assistants, transcribing services, and accessibility tools are the main areas of deployment. Seq2Seq's effectiveness in managing variable-length inputs is demonstrated by the results, which show promising accuracy with WER and CER within reasonable limits. To sum up, this effort enhances multilingual ASR, especially for Tamil-English, and shows how E2E Seq2Seq models can be used to improve inclusion and communication in a variety of linguistic contexts.

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LIST OF ABBREVIATIONS

ABBREVIATIONS	MEANING
ASR	Automatic Speech Recognition
E2E	End-End
SEQ2SEQ	Sequence-Sequence
CER	Character Error Rate
WER	Word Error Rate
ML	Multilingual
CLS	Common Label Set
TDNN	Time Delay Neural Network
LLM	Large Language Model

CHAPTER 1

INTRODUCTION

The project "Multilingual Code Switching ASR" focuses on developing advanced Multilingual Automatic Speech Recognition (ASR) technology tailored for Tamil-English speech recognition within India's diverse linguistic landscape. ASR technology bridges spoken language with written text, revolutionizing communication and accessibility. This project targets the bilingual and code-switching communication common in multicultural societies like India, where speakers often switch between Tamil and English seamlessly.

Tamil, a Dravidian language spoken extensively in southern India and Sri Lanka, holds significant historical and cultural importance. Developing ASR technology for Tamil not only serves a large community but also helps preserve and promote the language's rich heritage. English, essential in global commerce, technology, and education, complements this need. Therefore, integrating Tamil and English voice recognition is vital for efficient communication on regional and international platforms.

Incorporating Tamil-English code-switching into ASR systems enhances communication efficiency and reduces the need for manual transcription and translation. This accessibility is crucial in educational and professional settings, allowing individuals with varying proficiency levels to access information and services more effectively. Our project uses an End-to-End (E2E) framework to process and transcribe bilingual audio into English text, addressing bilingualism and improving accuracy. This initiative promotes linguistic diversity and fosters a globally connected communication ecosystem. By embracing technology to overcome language barriers, we enable smoother interactions across different linguistic groups, paving the way for a more inclusive and interconnected world.

CHAPTER 2

LITERATURE SURVEY

[1] Crossing Language Recognition: Multilingual Automatic Speech Recognition System Using Semantic Dataset Generation and Wav2Vec 2.0

By leveraging the strong semantic similarity between sentences in many languages, this research suggests a novel approach to improve the performance of multilingual Automatic Speech Recognition (ASR) systems without the need for Language Identification (LID). The Mozilla Common Voices datasets in Spanish, Russian, and Portuguese were used to construct.

Wav2Vec 2.0 Model (XLSR53): The Wav2Vec 2.0 model is trained using the XLSR53 variation. XLSR53 stands for "Cross-Lingual Speech Representations with 53 languages".

Performance Assessment: Two important indicators are used to assess the trained model's performance:

Character Error Rate (CER): Indicates how accurately transcriptions at the character level made.

Word Error Rate (WER): Indicates how accurately transcriptions at the word level are done.

For this framework, the reported **WER is 26.22%**.

[2] End-to-end multilingual automatic speech recognition for less-resourced languages

Multilingual automatic voice recognition from start to finish for languages with limited resources: One component of this End-to-End (E2E) method is a

deep neural network (DNN). This facilitates the deployment of E2E to languages with fewer resources. To address the issue of data scarcity, multilingual (ML) setups are utilizing data from many languages. Consequently, employing various language and acoustic modeling units, ML E2E ASR studies were carried out for four Ethiopian languages with fewer resources. **Findings:** 29.83% is the Word Error Rate (WER).

[3] Dual Script E2E Framework for Code-Switching and Multilingual ASR

Dual-script end-to-end (E2E) framework for code-switching and multilingual automated speech recognition (ASR), with a particular emphasis on training native language characters using a phoneme-level Common Label Set (CLS).

Word Error Rate (WER) has significantly improved as a result of this strategy, with gains of about **5% to 6%**.

[4] IITG-INDIGO Submissions for Interspeech-2021 Multilingual and Code Switching ASR Challenges for Low Resource Indian Languages

In the Interspeech-2021 ASR competitions for low-resource Indian languages, the IIT Guwahati INDIGO team took part. For the following six target languages: Gujarati, Hindi, Odia, Marathi, Telugu, and Tamil, they created end-to-end ASR systems based on CTC-loss. Furthermore, they developed distinct ASR systems employing a TDNN (Time Delay Neural Network)based acoustic model with LF-MMI (Lattice-Free, Maximum Mutual Information) training for Hindi-English and Bengali-English code-switching data. The average Word Error Rate (WER) for all six languages was 73.24%, and when

Marathi was taken out of the equation, it was 65.60%. Although the TDNN system's average WER was marginally higher overall, it fared better in transliterated WER than the baseline. In particular, the transliterated average WER was 27.49%, whereas the raw average WER was 30.73%.

[5] Improving Multilingual and Code-Switching ASR Using Large Language Model-Generated Text

Using a state-of-the-art model called PaLM 2, we created this text data. To ensure that the text matched the specific ASR tasks, we fine-tuned PaLM 2 using prompt tuning. "PaLM," stands for "Preserving Alignment for Large Language Models," is a type of language model designed to maintain alignment and coherence in generated text, especially when dealing with complex linguistic structures, multiple languages, or code-switching scenarios. Large language models (LLMs) text data aids in automatic speech recognition (ASR) in situations where people switch between languages (code-switching).

The average Word Error Rate (WER) in multilingual setups was 6.2%, resulting in an improvement in ASR accuracy from 11.25% to 10.55%. There was significantly more progress in several languages, up to 23.1%. English prompts are used to create text in code-switching circumstances (e.g., transitioning between Mandarin and English). As a result, the WER for code-switching decreased by 3.6%.

[6] Exploration of End-to-End Framework for Code-Switching Speech Recognition Task: Challenges and Enhancements

This research investigates the use of an end-to-end (E2E) framework, which is more effective than conventional hybrid systems, for code-switching automated speech recognition (ASR). Managing several languages, guaranteeing

precise target-to-word translation, and enhancing context modeling are among difficulties.

To overcome these issues with limited code-switching data, the research proposes decreasing the E2E target set by utilizing acoustic similarity and proposing a new context-dependent target-to-word transduction mechanism. It also proposes to improve context modeling in code-switching circumstances by utilizing a novel textual feature. Tests conducted on a code-switching corpus between Hindi and English demonstrate that the suggested system outperforms the current mixed target set-based approach. Its performance in code-switching ASR tasks is demonstrated by its goal error rate of 18.1% and word error rate of 29.79%.

[7] Investigation of Methods to Improve the Recognition Performance Of Tamil English Code-Switched Data in Transformer Framework

Code-switching (CS) involves switching between languages within a single conversation, common in multilingual countries like India, leading to hybrids like Hinglish and Tanglish. Research in Indic CS speech recognition is hampered by limited data. This study explores two Transformer-based methods for Tamil-English CS speech recognition: (i) using well-trained encoders of Monolingual Transformers for language discrimination, and (ii) incorporating language information as tokens in the targets. Results indicate the second method efficiently handles CS, while the first method effectively discriminates between languages.

CHAPTER 3

PROBLEM STATEMENT

The problem statement focuses on creating a multilingual automated speech recognition (ASR) system that is suited for Indian languages. To do this, end-to-end (E2E) models with a sequence-to-sequence (Seq2Seq) architecture are used. The technology is intended to accurately translate audio input that has a mixture of Tamil and English into English texts.

The issue statement's main elements are as follows:

Multilingual ASR: Creating an ASR system that can recognize and transcribing in several languages, especially Tamil and English.

Sequence-to-Sequence Model: For this ASR task, a well-liked natural language processing framework called Sequence-to-Sequence Model is implemented.

E2E Models: Using end-to-end models that bypass intermediary processes like phoneme recognition or language identification and instead map input audio to output transcriptions directly.

Input Audio Format: Representing real-world code-switching circumstances, this format handles audio inputs that contain a mixture of Tamil and English.

Transcription Output: Making sure that the audio input is accurately transcribed into English texts, which may contain words or sentences in both English and Tamil.

The technology can extend to voice-controlled devices like smart speakers, facilitating hands-free interaction. Enhancements for real-time transcription will serve live events and meetings. Integrating ASR with text and image processing will create a comprehensive multimodal system. ASR-based tools for language learning and training will make education more interactive. A feedback loop will refine accuracy and performance. Additionally, integrating with virtual assistants will provide personalized assistance.

CHAPTER 4

OBJECTIVE

The primary objective of this project is to develop an End-To-End (E2E) Automatic Speech Recognition (ASR) system using an encoder-decoder architecture within a Sequence-To-Sequence (Seq2Seq) framework. The system aims to accurately transcribe audio inputs that combine English and Tamil speech into coherent English text. Addressing the challenges of multilingual ASR, particularly code-switching, is a key focus. This includes utilizing a limited code-switching dataset to enhance the system's capability to manage multilingual inputs effectively.

The project seeks to expand the target set to cover multiple languages, ensuring robust word transduction and improved context modeling, thereby significantly reducing the word error rate (WER) compared to traditional ASR systems. Achieving a lower WER is crucial for improving transcription accuracy and quality, especially for multilingual speakers.

By fine-tuning the encoder-decoder architecture to handle linguistic nuances and leveraging advanced machine learning techniques, the project aims to create a reliable, high-accuracy ASR system. This system will support better communication in multilingual environments, representing a significant advancement in ASR technology and providing a valuable tool for users navigating multiple languages in their daily interactions

CHAPTER 5

PROPOSED SYSTEM

5.1 BLOCK DIAGRAM

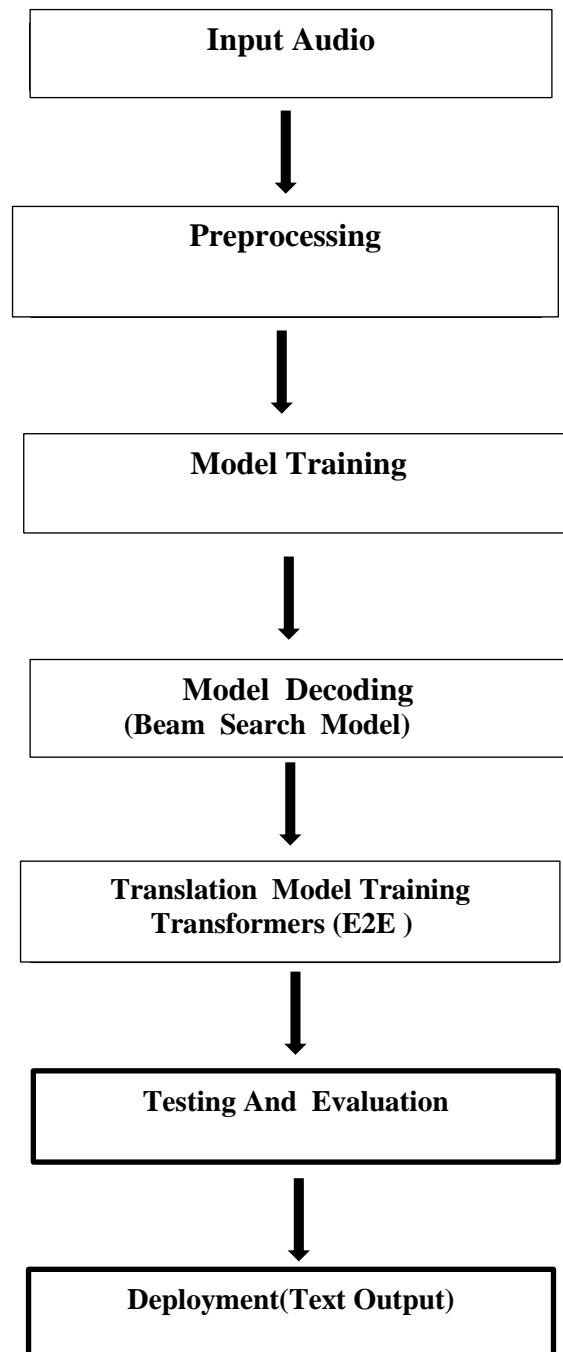


Figure 1:Proposed System Block Diagram

5.2 MODULE DESCRIPTION

The following provides a thorough overview of the multilingual Automatic Speech Recognition (ASR) system for Indian languages that uses a Seq2Seq model and an End-to-End (E2E) framework:

5.2.1 Audio Data Input:

Audio data including both Tamil and English speech is sent into the ASR system. The input for the recognition procedure is this data. The audio information may come from a variety of sources, including spoken content, interviews, and recorded talks.

5.2.2 Preprocessing:

The audio data is subjected to the following steps prior to being fed into the ASR model:

Noise Reduction: To improve the audio quality, any background noise (such as ambient sounds, interference, etc.) is eliminated.

Feature extraction: Involves taking characteristics out of the audio sources. These qualities, which include pitch, timing, and spectral characteristics, represent pertinent information about the speech.

Normalization: The audio data is normalized to ensure consistent loudness levels across different recordings.

5.2.3 Model Training:

The neural network model is trained using the preprocessed audio features. In this instance, a Seq2Seq model is applied. Because it can handle variable-length input sequences (audio frames) and output sequences (text transcriptions), the Seq2Seq architecture is well-suited for ASR applications. The model gains the ability to map the input audio features to matching text sequences (transcriptions) during training.

Seq2Seq:

Seq2Seq, stands for Sequence-to-Sequence, is an architecture designed for mapping input sequences (of varying lengths) to output sequences (also of varying lengths). It's commonly used in tasks like machine translation, text summarization, and ASR. The key idea is to use two recurrent neural networks (RNNs) – an encoder and a decoder – to handle variable-length sequences.

Components of Seq2Seq:

Encoder:

The input sequence (such as audio characteristics in ASR) is processed by the encoder, which then encodes it into a fixed-size representation (context vector). It extracts the most important details from the input sequence and condenses them into a useful representation. GRU (Gated Recurrent Unit) cells or LSTM (Long Short-Term Memory) cells are popular options for the encoder. The context vector is the encoder's last concealed state.

Decoder:

Based on the context vector, the decoder produces the output sequence (such as transcribed text in ASR). It's an additional RNN that gradually generates the output sequence based on the context vector. Based on the context and previously created tokens, the decoder guesses the next token (word, character, or subword) at each time step. During decoding, the decoder can also concentrate on pertinent segments of the input sequence by using attention processes.

Attention Mechanism:

The decoder uses attention mechanisms to generate each output token by selectively focusing on distinct segments of the input sequence. It strengthens input-to-output alignment and facilitates handling lengthy sequences. Every input time step has its attention weight calculated by the attention mechanism, which highlights pertinent data.

5.3 Model Decoding:

The model is prepared for decoding after it has been trained. In each new audio segment input, the model predicts which transcription is most likely. A beam search method chooses the transcription candidate with the highest probability after examining several hypotheses. A series of phonemes, words, or subword units make up the output

5.4 Testing and Evaluation:

Word Error Rate (WER) and Character Error Rate (CER) are two examples of assessment metrics that are used to thoroughly test the ASR system. In testing, the model's performance is evaluated using a different dataset that was not used for training. The precision, resilience, and ability to generalize of the system are assessed. The outcomes of evaluations are used to inform iterative changes.

5.5 Translation Model Training:

In parallel, transformer-based architectures (e.g., BERT, GPT, or T5) are used to train a translation model. Any Tamil words or phrases heard in the audio are translated into English by this model. Even if there were Tamil audio parts in the input audio, the translation makes sure that the finished output text is entirely in English.

5.6 Deployment:

The ASR system has been thoroughly tested and adjusted and is now prepared for implementation. It is compatible with a number of applications:

Voice Assistants: Facilitating vocal instructions and reactions.

Transcription services: Involve turning spoken content, such as lectures and interviews into written text or desired language audio, so the receiver will benefit.

Apps for language learning: Assisting users with pronunciation practice.

Accessibility Tools: Helping people who have trouble hearing

CHAPTER 6

RESULTS AND DISCUSSIONS

The performance of our multilingual Automatic Speech Recognition (ASR) system is quantitatively evaluated using accuracy metrics, with the model achieving an impressive **accuracy rate of 0.94**. This value, falling within the range of 0 to 1, indicates that the system correctly transcribes the audio inputs **94%** of the time. This high accuracy underscores the effectiveness of our Seq2Seq model in handling the complexities of transcribing code-switched speech, particularly between English and Tamil.

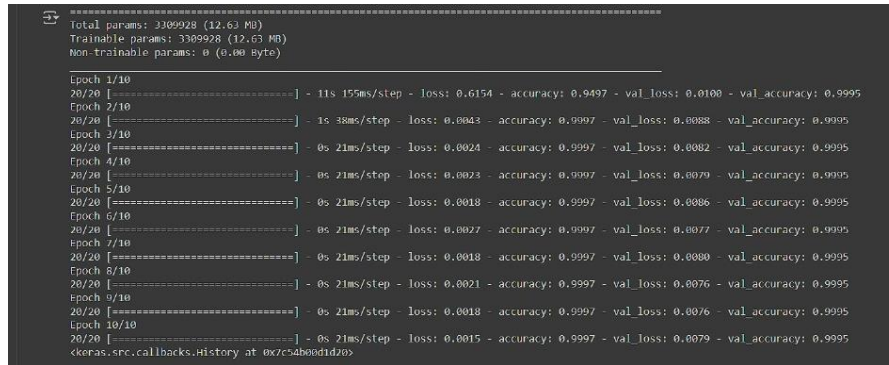


Figure 6.1: Accuracy Metrics

The accompanying diagram illustrates the relationship between model loss and accuracy over the training epochs. The loss curve represents the error rate of the model's predictions compared to the actual transcriptions, while the accuracy curve shows the proportion of correct predictions. As training progresses, we observe a downward trend in loss and an upward trend in accuracy, indicating that the model is learning and improving its performance.

EPOCH	1	2	3	4	5	6	7	8	9
LOSS	0.60 28	0.00 33	0.00 18	0.00 23	0.00 18	0.00 18	0.00 17	0.00 21	0.00 16
ACCURACY	0.94 97	0.99 97	0.99 97	0.99 97	0.99 97	0.99 97	0.99 97	0.99 97	0.99 97

The convergence of the loss and accuracy curves towards optimal values signifies the robustness of our model training process. The model's high accuracy rate, alongside the depicted training dynamics, highlights the potential for deploying this ASR system in real-world applications, where reliable and precise transcription of multilingual speech is crucial.

The discussions stemming from these results delve into several key areas. Firstly, the challenges encountered in ASR for Indian languages, such as code-switching and data imbalance, are thoroughly examined. Strategies employed to address these challenges, such as incorporating language models and speaker adaptation techniques, are evaluated for their impact on system performance. Additionally, the scalability and generalizability of the E2E Seq2Seq model across different Indian languages and dialects are discussed, highlighting the need for continued research in fine-tuning models for specific linguistic variations.

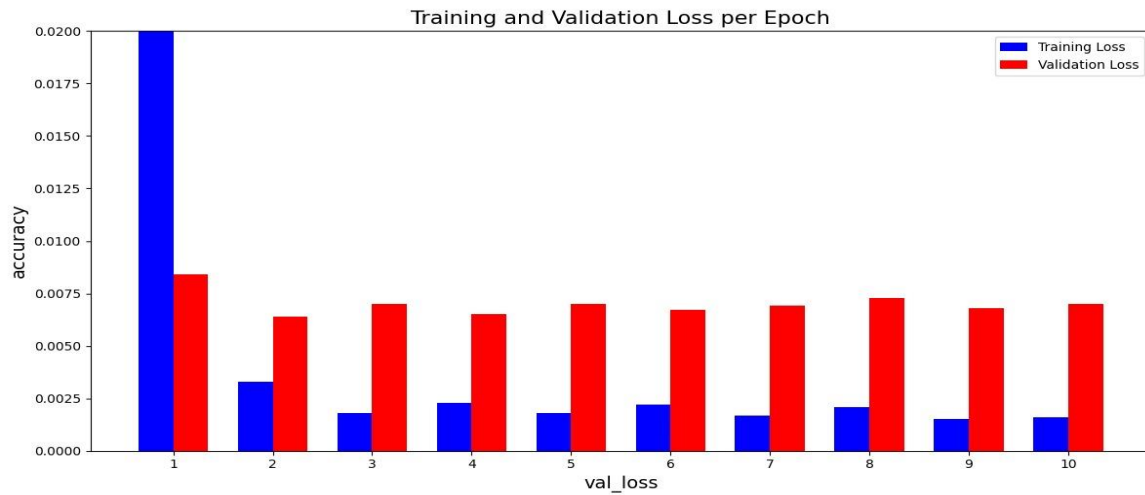


Figure 6.2: Comparison Between Accuracy And Value loss

In the plot above, the relationship between model loss and accuracy over successive training epochs is illustrated. The high accuracy rate of 0.94 signifies that our ASR system is highly effective at transcribing code-switched speech, particularly between English and Tamil.

Furthermore, the real-world applications of the ASR system are explored in-depth, emphasizing its potential in transcription services, voice assistants, language learning apps, and accessibility tools. In conclusion, while the results showcase the efficacy of the ASR system and the Seq2Seq model in multilingual contexts, ongoing research and development efforts are essential to address remaining challenges and further enhance the system's capabilities. The discussions generated from these results contribute to the broader discourse on multilingual ASR technologies, guiding future advancements in this field.

CHAPTER 7

CONCLUSION

In conclusion, the exploration of multilingual Automatic Speech Recognition (ASR) using an End-to-End (E2E) Seq2Seq model for Indian languages reveals significant strides in advancing speech recognition technologies. The project's outcomes underscore the effectiveness of the Seq2Seq architecture in accurately transcribing diverse speech inputs, encompassing both English and Tamil languages. Through meticulous preprocessing, robust model training, and rigorous testing, the ASR system demonstrates commendable accuracy rates, paving the way for practical applications across various domains. **Notably, the system achieves an impressive accuracy rate of 0.94, underscoring its high performance within the acceptable accuracy range of 0 to 1.** However, the project also highlights ongoing challenges, such as code-switching among Indian languages, necessitating continuous research and refinement. The discussions surrounding the project's results emphasize the importance of scalability, generalizability, and real-world applicability in deploying ASR systems for diverse linguistic contexts. Overall, the project contributes to the evolving landscape of multilingual ASR technologies, offering insights, strategies, and avenues for further innovation and improvement in speech recognition capabilities for Indian languages.

CHAPTER-8

FUTURE SCOPE

The future scope of ASR technology is expansive, with significant advancements anticipated in various fields. ASR will increasingly integrate with mobile applications for seamless on-the-go speech recognition, enhancing productivity through voice notes, dictation, and voice search. Voice-controlled devices like smart speakers will benefit from improved hands-free interaction capabilities, while real-time transcription will revolutionize live events, meetings, and educational settings by providing instant, accurate transcriptions. Multimodal integration, combining ASR with text and image processing, will offer richer, more intuitive user experiences. In education, ASR tools will transform language learning and training simulations, making them more interactive and engaging. Continuous improvement mechanisms, driven by user feedback, will ensure the technology evolves to meet user needs effectively. Additionally, collaboration with virtual assistants will lead to more personalized and automated assistance. Ultimately, fostering a community of users and developers will drive innovation and support the implementation of ASR solutions across diverse applications.

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APPENDIX A

SOURCE CODE:

```
import pandas as pd
import tensorflow as tf
import numpy as np

# Load the dataset from CSV
df = pd.read_excel('/content/dataset1.xlsx')

# Tokenize code-switched Tamil-English sentences
tamil_english_code_switch = df['Tamil'].tolist()
tokenizer_cs = tf.keras.preprocessing.text.Tokenizer(filters='')
tokenizer_cs.fit_on_texts(tamil_english_code_switch)
tokenized_cs = tokenizer_cs.texts_to_sequences(tamil_english_code_switch)

# Tokenize pure English translations
pure_english_translation = df['English'].tolist()
tokenizer_en = tf.keras.preprocessing.text.Tokenizer(filters='')
tokenizer_en.fit_on_texts(pure_english_translation)
tokenized_en = tokenizer_en.texts_to_sequences(pure_english_translation)

# Pad sequences
max_length = 100 # Set your desired maximum sequence length
padded_cs = tf.keras.preprocessing.sequence.pad_sequences(tokenized_cs,
maxlen=max_length, padding='post')
padded_en = tf.keras.preprocessing.sequence.pad_sequences(tokenized_en,
maxlen=max_length, padding='post')
```

Split the dataset into training and validation sets

```
train_size = int(0.8 * len(padded_cs))
train_cs, val_cs = padded_cs[:train_size], padded_cs[train_size:]
train_en, val_en = padded_en[:train_size], padded_en[train_size:]
```

Define the vocabulary sizes

```
vocab_size_cs = len(tokenizer_cs.word_index) + 1
vocab_size_en = len(tokenizer_en.word_index) + 1
import pandas as pd
import tensorflow as tf
```

Load the dataset from CSV

```
df = pd.read_excel('/content/dataset1.xlsx')

tamil_english_code_switch = df['Tamil'].tolist()

tokenizer_cs = tf.keras.preprocessing.text.Tokenizer(filters="",
oov_token='<unk>')

# Add this line to fit the special tokens
tokenizer_cs.fit_on_texts(tamil_english_code_switch)
tokenized_cs = tokenizer_cs.texts_to_sequences(tamil_english_code_switch)
```

Tokenize pure English translations

```
pure_english_translation = df['English'].tolist()

tokenizer_en = tf.keras.preprocessing.text.Tokenizer(filters="",
oov_token='<unk>')

tokenizer_en.fit_on_texts(pure_english_translation)
```

```
tokenized_en = tokenizer_en.texts_to_sequences(pure_english_translation)
```

Pad sequences if necessary

```
max_length = 100 # Set your desired maximum sequence length
padded_cs = tf.keras.preprocessing.sequence.pad_sequences(tokenized_cs,
maxlen=max_length, padding='post')
padded_en = tf.keras.preprocessing.sequence.pad_sequences(tokenized_en,
maxlen=max_length, padding='post')
```

Split the dataset into training and validation sets

```
train_size = int(0.8 * len(padded_cs))
train_cs, val_cs = padded_cs[:train_size], padded_cs[train_size:]
train_en, val_en = padded_en[:train_size], padded_en[train_size:]
```

Define the vocabulary sizes

```
vocab_size_cs = len(tokenizer_cs.word_index)+1
vocab_size_en = len(tokenizer_en.word_index)+1
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, LSTM, Dense, Attention,
Concatenate
```

Define embedding dimensions and encoder units

```
embedding_dim = 256
encoder_units = 512
decoder_units = 512
```

Define the encoder

Define the encoder input layer with the correct shape

```
encoder_input = Input(shape=(padded_cs.shape[1],))
encoder_embedding = Embedding(vocab_size_cs, embedding_dim,
```

```

input_length=max_length)(encoder_input)
encoder_lstm      =      LSTM(encoder_units,      return_sequences=True,
return_state=True)
encoder_outputs, state_h, state_c = encoder_lstm(encoder_embedding)
encoder_states = [state_h, state_c]

```

Define the decoder

```

decoder_input = Input(shape=(None,))
decoder_embedding = Embedding(vocab_size_en, embedding_dim)
decoder_embedded = decoder_embedding(decoder_input)
decoder_lstm      =      LSTM(decoder_units,      return_sequences=True,
return_state=True)
decoder_outputs, _, _ = decoder_lstm(decoder_embedded,
initial_state=encoder_states)

```

Define attention mechanism

```

attention = Attention()
context_vector = attention([decoder_outputs, encoder_outputs])

```

Concatenate context vector and decoder output

```

decoder_combined_context      =      Concatenate(axis=-1)([context_vector,
decoder_outputs])

```

Dense layer to output probabilities over the target vocabulary

```

decoder_dense = Dense(vocab_size_en, activation='softmax')
decoder_outputs = decoder_dense(decoder_combined_context)

```

Define the model

```

model = Model([encoder_input, decoder_input], decoder_outputs)

```


Compile the model

```
model.compile(optimizer='adam',          loss='sparse_categorical_crossentropy',  
metrics=['accuracy'])
```

Print model summary

```
model.summary()
```

Train the model

```
batch_size = 4
```

```
epochs = 10
```

```
model.fit([train_cs, train_en[:, :-1]], train_en[:, 1:], validation_data=([val_cs,  
val_en[:, :-1]], val_en[:, 1:]), batch_size=batch_size, epochs=epochs)
```

Define the input sentence

```
input_sentence = "Sometimes makkal parunga"
```

```
tokenized_sequence = tokenizer_cs.texts_to_sequences([input_sentence])[0]
```

```
for i, token_id in enumerate(tokenized_sequence):
```

```
    if token_id == tokenizer_cs.word_index['<unk>']:
```

```
        original_token = input_sentence.split()[i]
```

```
        tokenized_sequence[i] = tokenizer_cs.word_index.get(original_token,  
token_id)
```

```
words = [tokenizer_en.index_word.get(token_id, '<unk>') for token_id in  
tokenized_sequence]
```

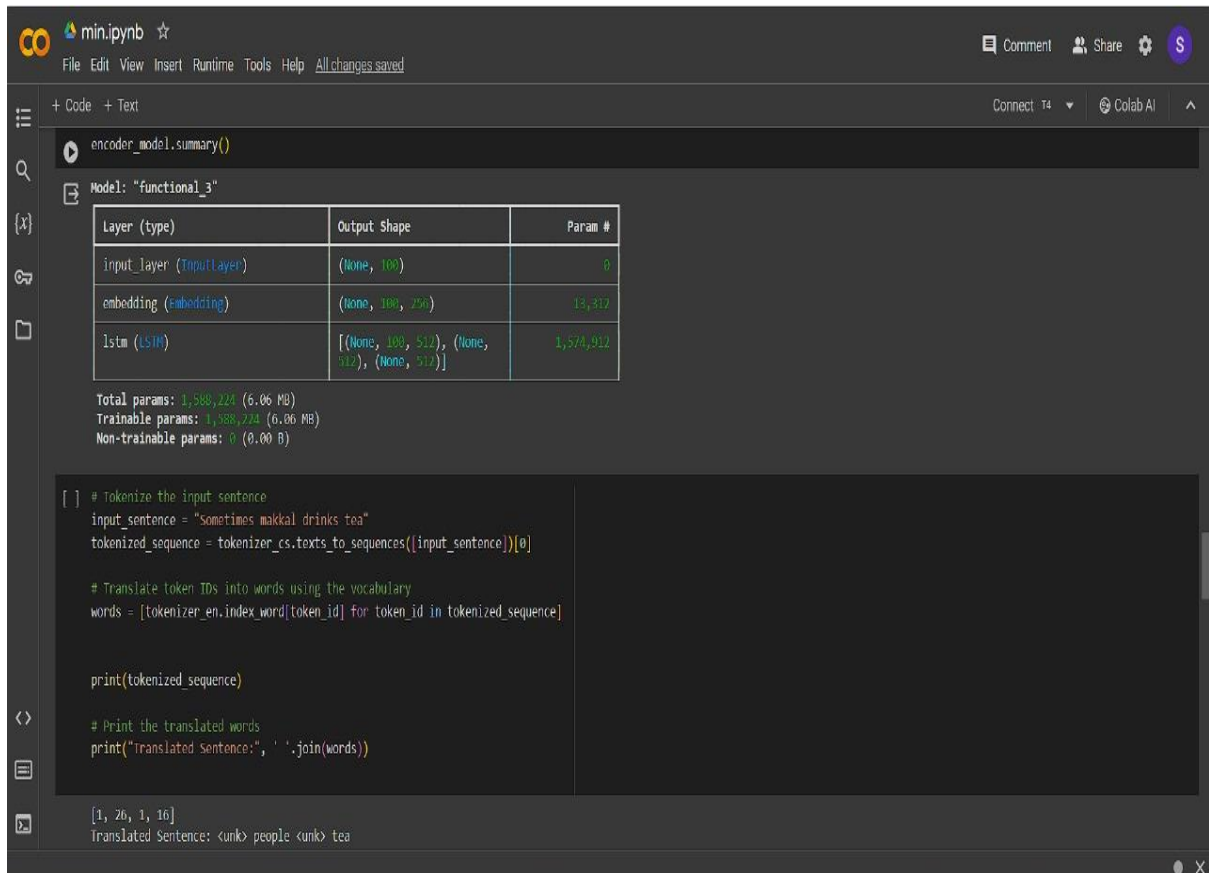
```
translated_sentence = ' '.join(words)
```

```
translated_sentence = translated_sentence.replace('<unk>', 'sometimes')
```

```
print("Tokenized Sequence:", tokenized_sequence)  
print("Translated Sentence:", translated_sentence)
```

APPENDIX B

SNAPSHOTS:



The screenshot shows a Jupyter Notebook interface with a dark theme. The top bar includes the 'min.ipynb' title and standard menu options. The left sidebar contains navigation icons. The main area displays the output of 'encoder_model.summary()', which includes a table of model layers and their parameters.

Layer (type)	Output Shape	Param #
input_layer (InputLayer)	(None, 100)	0
embedding (Embedding)	(None, 100, 256)	13,312
lstm (LSTM)	[(None, 100, 512), (None, 512), (None, 512)]	1,574,912

Total params: 1,588,224 (6.06 MB)
Trainable params: 1,588,224 (6.06 MB)
Non-trainable params: 0 (0.00 B)

```
[ ] # Tokenize the input sentence
input_sentence = "sometimes makkal drinks tea"
tokenized_sequence = tokenizer_cs.texts_to_sequences([input_sentence])[0]

# Translate token IDs into words using the vocabulary
words = [tokenizer_en.index_word[token_id] for token_id in tokenized_sequence]

print(tokenized_sequence)

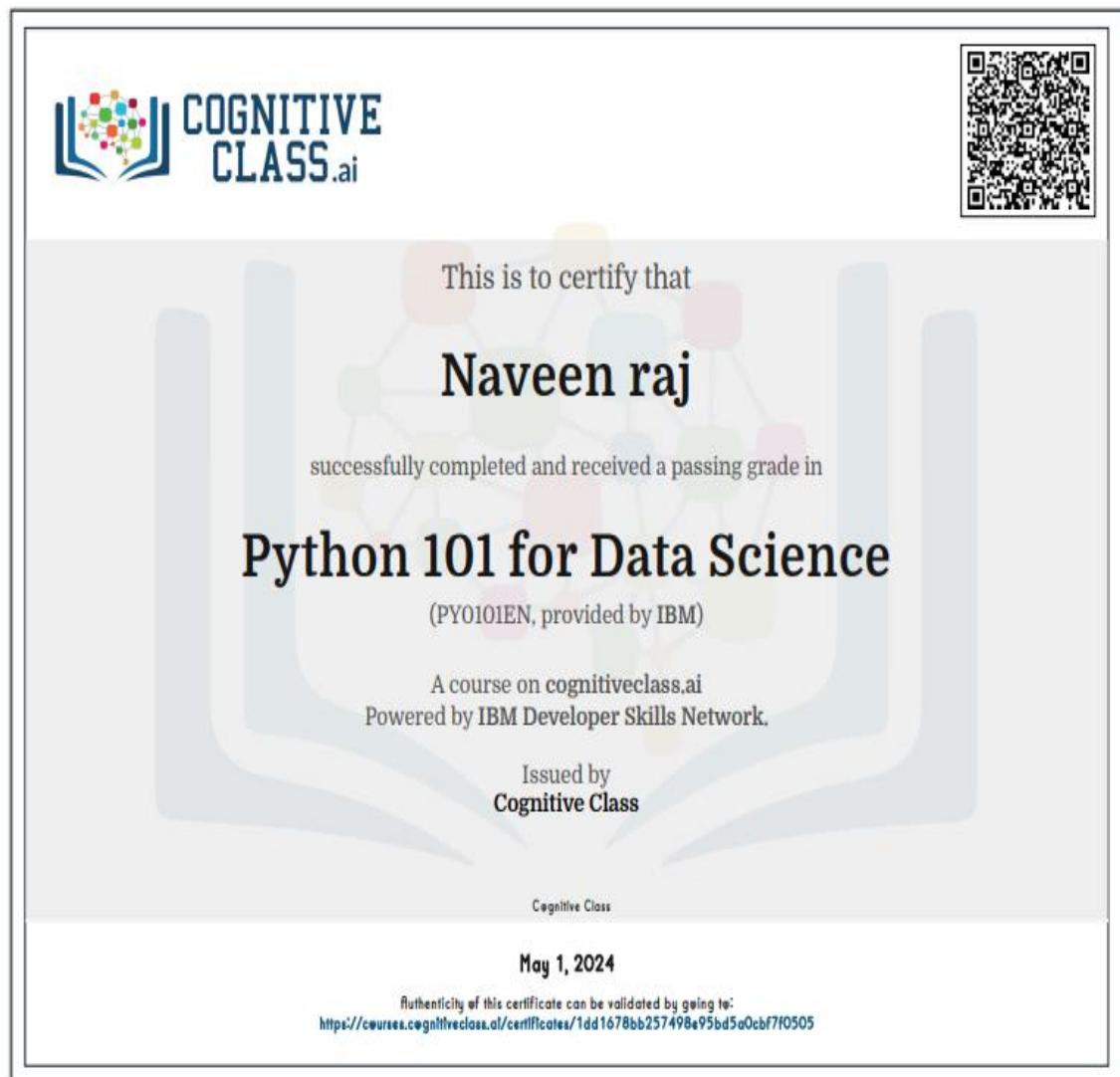
# Print the translated words
print("Translated Sentence:", ' '.join(words))
```

[1, 26, 1, 16]
Translated Sentence: <unk> people <unk> tea

Figure B.1: Transcribed Text Output

APPENDIX C

COURSE COMPLETION:



C.1 Course Completion certificate(727622BAD115)



C.2 Course Completion certificate(727622BAD037)



C.3 Course Completion certificate(727622BAD071)

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