ENGLISH TO TELUGU TEXT TRANSLATION SYSTEM

Thesis submitted

In partial fulfillment of requirements

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of

Bachelor of Technology

In Computer Science & Engineering

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May 2024

DECLARATION

We certify that

a. The work contained in this report is original and has been done by Jayanth Reddy G, Akhila Banoth under the guidance of our supervisor **Dr. Khelchandra thongam , Associate professor, Computer Science and Engineering, NIT MANIPUR**

b. The work has not been submitted to any other Institute for any degree or diploma.

c. We have followed the guidelines provided by the Institute in preparing the report.

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G. Jayanth Reddy B. Akhila

Jayanth Reddy Akhila Banothu

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Certificate

This is to certify that Dissertation Report entitled, "English to Telugu Text Translation System" Submitted by " ***Mr. Jayanth Reddy, Ms. Banothu Akhila*** " toNational Institute of Technology Manipur, India ,is a record of bonafide Project work carried out by them under the supervision of **Dr. Khelchandra Thongam**, **Associate professor of NIT Manipur** under the department of **Computer Science & Engineering**, NIT Manipur and is worthy of consideration for the award of the degree of Bachelor of Technology in **Computer Science & Engineering Department** of the Institute.

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Date: 23rd May 2024

ABSTRACT

In our rapidly globalizing world, the ability to seamlessly communicate across linguistic boundaries is more crucial than ever. As a response to the growing demand for efficient language translation systems, our project focuses on the "Design and Development of an English to Telugu Translation System based on Transformer with Deep Learning."

This project harnesses the power of Transformers, combined with deep learning techniques, to create a robust and accurate translation system. The choice of English to Telugu translation serves as a testament to our commitment to addressing linguistic diversity and enabling information exchange for the Telugu-speaking community.

Our system aims not only to bridge the language gap but also to enhance translation quality, ensuring that nuances and cultural context are preserved in the process. The deep learning algorithms employed in this project undergo extensive training on large parallel corpora of English and Telugu text, enabling the model to grasp the intricacies of both languages

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INTRODUCTION AND LITERATURE REVIEW

INTRODUCTION

1.1 Problem Statement

Develop an efficient and accurate English to Telugu text translation system using deep learning techniques, specifically leveraging transformer architectures and to bridge language barriers, enhance communication, and accessibility by providing an advanced tool for seamless translation between English and Telugu.

1.2 Introduction to transformers

In the ever-evolving landscape of natural language processing (NLP), the advent of transformer-based models has revolutionized the field, offering unprecedented capabilities in tasks like text-to-text translation. Transformers, with their attention mechanisms and parallel processing, have proven to be a game-changer by capturing contextual nuances and dependencies within language. This innovation has not only overcome traditional limitationsin translation but has also paved the way for more accurate, context-aware, and fluent translations across a multitude of languages. This article explores the transformative impact of employing transformers in text-to-text translation, delving into the underlying mechanismsthat make these models highly effective and showcasing their potential to bridge linguistic gaps in our interconnected globalized world.

1.3 Objectives

1. Implement a transformer-based deep learning model for text translation
2. Fine-tune the model to handle language-specific nuances and improve performance

3. Implement appropriate evaluation metrics (e.g., BLEU score, accuracy) to quantitatively

   assess the translation quality.
4. Create an intuitive and user-friendly interface for users to input English text and receive thecorresponding translated Telugu text.

1.4 Motivation

Our project, aiming to create an English to Telugu transformer-based translation system, is fueled by the commitment to empower the Telugu-speaking community. By breaking language barriers, this initiative provides seamless access to global information, education, and diverse perspectives, allowing the Telugu community to express themselves on a broader stage.

This transformative tool not only translates words but preserves the cultural nuances of Telugu, fostering cross-cultural communication and understanding. Beyond convenience, it becomes a vital resource for students, professionals, and enthusiasts, contributing to the preservation and revitalization of the Telugu language in the digital age.
In essence, our motivation is to build a bridge between languages, enhancing accessibility and fostering a more interconnected world where the richness of Telugu culture can thrive alongside global conversations.

1.5 Scope

1. **Language-specific Challenges:**

   Address Telugu's linguistic nuances to ensure contextually accurate translations.
2. **User Interface Design:**

   Develop an intuitive interface for seamless English to Telugu text translation.

3. **Real-time Translation:**

   Strive for real-time translation capabilities to enhance user experience.

4. **Cross-Platform Compatibility:**

   Ensure the system is compatible across various platforms and devices.

5. **Scalability:**

   Design the system to be scalable for potential expansion to additional languages or model enhancements.

1.6 Literature Review

Survey - 1

[1] Lingam, K., Ramalakshmi, E., & Inturi, S. (2014). English to Telugu Rule-based Machine Translation System: A Hybrid Approach. International Journal of Computer Applications, Computer Science, Linguistics. Published September 18, 2014.

Rule-Based Machine Translation (RBMT):

1. RBMT relies on explicit linguistic rules and grammatical structures to translate text from one language to another. These rules are typically created by linguists and translation experts and may involve syntax, semantics, and morphology.
2. RBMT systems heavily depend on linguistic knowledge and require extensive manual rule creation. Linguists need to encode language-specific rules and translation
3. RBMT systems may struggle with adapting to new language pairs or handling informallanguage. They are less flexible and may not capture the dynamic nature of languagesin various contexts.

4. Handling polysemy and ambiguity can be challenging for RBMT systems. The rigid rule structures may not effectively navigate through multiple possible translations or diverse interpretations.
5. Updating or modifying an RBMT system requires manual intervention by linguistic experts. This makes these systems less adaptable to evolving languages and dynamic linguistic environments.

Survey - 2

[2] Premjith, B., Kumar, M. A., & Soman, K. P. (2019). Neural Machine Translation System for English to Indian Language Translation Using MTIL Parallel Corpus. Journal of Intelligent Systems, 28(3), Special Issue on Natural Language Processing. De Gruyter. DOI:10.1515/jisys-2019-2510. License: CC BY-NC-ND 3.0

Statistical Machine Translation (SMT):

1. SMT relies on a combination of rule-based and statistical methods. It involves the creation of linguistic rules and the estimation of statistical models based on bilingual corpora.
2. SMT often operates on a phrase-based translation model, where translation units arephrases or subphrases rather than individual words. These units are aligned across parallel corpora to learn translation probabilities.
3. SMT systems require extensive feature engineering, where linguistic experts manually design features and weights to capture translation patterns, word alignments, and other linguistic phenomena.
4. SMT may struggle to capture long-range dependencies and contextual nuances in language, as it typically relies on local context and may not consider the entire sentence during translation.

Survey – 3

[3] Swaroopa, P., Vishnu, K., Akshay, P., Sandip, S. S. S., & Vivek, V. (2022).
A Survey on Formal Language Translation (Telugu - English).
ACE Engineering College, Hyderabad, Telangana, India.

LSTM (Long Short-Term Memory):

1. LSTM – long short term memory , LSTMs have hidden states and memory cells that enable them to capture and store information over long sequences. The memory cells help in mitigating the vanishing gradient problem associated with standard RNNs.
2. Computation in LSTMs is performed step by step, where the model updates its hiddenstates and memory cells at each time step based on the current input and the information stored in the previous hidden states and memory cells.
3. Due to their sequential nature, LSTMs face challenges in parallelizing computations, limiting their ability to efficiently utilize parallel processing capabilities of modern hardware.

Why Transformers?

1. Transformers leverage self-attention mechanisms, allowing the model to focus on different parts of the input sequence when generating each part of the output sequence. This attention mechanism captures dependencies effectively and enables the model to handle long-range dependencies.
2. Transformer-based machine translation follows an end-to-end learning approach. It learns representations directly from parallel corpora without explicit rule-based feature engineering, making the training process more data-driven.

3. The attention mechanisms in Transformers allow for efficient parallelization of training and inference, making them computationally efficient. This scalability is particularly advantageous for handling large datasets and accelerating translation processes.
4. Transformers excel at capturing contextual understanding, as they consider the entire context of a sentence during both training and inference. This enables them to generate translations that are more contextually relevant and coherent.
5. Transformer-based models can be fine-tuned with additional data, facilitating continuous learning and adaptation to evolving language patterns. This adaptability contributes to the system's ability to improve over time.

1.7 Software and Hardware Requirements

Software Requirements

1. Python
2. Pandas and Numpy
3. Tensorflow
4. Torch
5. Flask

Hardware Requirements

1. GPU - Training deep learning models, especially Transformer architectures, can becomputationally intensive. Having a GPU accelerates the training process
2. RAM - 16GB or higher
3. CPU - A multi-core CPU, such as an Intel Core i7 or higher, is beneficial for parallelprocessing during training.

CHAPTER – 2

METHODOLOGY

METHODOLOGY

2.1 Project Flow

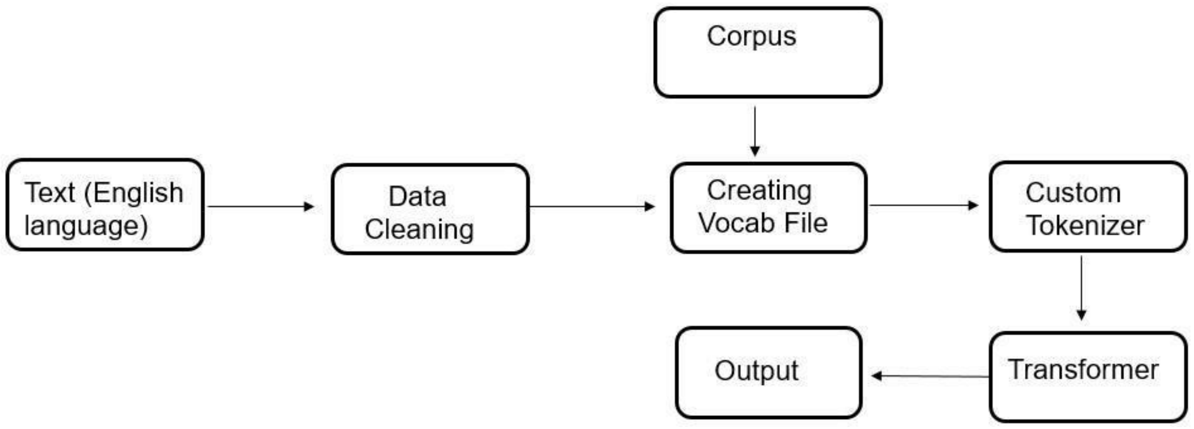


Fig 2.1 Project Flow Image

2.2 Data Preprocessing

2.2.1 Data Cleaning

Decontractions(phrase):

This function takes a text phrase and expands English contractions into their full forms. For instance, it replaces "won't" with "will not" and "can't" with "can not." It covers various contraction patterns using regular expressions.

Preprocess_english(text):

Converts all text to lowercase to ensure consistency**.** Utilizes the decontractions function to expand contractions in the text. Adds spaces around punctuation marks like question marks, periods, exclamation marks, and commas for better tokenization. Removes extra spaces to clean up the text. Eliminates special characters, keeping only letters and essential punctuation. Appends '<start>' at the beginning and '<end>' at the end of the text to indicate the start andend of a sequence.

Strips any leading or trailing spaces to finalize the preprocessing.

In essence, these operations collectively prepare English text data for subsequent natural language processing tasks by addressing common language nuances and ensuring a standardized, cleaned-up format for analysis or model training.

2.3 Creating a vocab file from our corpus

1. **Reading Data:**

   Reading text data from a specified file (path) and stores it in a list called data.

2. **Creating TensorFlow Dataset:**

   Converting the list of text data (data) into a format suitable for TensorFlow processing.

3. **Setting BERT Tokenizer Parameters:**

   It decides how the BERT tokenizer should handle the text, such as converting it to lowercase.Reserved tokens like "[PAD]", "[UNK]", "[START]", and "[END]" are specified.

4. **Defining BERT Vocabulary Parameters:**

   It sets up parameters for creating the vocabulary using BERT methods This includes specifying the target vocabulary size (150,000) and using the previously defined tokenizer parameters.

5. **Creating Vocabulary:**

   Generating the vocabulary from the dataset using BERT vocabulary functions.

6. **Writing Vocabulary to File:**

   Finally, saving the generated vocabulary to a file at the specified location (saving_path).

2.4 Custom Tokenizer

BERT tokenizer considers the bidirectional context of words, meaning it takes into account thesurrounding words on both sides when encoding a word. This helps capture richer contextualinformation compared to traditional tokenization methods.

BERT tokenizer utilizes WordPiece tokenization, breaking down words into smaller subwordsor pieces. This is particularly useful for handling rare words, out-of-vocabulary terms, and morphologically rich languages.

Typically, BERT tokenizers convert text to lowercase. This ensures consistency in representation, preventing the model from treating differently cased words as distinct entities. BERT introduces special tokens like "[CLS]" (classification token), "[SEP]" (separator token), "[PAD]" (padding token), "[MASK]" (mask token), "[START]", and "[END]". These tokens servespecific purposes during model training and inference.

BERT tokenization is often applied in conjunction with pre-trained BERT models. The tokenizer is used to process input text, and the pre-trained model produces embeddings (contextualized representations) for each token.

During training, BERT utilizes a masked language model (MLM) objective. Some tokens in theinput sequence are randomly replaced with the "[MASK]" token, and the model is trained to predict the original words based on the context.

BERT tokenizer is widely used in various natural language processing (NLP) tasks, such as textclassification, named entity recognition, sentiment analysis, and machine translation. It has become a foundational tool in the NLP landscape due to its ability to capture intricate language patterns.

2.5 Architecture of Model

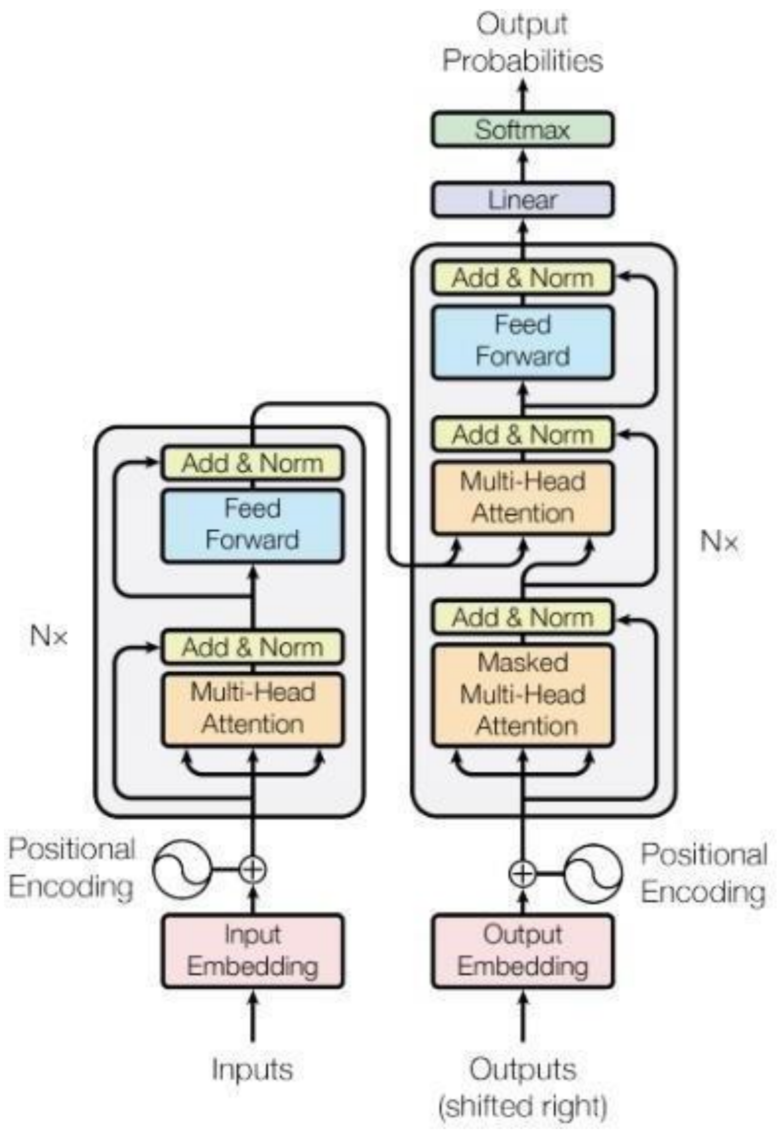


Fig 2.2 Architecture of Model Image

2.6 Positional Encoding

```
def get_angles(pos, i, d_model):
  angle_rates = 1 / np.power(10000, (2 * (i//2)) / np.float32(d_model))
  return pos * angle_rates
```

```
def positional_encoding(position, d_model):
  angle_rads = get_angles(np.arange(position)[:, np.newaxis],
                          np.arange(d_model)[np.newaxis, :],
                          d_model)

  # apply sin to even indices in the array; 2i
  angle_rads[:, 0::2] = np.sin(angle_rads[:, 0::2])

  # apply cos to odd indices in the array; 2i+1
  angle_rads[:, 1::2] = np.cos(angle_rads[:, 1::2])

  pos_encoding = angle_rads[np.newaxis, ...]

  return tf.cast(pos_encoding, dtype=tf.float32)
```

```
n, d = 2048, 512
pos_encoding = positional_encoding(n, d)
print(pos_encoding.shape)
pos_encoding = pos_encoding[0]

# Juggle the dimensions for the plot
pos_encoding = tf.reshape(pos_encoding, (n, d//2, 2))
pos_encoding = tf.transpose(pos_encoding, (2, 1, 0))
pos_encoding = tf.reshape(pos_encoding, (d, n))

plt.pcolormesh(pos_encoding, cmap='RdBu')
plt.ylabel('Depth')
plt.xlabel('Position')
plt.colorbar()
plt.show()
```

```
(1, 2048, 512)
```

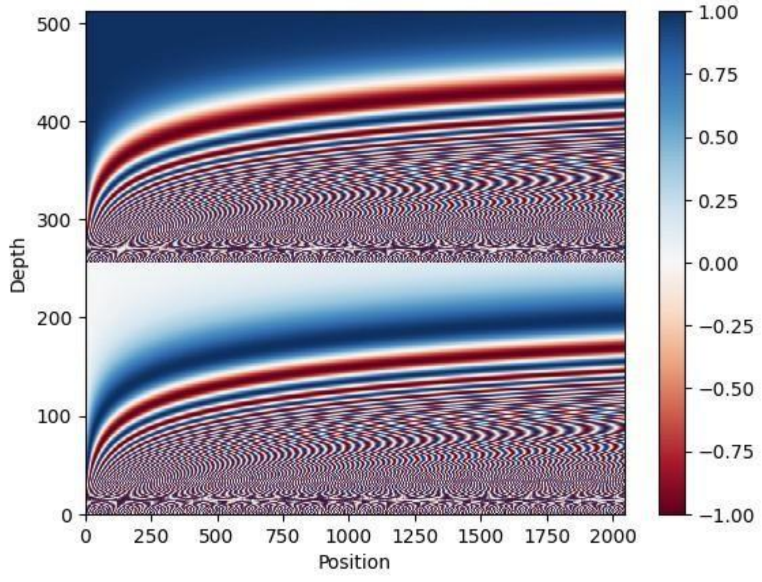


Fig 2.3 Positional Encoding function Image

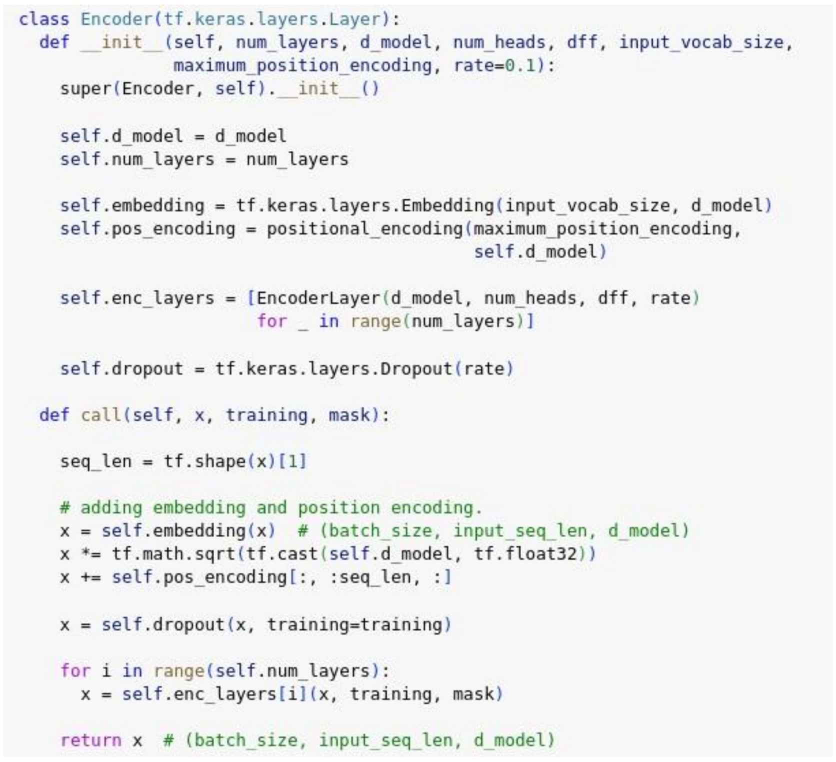
Since this model doesn’t contain any recurrence or convolution, positional encoding is addedto give the model some information about the relative position of the words in the sentence.The positional encoding vector is added to the embedding vector. Embedding represent a token in a d-dimensional space where tokens with similar meaning will be closer to each other. But the embedding do not encode the relative position of words in a sentence. So, after adding the positional encoding, words will be closer to each other based on the similarity of their meaning and their position in the sentence, in the d-dimensional space. The formula for calculating the positional encoding is as follows:

$$PE_{(pos,2i)} = sin(pos/10000^{2i/d_{model}})$$

$$PE_{(pos,2i+1)} = cos(pos/10000^{2i/d_{model}})$$

Fig 2.4 Positional Encoding formula Image

2.7 Encoder



```
class Encoder(tf.keras.layers.Layer):
  def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
               maximum_position_encoding, rate=0.1):
    super(Encoder, self).__init__()

    self.d_model = d_model
    self.num_layers = num_layers

    self.embedding = tf.keras.layers.Embedding(input_vocab_size, d_model)
    self.pos_encoding = positional_encoding(maximum_position_encoding,
                                            self.d_model)

    self.enc_layers = [EncoderLayer(d_model, num_heads, dff, rate)
                       for _ in range(num_layers)]

    self.dropout = tf.keras.layers.Dropout(rate)

  def call(self, x, training, mask):

    seq_len = tf.shape(x)[1]

    # adding embedding and position encoding.
    x = self.embedding(x)  # (batch_size, input_seq_len, d_model)
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x += self.pos_encoding[:, :seq_len, :]

    x = self.dropout(x, training=training)

    for i in range(self.num_layers):
      x = self.enc_layers[i](x, training, mask)

    return x  # (batch_size, input_seq_len, d_model)
```

Fig 2.5 Encoder Function Image

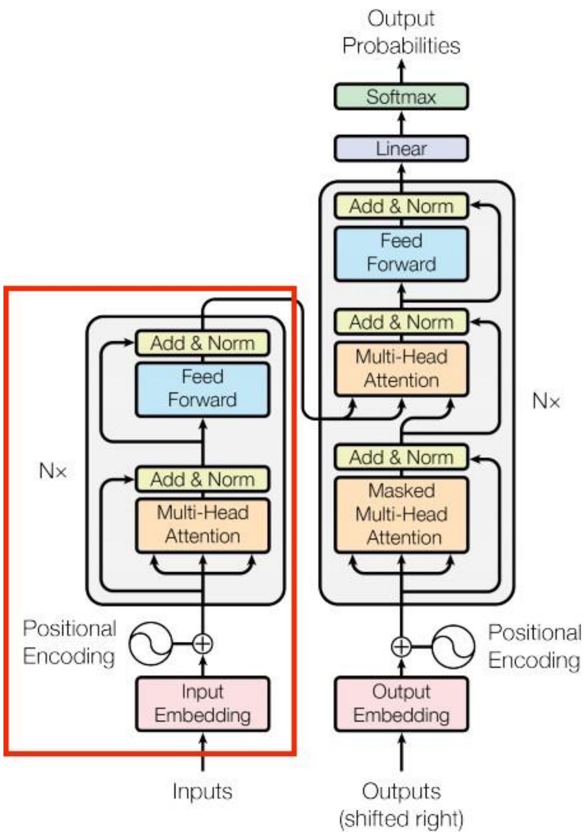


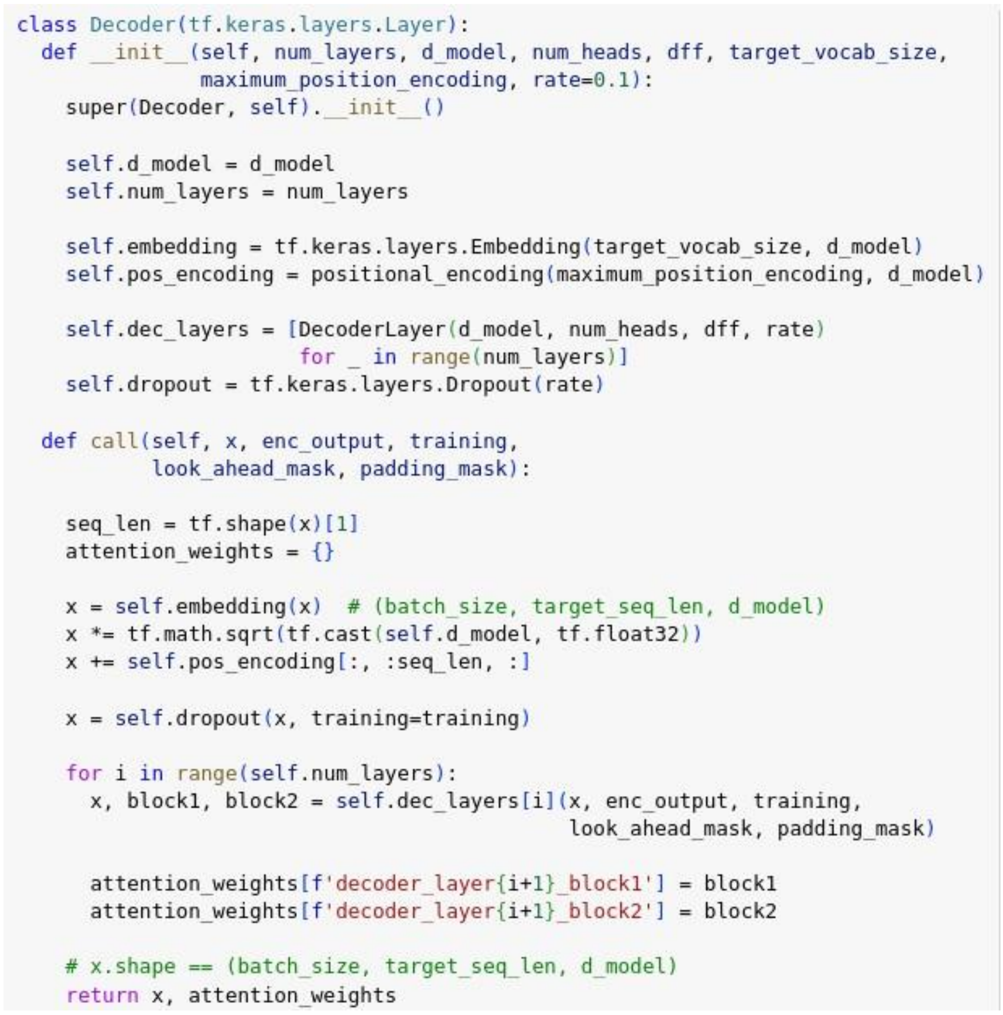
Fig 2.6 Transformer highlighting encoder Image

The encoder consists of:

- A PositionalEmbedding layer at the input.
- A stack of EncoderLayer layers.

The encoder receives the embedding vectors as a list of vectors, each of 512 (can be tuned as a hyper-parameter) size dimension. Both the encoder and the decoder add a positional encoding (that will be explained later) to their input. Both also use a bypass that is called a residual connection followed by an addition of the original input of the sub-layer and another normalization layer (which is also known as a batch normalization).

2.8 Decoder



```
class Decoder(tf.keras.layers.Layer):
  def __init__(self, num_layers, d_model, num_heads, dff, target_vocab_size,
               maximum_position_encoding, rate=0.1):
    super(Decoder, self).__init__()

    self.d_model = d_model
    self.num_layers = num_layers

    self.embedding = tf.keras.layers.Embedding(target_vocab_size, d_model)
    self.pos_encoding = positional_encoding(maximum_position_encoding, d_model)

    self.dec_layers = [DecoderLayer(d_model, num_heads, dff, rate)
                       for _ in range(num_layers)]
    self.dropout = tf.keras.layers.Dropout(rate)

  def call(self, x, enc_output, training,
           look_ahead_mask, padding_mask):

    seq_len = tf.shape(x)[1]
    attention_weights = {}

    x = self.embedding(x)  # (batch_size, target_seq_len, d_model)
    x *= tf.math.sqrt(tf.cast(self.d_model, tf.float32))
    x += self.pos_encoding[:, :seq_len, :]

    x = self.dropout(x, training=training)

    for i in range(self.num_layers):
      x, block1, block2 = self.dec_layers[i](x, enc_output, training,
                                             look_ahead_mask, padding_mask)

      attention_weights[f'decoder_layer{i+1}_block1'] = block1
      attention_weights[f'decoder_layer{i+1}_block2'] = block2

    # x.shape == (batch_size, target_seq_len, d_model)
    return x, attention_weights
```

Fig 2.7 Decoder Function Image

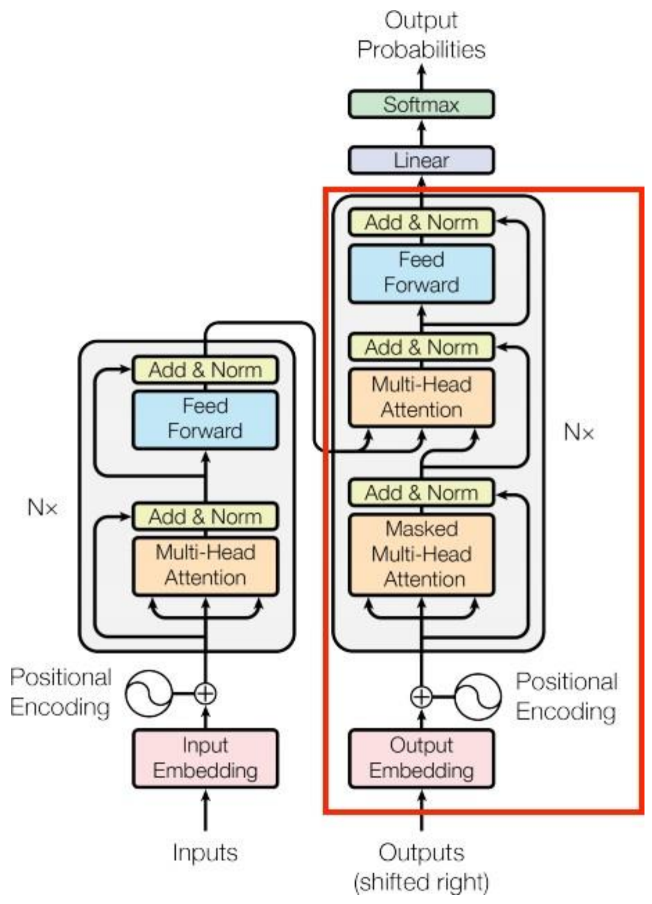
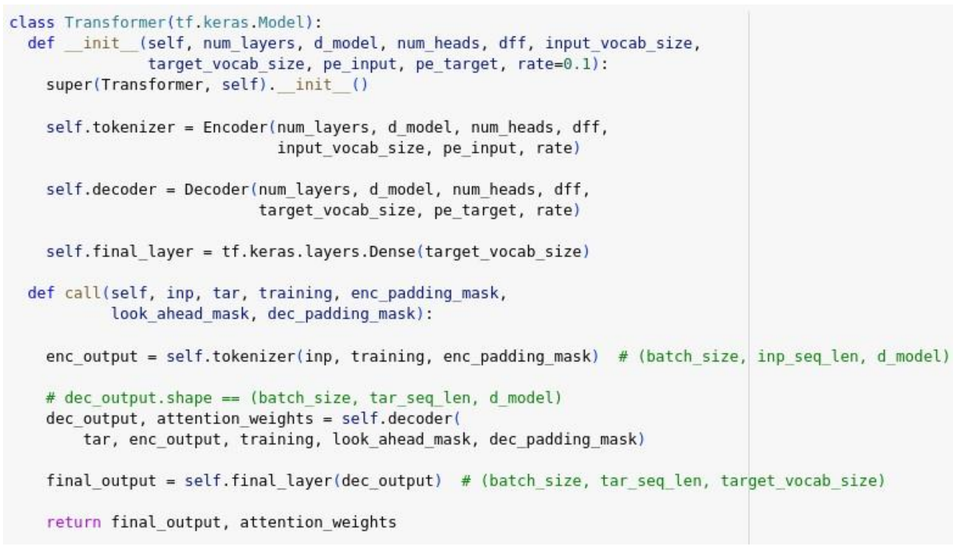


Fig 2.8 Transformer highlighting decoder Image

- The decoder's stack is slightly more complex, with each DecoderLayer containing a CausalSelfAttention, a CrossAttention, and a FeedForward layer Similar to the Encoder.
- The Decoder consists of a PositionalEmbedding, and a stack of DecoderLayers Unlike the encoder, the decoder uses an addition to the Multi-head attention that is called masking.
- This operation is intended to prevent exposing posterior information from the decoder.It means that in the training level the decoder doesn’t get access to tokens in the target sentence that will reveal the correct answer and will disrupt the learning procedure.
- It’s really important part in the decoder because if we will not use the masking the model will not learn anything and will just repeat the target sentence

2.9 Transformer

We now have Encoder and Decoder. To complete the Transformer model, we need to put them together and add a final linear (Dense) layer which converts the resulting vector at each location into output token probabilities.



```
class Transformer(tf.keras.Model):
  def __init__(self, num_layers, d_model, num_heads, dff, input_vocab_size,
               target_vocab_size, pe_input, pe_target, rate=0.1):
    super(Transformer, self).__init__()

    self.tokenizer = Encoder(num_layers, d_model, num_heads, dff,
                             input_vocab_size, pe_input, rate)

    self.decoder = Decoder(num_layers, d_model, num_heads, dff,
                           target_vocab_size, pe_target, rate)

    self.final_layer = tf.keras.layers.Dense(target_vocab_size)

  def call(self, inp, tar, training, enc_padding_mask,
           look_ahead_mask, dec_padding_mask):

    enc_output = self.tokenizer(inp, training, enc_padding_mask)  # (batch_size, inp_seq_len, d_model)

    # dec_output.shape == (batch_size, tar_seq_len, d_model)
    dec_output, attention_weights = self.decoder(
        tar, enc_output, training, look_ahead_mask, dec_padding_mask)

    final_output = self.final_layer(dec_output)  # (batch_size, tar_seq_len, target_vocab_size)

    return final_output, attention_weights
```

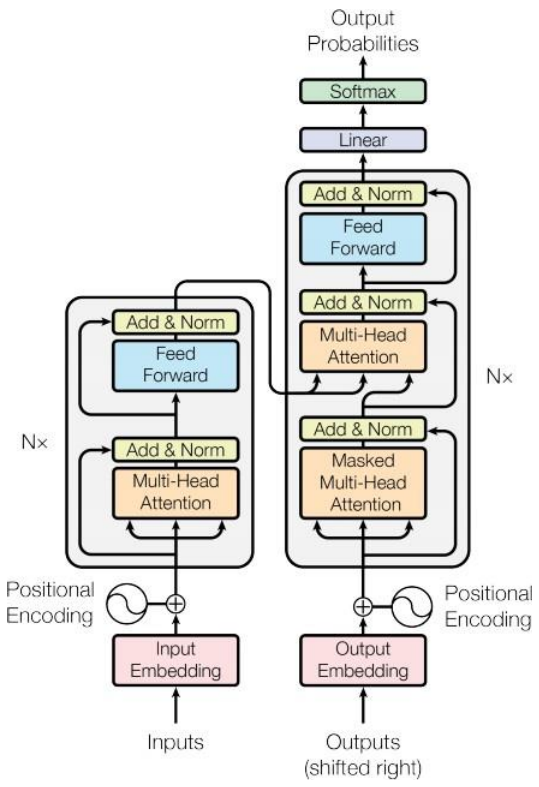
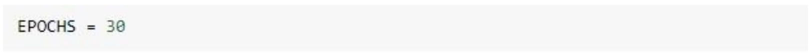
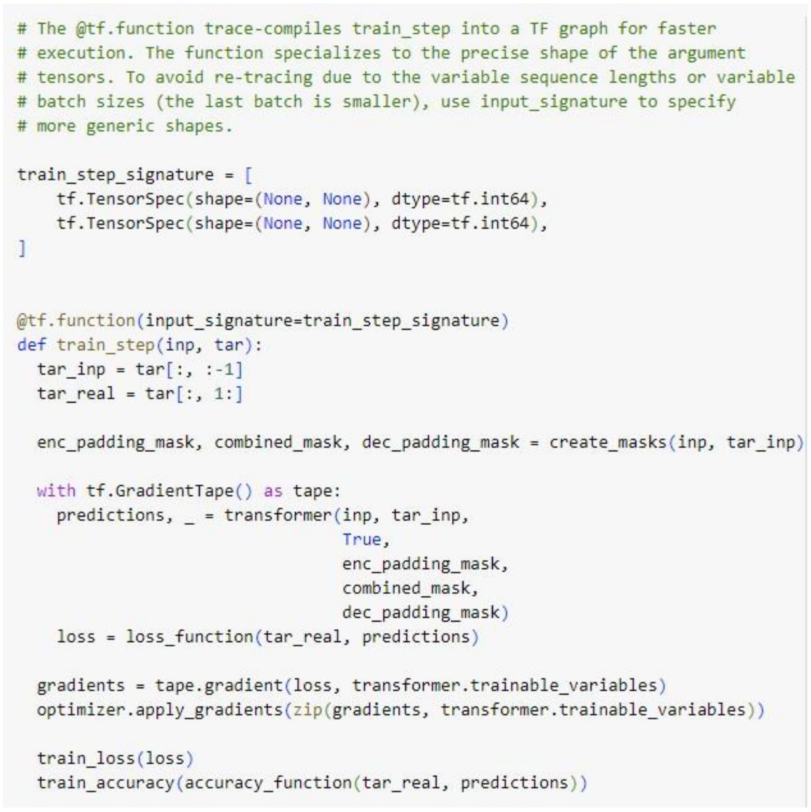


Fig 2.9 Transformer Model Image

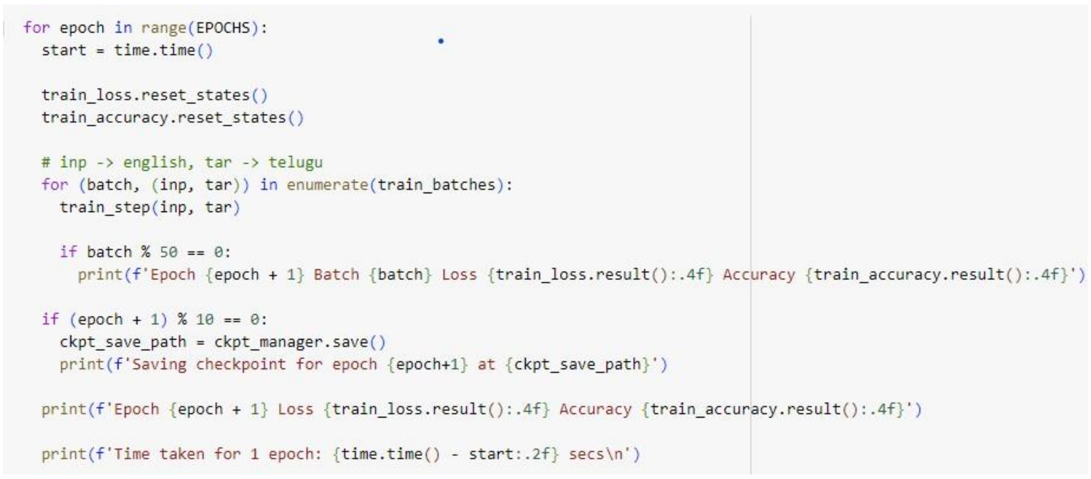
2.10 Training



```
EPOCHS = 30
```



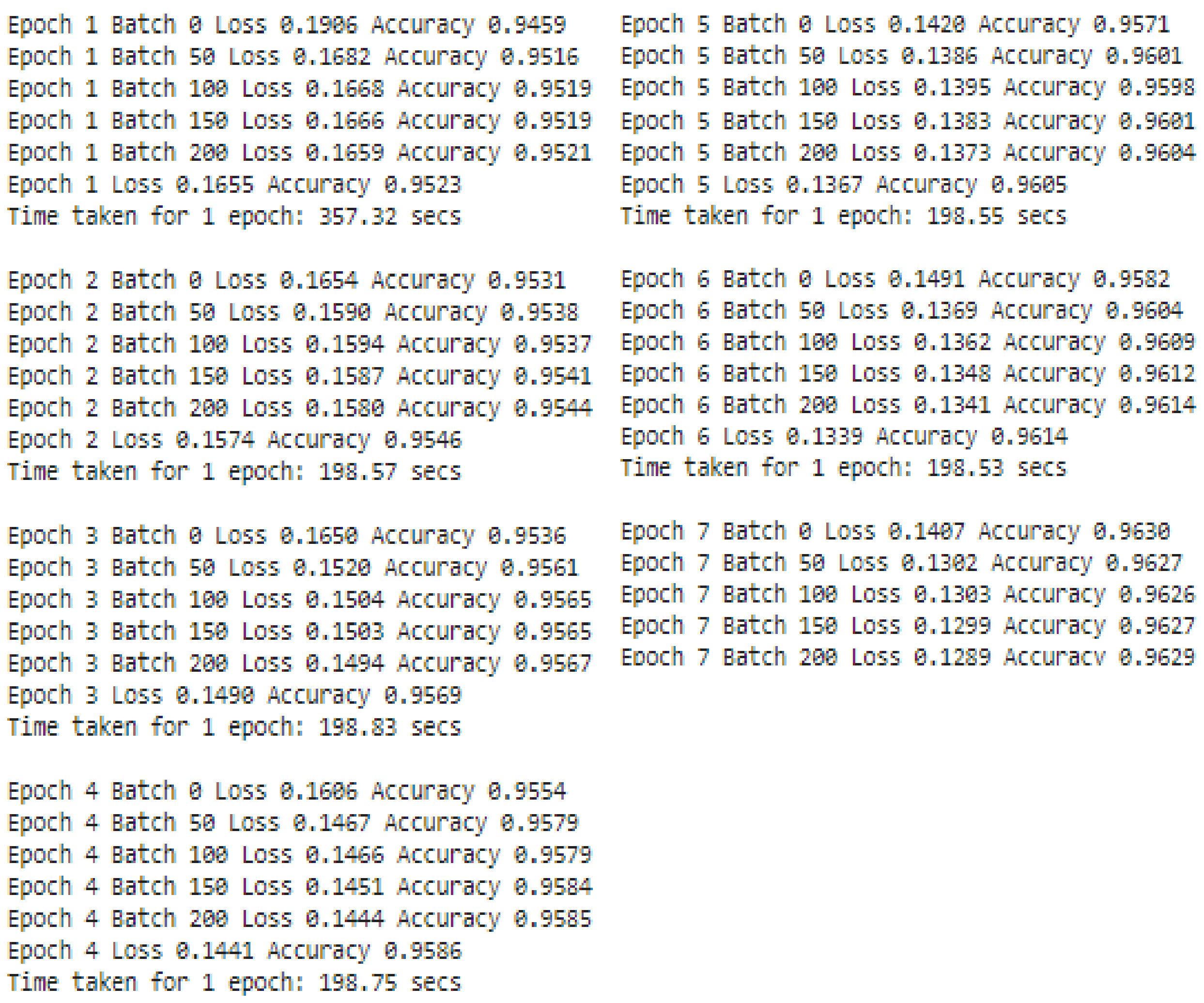
```
# The @tf.function trace-compiles train_step into a TF graph for faster
# execution. The function specializes to the precise shape of the argument
# tensors. To avoid re-tracing due to the variable sequence lengths or variable
# batch sizes (the last batch is smaller), use input_signature to specify
# more generic shapes.

train_step_signature = [
    tf.TensorSpec(shape=(None, None), dtype=tf.int64),
    tf.TensorSpec(shape=(None, None), dtype=tf.int64),
]


@tf.function(input_signature=train_step_signature)
def train_step(inp, tar):
  tar_inp = tar[:, :-1]
  tar_real = tar[:, 1:]

  enc_padding_mask, combined_mask, dec_padding_mask = create_masks(inp, tar_inp)

  with tf.GradientTape() as tape:
    predictions, _ = transformer(inp, tar_inp,
                                 True,
                                 enc_padding_mask,
                                 combined_mask,
                                 dec_padding_mask)
    loss = loss_function(tar_real, predictions)

  gradients = tape.gradient(loss, transformer.trainable_variables)
  optimizer.apply_gradients(zip(gradients, transformer.trainable_variables))

  train_loss(loss)
  train_accuracy(accuracy_function(tar_real, predictions))
```



```
for epoch in range(EPOCHS):
  start = time.time()

  train_loss.reset_states()
  train_accuracy.reset_states()

  # inp -> english, tar -> telugu
  for (batch, (inp, tar)) in enumerate(train_batches):
    train_step(inp, tar)

    if batch % 50 == 0:
      print(f'Epoch {epoch + 1} Batch {batch} Loss {train_loss.result():.4f} Accuracy {train_accuracy.result():.4f}')

  if (epoch + 1) % 10 == 0:
    ckpt_save_path = ckpt_manager.save()
    print(f'Saving checkpoint for epoch {epoch+1} at {ckpt_save_path}')

  print(f'Epoch {epoch + 1} Loss {train_loss.result():.4f} Accuracy {train_accuracy.result():.4f}')

  print(f'Time taken for 1 epoch: {time.time() - start:.2f} secs\n')
```

Fig 2.10 Training Function Image

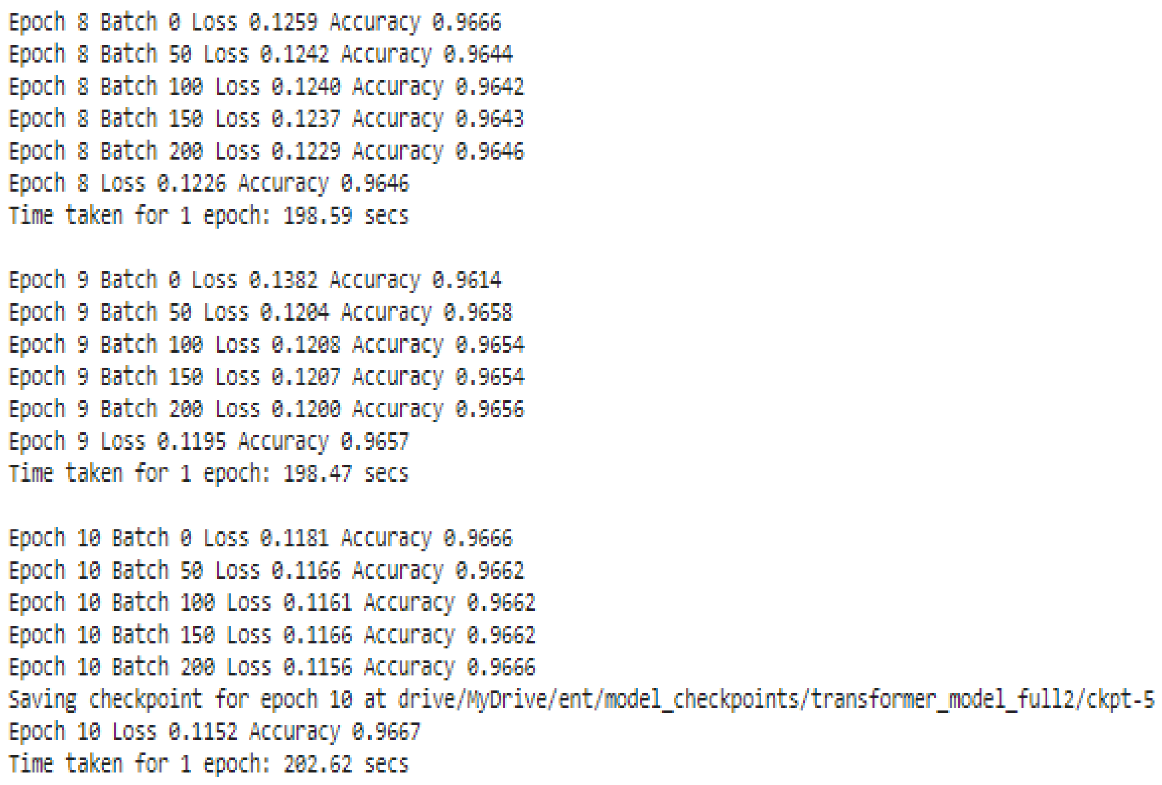
- The drivemountpath ("drive/MyDrive/ent/model_checkpoints/transformer_model_full2") where we store our training steps result , training step is defined where we take inputs target_input and target_real and then call transformer model on it.
- After model is trained, The loss is calculated using the loss_function, which likely computes the Sparse Categorical Crossentropy loss.
- Gradients of the loss with respect to the trainable variables of the transformer model are computed using automatic differentiation (tf.GradientTape).
- The optimizer is then applied to update the model's parameters based on the computed gradients



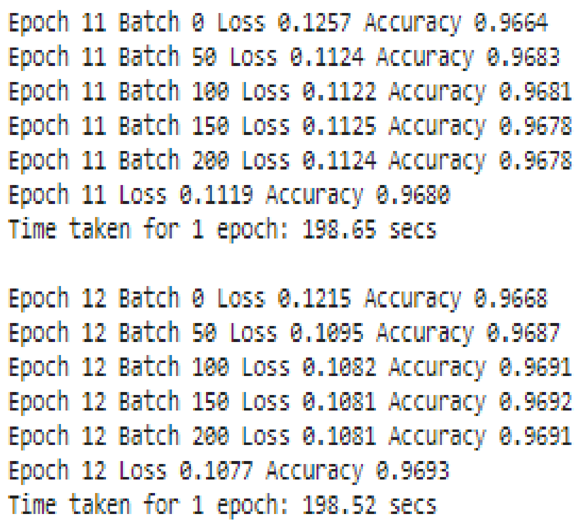
```
Epoch 1 Batch 0 Loss 0.1906 Accuracy 0.9459
Epoch 1 Batch 50 Loss 0.1682 Accuracy 0.9516
Epoch 1 Batch 100 Loss 0.1668 Accuracy 0.9519
Epoch 1 Batch 150 Loss 0.1666 Accuracy 0.9519
Epoch 1 Batch 200 Loss 0.1659 Accuracy 0.9521
Epoch 1 Loss 0.1655 Accuracy 0.9523
Time taken for 1 epoch: 357.32 secs

Epoch 2 Batch 0 Loss 0.1654 Accuracy 0.9531
Epoch 2 Batch 50 Loss 0.1590 Accuracy 0.9538
Epoch 2 Batch 100 Loss 0.1594 Accuracy 0.9537
Epoch 2 Batch 150 Loss 0.1587 Accuracy 0.9541
Epoch 2 Batch 200 Loss 0.1580 Accuracy 0.9544
Epoch 2 Loss 0.1574 Accuracy 0.9546
Time taken for 1 epoch: 198.57 secs

Epoch 3 Batch 0 Loss 0.1650 Accuracy 0.9536
Epoch 3 Batch 50 Loss 0.1520 Accuracy 0.9561
Epoch 3 Batch 100 Loss 0.1504 Accuracy 0.9565
Epoch 3 Batch 150 Loss 0.1503 Accuracy 0.9565
Epoch 3 Batch 200 Loss 0.1494 Accuracy 0.9567
Epoch 3 Loss 0.1490 Accuracy 0.9569
Time taken for 1 epoch: 198.83 secs

Epoch 4 Batch 0 Loss 0.1606 Accuracy 0.9554
Epoch 4 Batch 50 Loss 0.1467 Accuracy 0.9579
Epoch 4 Batch 100 Loss 0.1466 Accuracy 0.9579
Epoch 4 Batch 150 Loss 0.1451 Accuracy 0.9584
Epoch 4 Batch 200 Loss 0.1444 Accuracy 0.9585
Epoch 4 Loss 0.1441 Accuracy 0.9586
Time taken for 1 epoch: 198.75 secs

Epoch 5 Batch 0 Loss 0.1420 Accuracy 0.9571
Epoch 5 Batch 50 Loss 0.1386 Accuracy 0.9601
Epoch 5 Batch 100 Loss 0.1395 Accuracy 0.9598
Epoch 5 Batch 150 Loss 0.1383 Accuracy 0.9601
Epoch 5 Batch 200 Loss 0.1373 Accuracy 0.9604
Epoch 5 Loss 0.1367 Accuracy 0.9605
Time taken for 1 epoch: 198.55 secs

Epoch 6 Batch 0 Loss 0.1491 Accuracy 0.9582
Epoch 6 Batch 50 Loss 0.1369 Accuracy 0.9604
Epoch 6 Batch 100 Loss 0.1362 Accuracy 0.9609
Epoch 6 Batch 150 Loss 0.1348 Accuracy 0.9612
Epoch 6 Batch 200 Loss 0.1341 Accuracy 0.9614
Epoch 6 Loss 0.1339 Accuracy 0.9614
Time taken for 1 epoch: 198.53 secs

Epoch 7 Batch 0 Loss 0.1407 Accuracy 0.9630
Epoch 7 Batch 50 Loss 0.1302 Accuracy 0.9627
Epoch 7 Batch 100 Loss 0.1303 Accuracy 0.9626
Epoch 7 Batch 150 Loss 0.1299 Accuracy 0.9627
Epoch 7 Batch 200 Loss 0.1289 Accuracy 0.9629
```

Fig 2.11 Epochs – I Image

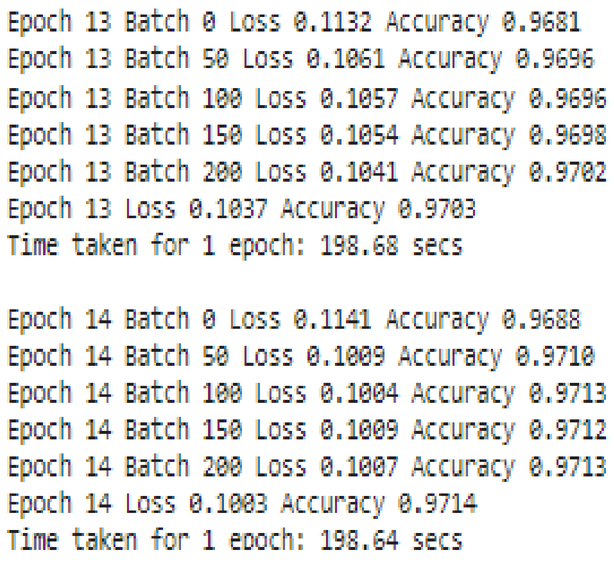
- The training step where we have EPOCHS set to 30 and call train_step function we defined



```
Epoch 8 Batch 0 Loss 0.1259 Accuracy 0.9666
Epoch 8 Batch 50 Loss 0.1242 Accuracy 0.9644
Epoch 8 Batch 100 Loss 0.1240 Accuracy 0.9642
Epoch 8 Batch 150 Loss 0.1237 Accuracy 0.9643
Epoch 8 Batch 200 Loss 0.1229 Accuracy 0.9646
Epoch 8 Loss 0.1226 Accuracy 0.9646
Time taken for 1 epoch: 198.59 secs

Epoch 9 Batch 0 Loss 0.1382 Accuracy 0.9614
Epoch 9 Batch 50 Loss 0.1204 Accuracy 0.9658
Epoch 9 Batch 100 Loss 0.1208 Accuracy 0.9654
Epoch 9 Batch 150 Loss 0.1207 Accuracy 0.9654
Epoch 9 Batch 200 Loss 0.1200 Accuracy 0.9656
Epoch 9 Loss 0.1195 Accuracy 0.9657
Time taken for 1 epoch: 198.47 secs

Epoch 10 Batch 0 Loss 0.1181 Accuracy 0.9666
Epoch 10 Batch 50 Loss 0.1166 Accuracy 0.9662
Epoch 10 Batch 100 Loss 0.1161 Accuracy 0.9662
Epoch 10 Batch 150 Loss 0.1166 Accuracy 0.9662
Epoch 10 Batch 200 Loss 0.1156 Accuracy 0.9666
Saving checkpoint for epoch 10 at drive/MyDrive/ent/model_checkpoints/transformer_model_full2/ckpt-5
Epoch 10 Loss 0.1152 Accuracy 0.9667
Time taken for 1 epoch: 202.62 secs
```



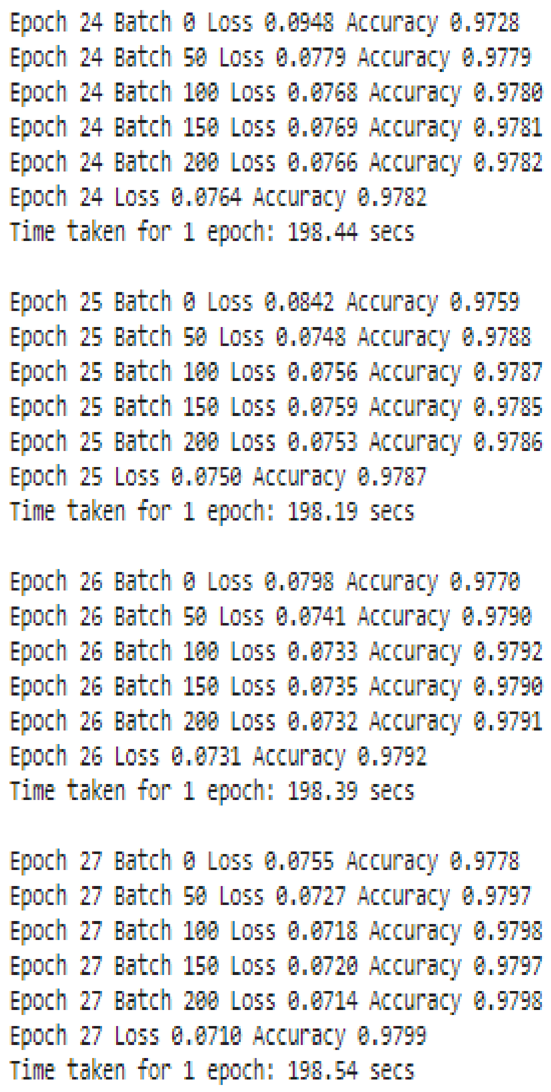
```
Epoch 11 Batch 0 Loss 0.1257 Accuracy 0.9664
Epoch 11 Batch 50 Loss 0.1124 Accuracy 0.9683
Epoch 11 Batch 100 Loss 0.1122 Accuracy 0.9681
Epoch 11 Batch 150 Loss 0.1125 Accuracy 0.9678
Epoch 11 Batch 200 Loss 0.1124 Accuracy 0.9678
Epoch 11 Loss 0.1119 Accuracy 0.9680
Time taken for 1 epoch: 198.65 secs

Epoch 12 Batch 0 Loss 0.1215 Accuracy 0.9668
Epoch 12 Batch 50 Loss 0.1095 Accuracy 0.9687
Epoch 12 Batch 100 Loss 0.1082 Accuracy 0.9691
Epoch 12 Batch 150 Loss 0.1081 Accuracy 0.9692
Epoch 12 Batch 200 Loss 0.1081 Accuracy 0.9691
Epoch 12 Loss 0.1077 Accuracy 0.9693
Time taken for 1 epoch: 198.52 secs
```



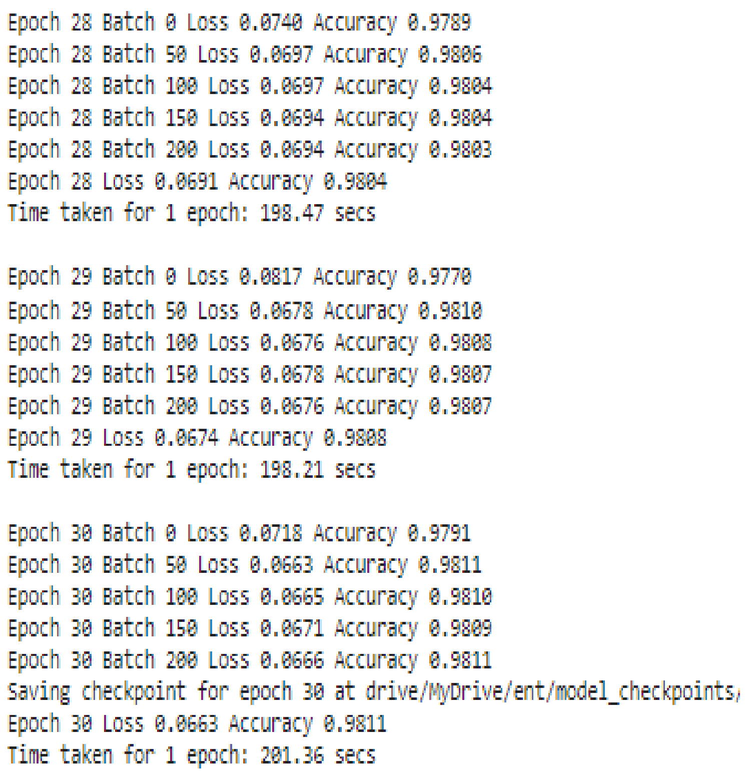
```
Epoch 13 Batch 0 Loss 0.1132 Accuracy 0.9681
Epoch 13 Batch 50 Loss 0.1061 Accuracy 0.9696
Epoch 13 Batch 100 Loss 0.1057 Accuracy 0.9696
Epoch 13 Batch 150 Loss 0.1054 Accuracy 0.9698
Epoch 13 Batch 200 Loss 0.1041 Accuracy 0.9702
Epoch 13 Loss 0.1037 Accuracy 0.9703
Time taken for 1 epoch: 198.68 secs

Epoch 14 Batch 0 Loss 0.1141 Accuracy 0.9688
Epoch 14 Batch 50 Loss 0.1009 Accuracy 0.9710
Epoch 14 Batch 100 Loss 0.1004 Accuracy 0.9713
Epoch 14 Batch 150 Loss 0.1009 Accuracy 0.9712
Epoch 14 Batch 200 Loss 0.1007 Accuracy 0.9713
Epoch 14 Loss 0.1003 Accuracy 0.9714
Time taken for 1 epoch: 198.64 secs
```

Fig 2.12 Epochs – II Image

And so on …

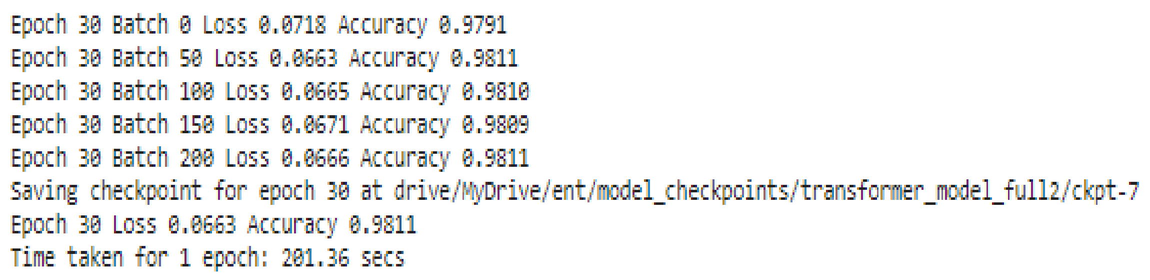


```
Epoch 24 Batch 0 Loss 0.0948 Accuracy 0.9728
Epoch 24 Batch 50 Loss 0.0779 Accuracy 0.9779
Epoch 24 Batch 100 Loss 0.0768 Accuracy 0.9780
Epoch 24 Batch 150 Loss 0.0769 Accuracy 0.9781
Epoch 24 Batch 200 Loss 0.0766 Accuracy 0.9782
Epoch 24 Loss 0.0764 Accuracy 0.9782
Time taken for 1 epoch: 198.44 secs

Epoch 25 Batch 0 Loss 0.0842 Accuracy 0.9759
Epoch 25 Batch 50 Loss 0.0748 Accuracy 0.9788
Epoch 25 Batch 100 Loss 0.0756 Accuracy 0.9787
Epoch 25 Batch 150 Loss 0.0759 Accuracy 0.9785
Epoch 25 Batch 200 Loss 0.0753 Accuracy 0.9786
Epoch 25 Loss 0.0750 Accuracy 0.9787
Time taken for 1 epoch: 198.19 secs

Epoch 26 Batch 0 Loss 0.0798 Accuracy 0.9770
Epoch 26 Batch 50 Loss 0.0741 Accuracy 0.9790
Epoch 26 Batch 100 Loss 0.0733 Accuracy 0.9792
Epoch 26 Batch 150 Loss 0.0735 Accuracy 0.9790
Epoch 26 Batch 200 Loss 0.0732 Accuracy 0.9791
Epoch 26 Loss 0.0731 Accuracy 0.9792
Time taken for 1 epoch: 198.39 secs

Epoch 27 Batch 0 Loss 0.0755 Accuracy 0.9778
Epoch 27 Batch 50 Loss 0.0727 Accuracy 0.9797
Epoch 27 Batch 100 Loss 0.0718 Accuracy 0.9798
Epoch 27 Batch 150 Loss 0.0720 Accuracy 0.9797
Epoch 27 Batch 200 Loss 0.0714 Accuracy 0.9798
Epoch 27 Loss 0.0710 Accuracy 0.9799
Time taken for 1 epoch: 198.54 secs
```



```
Epoch 28 Batch 0 Loss 0.0740 Accuracy 0.9789
Epoch 28 Batch 50 Loss 0.0697 Accuracy 0.9806
Epoch 28 Batch 100 Loss 0.0697 Accuracy 0.9804
Epoch 28 Batch 150 Loss 0.0694 Accuracy 0.9804
Epoch 28 Batch 200 Loss 0.0694 Accuracy 0.9803
Epoch 28 Loss 0.0691 Accuracy 0.9804
Time taken for 1 epoch: 198.47 secs

Epoch 29 Batch 0 Loss 0.0817 Accuracy 0.9770
Epoch 29 Batch 50 Loss 0.0678 Accuracy 0.9810
Epoch 29 Batch 100 Loss 0.0676 Accuracy 0.9808
Epoch 29 Batch 150 Loss 0.0678 Accuracy 0.9807
Epoch 29 Batch 200 Loss 0.0676 Accuracy 0.9807
Epoch 29 Loss 0.0674 Accuracy 0.9808
Time taken for 1 epoch: 198.21 secs

Epoch 30 Batch 0 Loss 0.0718 Accuracy 0.9791
Epoch 30 Batch 50 Loss 0.0663 Accuracy 0.9811
Epoch 30 Batch 100 Loss 0.0665 Accuracy 0.9810
Epoch 30 Batch 150 Loss 0.0671 Accuracy 0.9809
Epoch 30 Batch 200 Loss 0.0666 Accuracy 0.9811
Saving checkpoint for epoch 30 at drive/MyDrive/ent/model_checkpoints/
Epoch 30 Loss 0.0663 Accuracy 0.9811
Time taken for 1 epoch: 201.36 secs
```

These are the epochs during training Total of 30 epochs



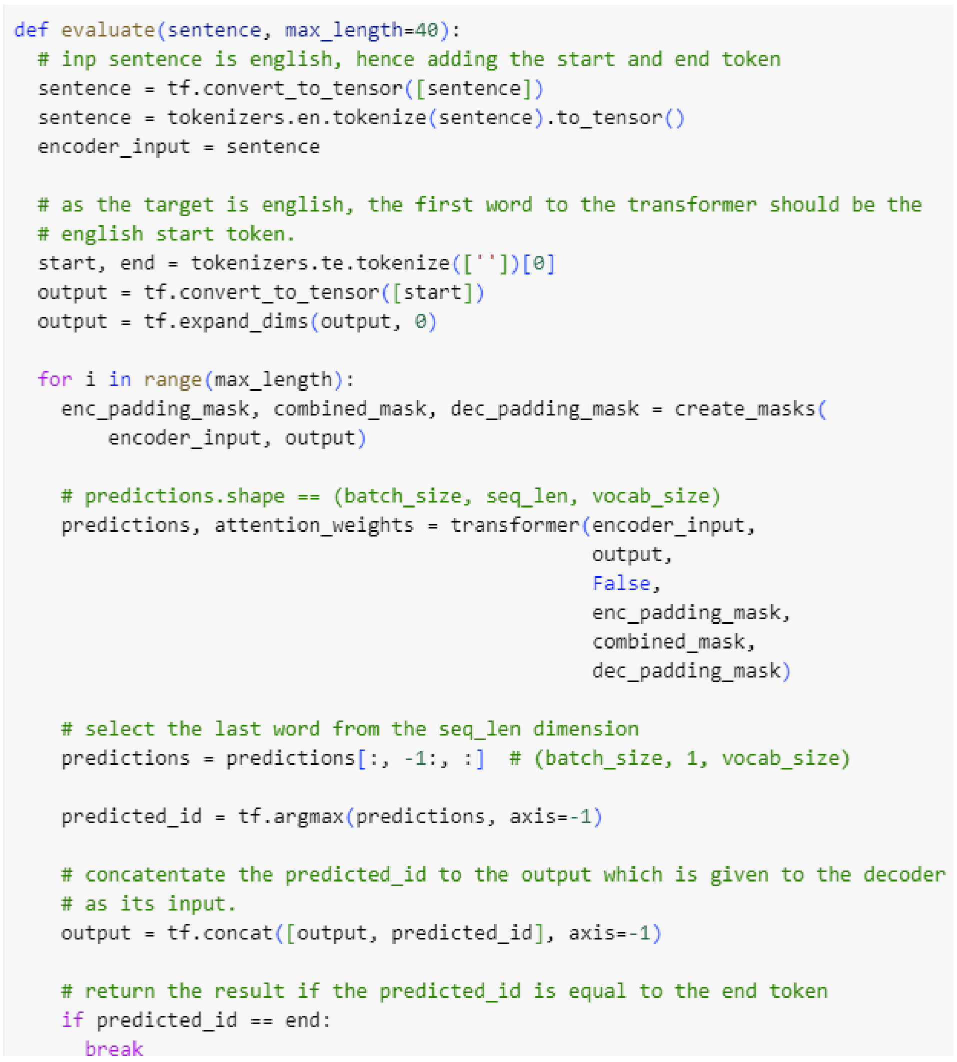
```
Epoch 30 Batch 0 Loss 0.0718 Accuracy 0.9791
Epoch 30 Batch 50 Loss 0.0663 Accuracy 0.9811
Epoch 30 Batch 100 Loss 0.0665 Accuracy 0.9810
Epoch 30 Batch 150 Loss 0.0671 Accuracy 0.9809
Epoch 30 Batch 200 Loss 0.0666 Accuracy 0.9811
Saving checkpoint for epoch 30 at drive/MyDrive/ent/model_checkpoints/transformer_model_full2/ckpt-7
Epoch 30 Loss 0.0663 Accuracy 0.9811
Time taken for 1 epoch: 201.36 secs
```

Fig 2.13 Epochs - III Image

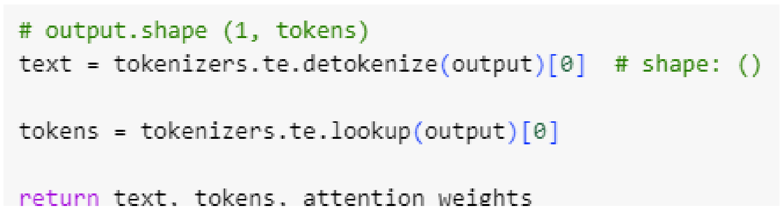
The epoch number 30 is last epoch with loss of 0.0663 and accuracy of 0.9811 (98%)

Each epoch has training sets in batches with their respective loss and accuracy , these trained batchis stored in google drive with given mount path , and time taken for each epoch is also displayed with cumulative loss and accuracy.

2.11 Testing

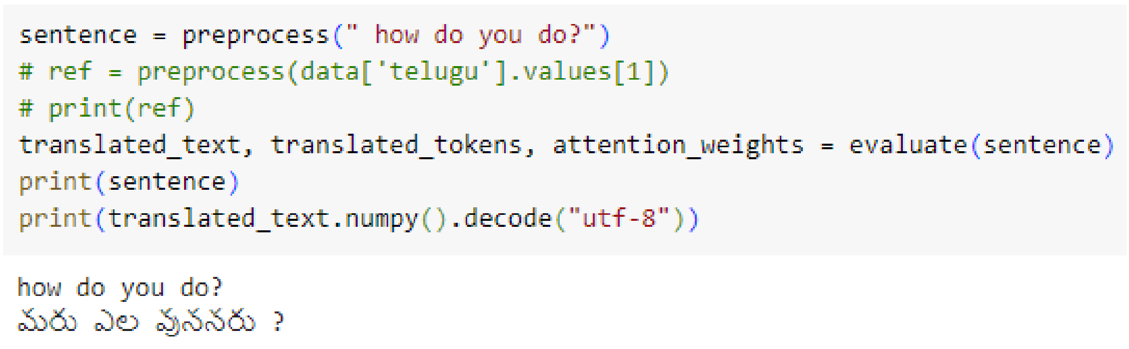


```python
def evaluate(sentence, max_length=40):
  # inp sentence is english, hence adding the start and end token
  sentence = tf.convert_to_tensor([sentence])
  sentence = tokenizers.en.tokenize(sentence).to_tensor()
  encoder_input = sentence

  # as the target is english, the first word to the transformer should be the
  # english start token.
  start, end = tokenizers.te.tokenize([''])[0]
  output = tf.convert_to_tensor([start])
  output = tf.expand_dims(output, 0)

  for i in range(max_length):
    enc_padding_mask, combined_mask, dec_padding_mask = create_masks(
        encoder_input, output)

    # predictions.shape == (batch_size, seq_len, vocab_size)
    predictions, attention_weights = transformer(encoder_input,
                                                 output,
                                                 False,
                                                 enc_padding_mask,
                                                 combined_mask,
                                                 dec_padding_mask)

    # select the last word from the seq_len dimension
    predictions = predictions[:, -1:, :]  # (batch_size, 1, vocab_size)

    predicted_id = tf.argmax(predictions, axis=-1)

    # concatentate the predicted_id to the output which is given to the decoder
    # as its input.
    output = tf.concat([output, predicted_id], axis=-1)

    # return the result if the predicted_id is equal to the end token
    if predicted_id == end:
      break
```



```python
# output.shape (1, tokens)
text = tokenizers.te.detokenize(output)[0]  # shape: ()

tokens = tokenizers.te.lookup(output)[0]

return text, tokens, attention_weights
```

Fig 2.14 Testing Function Image



```
sentence = preprocess(" how do you do?")
# ref = preprocess(data['telugu'].values[1])
# print(ref)
translated_text, translated_tokens, attention_weights = evaluate(sentence)
print(sentence)
print(translated_text.numpy().decode("utf-8"))
```

```
how do you do?
మరు ఎల వృననరు ?
```

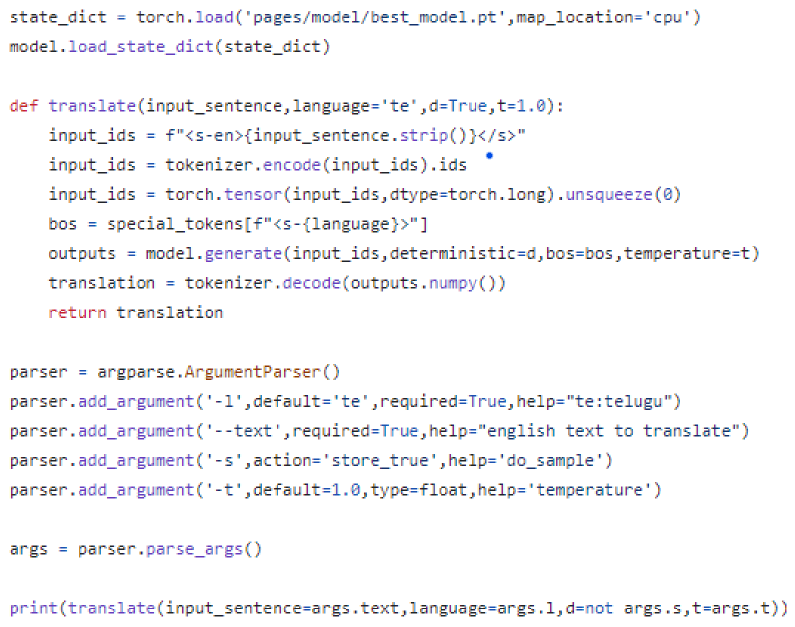
Fig 2.15 Sample Testing Result Image

Evaluation is done by first preprocessing the input , getting output as text, tokens, weights after predicting using transformer model which is already trained

2.12 Deployment

2.12.1 Argument Parser (argparse.ArgumentParser)

The implementation supports command-line arguments for customization. Specifically, the following arguments are utilized:



```
state_dict = torch.load('pages/model/best_model.pt',map_location='cpu')
model.load_state_dict(state_dict)

def translate(input_sentence,language='te',d=True,t=1.0):
    input_ids = f"<s-en>{input_sentence.strip()}</s>"
    input_ids = tokenizer.encode(input_ids).ids
    input_ids = torch.tensor(input_ids,dtype=torch.long).unsqueeze(0)
    bos = special_tokens[f"<s-{language}>"]
    outputs = model.generate(input_ids,deterministic=d,bos=bos,temperature=t)
    translation = tokenizer.decode(outputs.numpy())
    return translation

parser = argparse.ArgumentParser()
parser.add_argument('-l',default='te',required=True,help="te:telugu")
parser.add_argument('--text',required=True,help="english text to translate")
parser.add_argument('-s',action='store_true',help='do_sample')
parser.add_argument('-t',default=1.0,type=float,help='temperature')

args = parser.parse_args()

print(translate(input_sentence=args.text,language=args.l,d=not args.s,t=args.t))
```

Fig 2.16 Argument Parser I Image

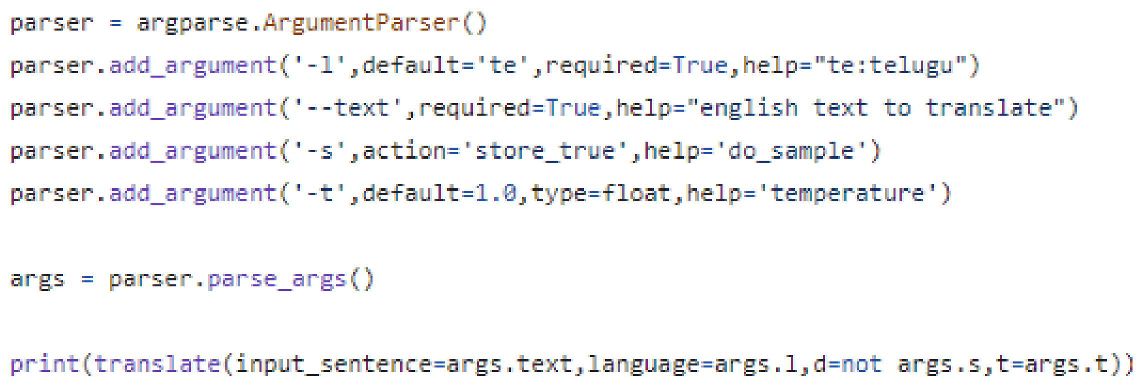
This implementation allows for seamless integration of language translation functionalities, providing users with a versatile tool for processing multilingual text inputs.

-l: Denotes the language. Presently, the system is configured for Telugu but can be generalized and extended to accommodate other languages.

--text: Represents the input text. Currently, the system accepts English input but can be expanded to support other languages.

-s: Enables sampling.

-t: Represents the temperature parameter, facilitating the generation of diverse contextual outputs.

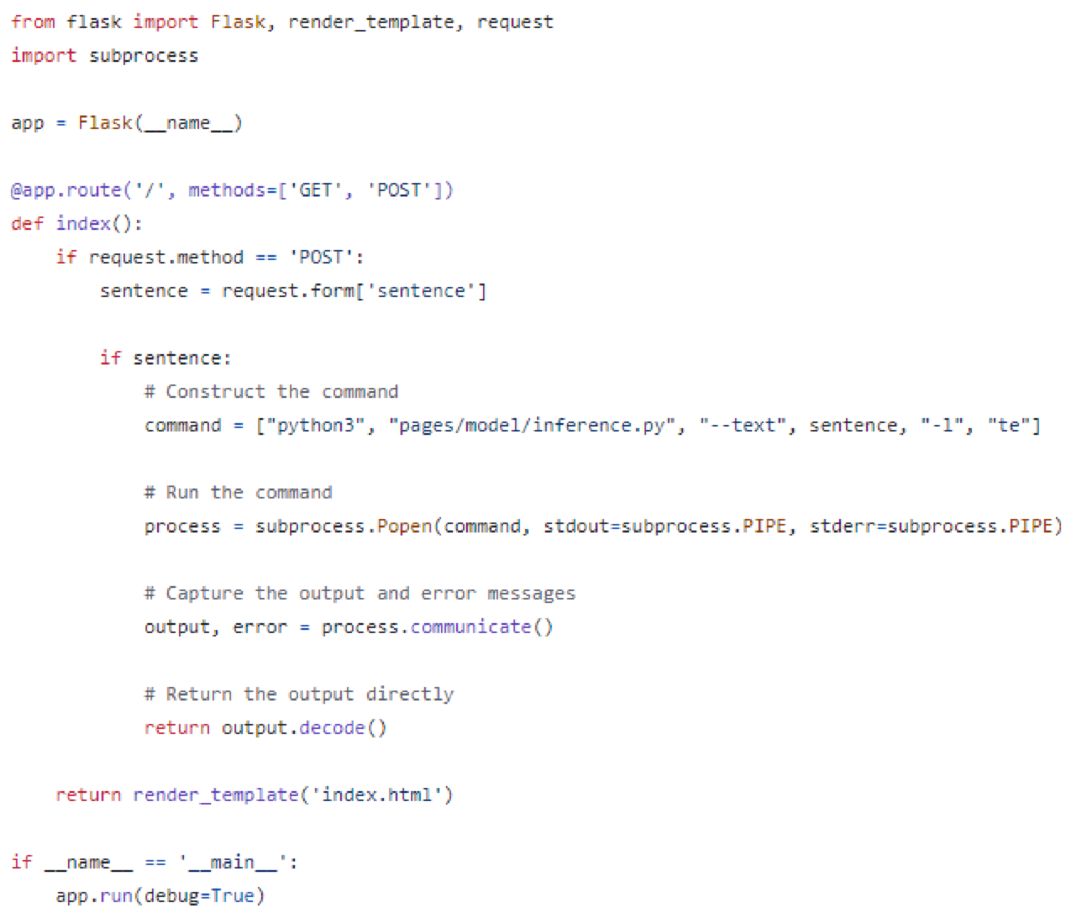


```
parser = argparse.ArgumentParser()
parser.add_argument('-l',default='te',required=True,help="te:telugu")
parser.add_argument('--text',required=True,help="english text to translate")
parser.add_argument('-s',action='store_true',help='do_sample')
parser.add_argument('-t',default=1.0,type=float,help='temperature')

args = parser.parse_args()

print(translate(input_sentence=args.text,language=args.l,d=not args.s,t=args.t))
```

Fig 2.17 Argument Parser II Image

2.12.2 Flask

Flask is a lightweight and flexible web framework for Python, designed to make web development simple and scalable. With its minimalist design philosophy, Flask provides developers with the essential tools needed to build web applications quickly and efficiently. Its modular structure and extensive documentation make it easy to get started, while still offering the flexibility to customize and extend as needed. Flask is known for its simplicity and ease of use, making it an ideal choice for projects ranging from small prototypes to large-scale web applications. Its built-in development server, Jinja templating engine, and support for extensions contribute to its popularity among developers. Additionally, Flask's active community and ecosystem of third-party extensions provide a wealth of resources and support for building robust and feature-rich web applications. Overall, Flask empowers developers to focus on writing clean and maintainable code, while providing the tools necessary to bring their web projects to life.



```python
from flask import Flask, render_template, request
import subprocess

app = Flask(__name__)

@app.route('/', methods=['GET', 'POST'])
def index():
    if request.method == 'POST':
        sentence = request.form['sentence']

        if sentence:
            # Construct the command
            command = ["python3", "pages/model/inference.py", "--text", sentence, "-1", "te"]

            # Run the command
            process = subprocess.Popen(command, stdout=subprocess.PIPE, stderr=subprocess.PIPE)

            # Capture the output and error messages
            output, error = process.communicate()

            # Return the output directly
            return output.decode()

    return render_template('index.html')

if __name__ == '__main__':
    app.run(debug=True)
```

Fig 2.18 Flask Code Image

2.12.3 HTML and CSS

For our project, we've employed HTML and CSS within Flask to create a user-friendly interface for our English to Telugu translation system. Our HTML template features a form where users can submit English sentences for translation. This form provides a seamless way for users to interact with our system, simplifying the process of inputting text to be translated. Additionally, we've utilized CSS to enhance the visual appeal and layout of our web page, ensuring a polished and professional look.

In our Flask application, we render this HTML template dynamically, allowing users to access it through their web browsers. Flask handles the logic behind processing user inputs and generating translation outputs, seamlessly integrating with our HTML and CSS templates. This student-led project showcases our skills in web development and demonstrates our ability to utilize modern technologies like Flask, HTML, and CSS to create practical user-centric apps.

CHAPTER – 3

EXPERIMENTAL STUDY OF PROJECT

EXPERIMENTAL STUDY OF PROJECT

3.1 Algorithm for text to text translation using transformers

1. Regex To Convert Contractions Into Natural Form ,For example, won't to Will not
2. Custom Tokenizer Using Bert
3. Positional Encoding to give the model some information about the relative position of the words in the sentence
4. The Attention Function used by transformer takes three inputs q(query) k(key) v(value). used multi head attention consisting of four parts linear layer and split into heads scales dot product attention concatenation of heads final linear layer
5. Implementation Of Evaluation Metric BLEU

3.2 History of transformers

- **Introduction of Transformers (2017):**

  Vaswani et al. introduced transformers, revolutionizing sequence transduction tasks with self-attention mechanisms.

- **BERT Model (2018):**

  Devlin et al. presented BERT, pre-training transformers on vast unlabeled text data, achieving state-of-the-art NLP performance.

- **GPT-2 and GPT-3 Models (2019-2020):**

  OpenAI's GPT series, especially GPT-3, set new benchmarks in language understandingand generation.

- **Transformer-Based Machine Translation Models (2018 Onward):**

  Transformers became dominant in machine translation, with models like Transformer, BERT-based translation models, and M4 showcasing impressive results.

- **T5 Model (2019):**

  Google's T5 proposed a unified framework for NLP tasks, treating them as text-to-text, highlighting the versatility of transformers.

- **Ongoing Developments (2021 Onward):**

  Research continues in areas like multilingual models, domain adaptation, and training strategies to enhance transformer-based translation systems. In summary, transformers have reshaped text-to-text translation, from their foundational introduction to the latest state-of-the-art models, driving advancements in natural language processing.

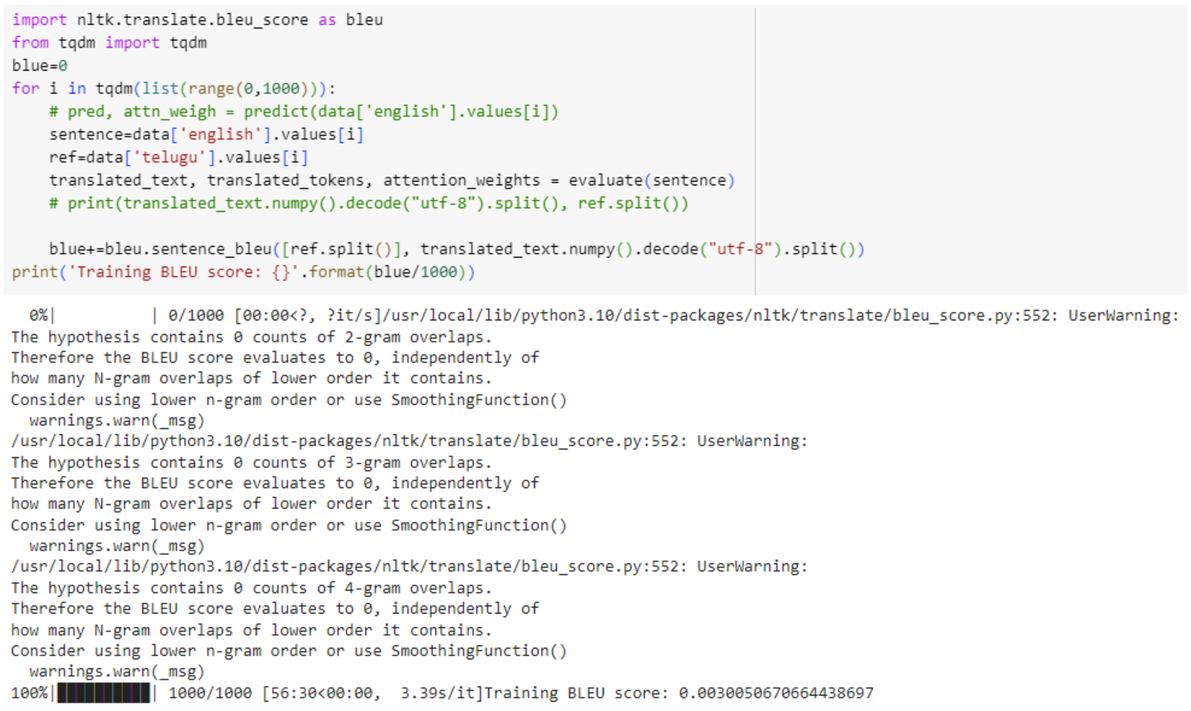
CHAPTER – 4

RESULTS AND DISCUSSIONS

RESULTS & DISCUSSIONS

4.1 Evaluation Metrics

4.1.1 BLEU Score



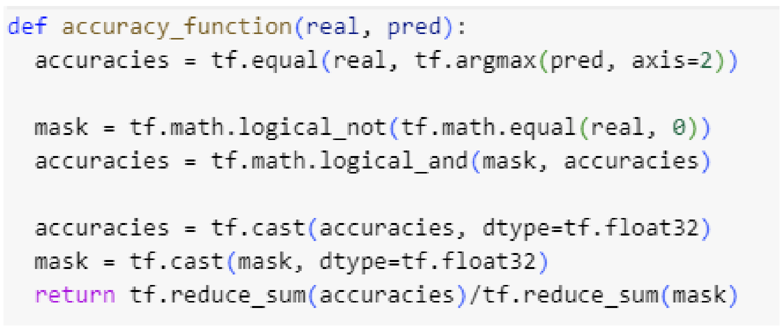
```
import nltk.translate.bleu_score as bleu
from tqdm import tqdm
blue=0
for i in tqdm(list(range(0,1000))):
    # pred, attn_weigh = predict(data['english'].values[i])
    sentence=data['english'].values[i]
    ref=data['telugu'].values[i]
    translated_text, translated_tokens, attention_weights = evaluate(sentence)
    # print(translated_text.numpy().decode("utf-8").split(), ref.split())

    blue+=bleu.sentence_bleu([ref.split()], translated_text.numpy().decode("utf-8").split())
print('Training BLEU score: {}'.format(blue/1000))
```

```
  0%|          | 0/1000 [00:00<?, ?it/s]/usr/local/lib/python3.10/dist-packages/nltk/translate/bleu_score.py:552: UserWarning:
The hypothesis contains 0 counts of 2-gram overlaps.
Therefore the BLEU score evaluates to 0, independently of
how many N-gram overlaps of lower order it contains.
Consider using lower n-gram order or use SmoothingFunction()
  warnings.warn(_msg)
/usr/local/lib/python3.10/dist-packages/nltk/translate/bleu_score.py:552: UserWarning:
The hypothesis contains 0 counts of 3-gram overlaps.
Therefore the BLEU score evaluates to 0, independently of
how many N-gram overlaps of lower order it contains.
Consider using lower n-gram order or use SmoothingFunction()
  warnings.warn(_msg)
/usr/local/lib/python3.10/dist-packages/nltk/translate/bleu_score.py:552: UserWarning:
The hypothesis contains 0 counts of 4-gram overlaps.
Therefore the BLEU score evaluates to 0, independently of
how many N-gram overlaps of lower order it contains.
Consider using lower n-gram order or use SmoothingFunction()
  warnings.warn(_msg)
100%|██████████| 1000/1000 [56:30<00:00,  3.39s/it]Training BLEU score: 0.0030050670664438697
```

Fig 4.1 BLEU Score Image

The BLEU (Bilingual Language Evaluation Understudy) score compares a sentence against one or more reference sentences and tells how well does the candidate sentence matched the list of reference sentences. It gives an output score between 0 and 1

4.1.2 Accuracy



```python
def accuracy_function(real, pred):
  accuracies = tf.equal(real, tf.argmax(pred, axis=2))

  mask = tf.math.logical_not(tf.math.equal(real, 0))
  accuracies = tf.math.logical_and(mask, accuracies)

  accuracies = tf.cast(accuracies, dtype=tf.float32)
  mask = tf.cast(mask, dtype=tf.float32)
  return tf.reduce_sum(accuracies)/tf.reduce_sum(mask)
```

Fig 4.2 Accuracy function Image

tf.equal(real, tf.argmax(pred, axis=2)) returns a tensor where each element is True if the corresponding element in

real matches the index of the maximum value in the corresponding position of pred, and False otherwise

mask =tf.math.logical_not(tf.math.equal(real, 0)): This creates a boolean mask where True indicates positions where the real values are not equal to 0 (non-padding positions).

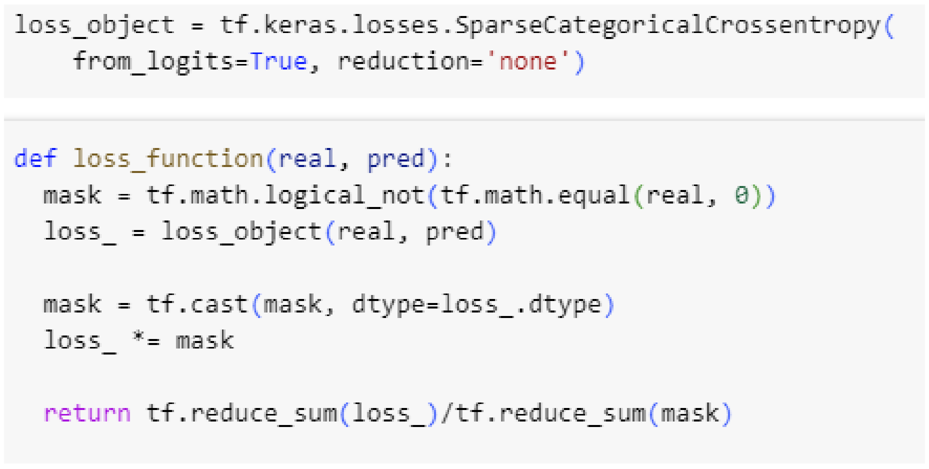
tf.math.logical_and(mask, accuracies): Here, the mask is further refined by performing a logical AND operation with the previously computed accuracies. This ensures that only positions where the real values are not padding and the predictions are correct contribute to the accuracy calculation.

accuracies = tf.cast(accuracies, dtype=tf.float32): Converts the boolean tensor of accuracies to float32 data type. This conversion is necessary for subsequent calculations.

mask = tf.cast(mask, dtype=tf.float32): Similarly, converts the boolean mask to float32 data type. This will be used for normalization in the accuracy calculation.

Finally **mean accuracy** is calculated

4.1.3 Loss



```
loss_object = tf.keras.losses.SparseCategoricalCrossentropy(
    from_logits=True, reduction='none')
```

```
def loss_function(real, pred):
  mask = tf.math.logical_not(tf.math.equal(real, 0))
  loss_ = loss_object(real, pred)

  mask = tf.cast(mask, dtype=loss_.dtype)
  loss_ *= mask

  return tf.reduce_sum(loss_)/tf.reduce_sum(mask)
```

Fig 4.3 Loss function Image

tf.keras.losses.SparseCategoricalCrossentropy: This is an implementation of the Sparse Categorical Crossentropy loss function provided by TensorFlow's Keras API. It's commonly used for multi-class classification tasks where the target labels are integers.

loss_object=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True, reduction='none'): This line creates an instance of the SparseCategoricalCrossentropy loss function.

from_logits=True: Indicates that the input predictions are not normalized (i.e., they are raw logits) and need to be normalized (e.g., via a softmax activation) before being used in the loss calculation.

reduction='none': Specifies that no reduction should be applied to the individual losses. This means that the loss will be calculated separately for each sample in the batch, rather than being aggregated across the batch.

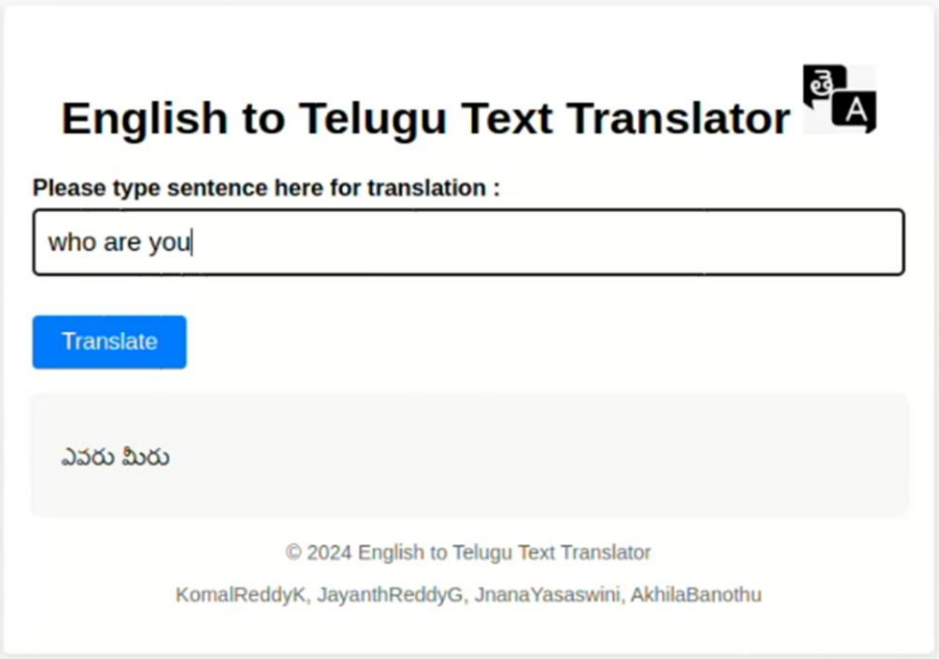
mask = tf.math.logical_not(tf.math.equal(real, 0)): This line creates a mask tensor where elements of real that are equal to 0 are marked as False and all other elements are marked as True. This is typically used to mask out padding elements in sequence data.

loss_ = loss_object(real, pred): This line calculates the loss using the SparseCategoricalCrossentropy loss function created earlier. Since reduction='none', this will return a tensor containing the individual losses
for each sample in the batch.

mask = tf.cast(mask, dtype=loss_.dtype): This line casts the mask tensor to the same data type as the computed loss tensor.

loss_ *= mask: This line applies the mask to the computed loss tensor. This effectively zeros out the loss for padding elements, as they are marked as False in the mask. And at last we calculate **mean losses**

4.2 Deployment



English to Telugu Text Translator

Please type sentence here for translation :

who are you

ఎవరు మీరు

© 2024 English to Telugu Text Translator

KomalReddyK, JayanthReddyG, JnanaYasaswini, AkhilaBanothu

Fig 4.4 Deployment Image

CHAPTER – 5

CONCLUSION AND FUTURE SCOPE OF STUDY

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

In conclusion, the English to Telugu text translation system employs a Transformers model, facilitating accurate and contextually rich translations. This model is deployed using Flask, a lightweight web framework, which orchestrates the execution of commands upon receiving POST requests from user forms. Leveraging Flask's capabilities, the system seamlessly integrates the prediction functionality, with the model loaded via a pickle file, and utilizes HTML and CSS for rendering templates, ensuring an intuitive and visually appealing user interface.

5.2 Future Scope

In the future, our aim is to enhance the English to Telugu text translation system by deploying it on a global scale rather than locally, thereby increasing its accessibility and reach. Additionally, acquiring a larger dataset and conducting thorough training would be pivotal in improving the system's translation quality, thereby enhancing its BLEU score. This expansion and refinement of the system would enable it to better serve users across diverse linguistic contexts and contribute to more accurate and nuanced translations between English and Telugu.

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