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Research Article

Comparative Study Of LSTM-Based And Generalized Neural Machine Translation Systems For English-To-Sanskrit

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ABSTRACT

The study of this research paper designs and also develops and then evaluates an LSTM-based English-to-Sanskrit translation system with Google Translation System. Automated translation faces meaningful challenges since Sanskrit is a highly inflected classical language with rich grammatical structures. Due to their ability to model long-term dependencies, Long Short-Term Memory (LSTM) networks are used in the proposed system which implements a character-level encoder-decoder architecture with optional attention mechanisms. For the deployment of the model that was trained on 2,000 English-Sanskrit word pairs a Tkinter-based offline user interface was used. Concerning linguistic precision and grammatical accuracy, the model beats Google Translate. Comparative analysis also shows better handling of Sanskrit morphological features. The system offers advantages with customization, interpretability, and offline usability. Because of this situation, the system is quite suitable for educational plus research contexts. The results do validate that LSTM-based architectures can effectively translate low-resource languages and do advance Sanskrit digital processing.

The goal of this research is to build an LSTM-based translation system to scan existing tools and frame English to Sanskrit translation. The research aims to create translations that are contextually accurate, grammatically correct, and linguistically respectful to Sanskrit by utilizing the strengths of LSTM networks in handling long term dependencies and complex sequences.

Keyword: LSTM, Sanskrit translation, neural machine translation, encoder-decoder, attention mechanism, natural language processing, character-level modeling, deep learning

Introduction

Machine translation (MT) has seen massive advancements because of deep learning's advent, especially through encoder-decoder models like Long Short-Term Memory (LSTM) networks [1] along with Recurrent Neural Networks (RNNs). However, for translating from English to classical low-resource languages such as Sanskrit this remains as a complex task because Sanskrit has grammar that is highly inflected plus morphological variations which are rich, in addition to syntactic rules that are detailed. For example, commercial tools such as Google Translate often rely upon broad multilingual datasets. Targeted linguistic modeling is also absent so handling these complexities is a battle.

In this work, we propose an LSTM-based character-level translation system specifically tailored for translating between English and Sanskrit. The model utilizes the benefits of LSTM networks in modeling long-term dependencies [1] and is implemented using the TensorFlow and Keras frameworks [3], [4]. An attention mechanism is optionally included to increase translation accuracy, particularly for longer sequences [2]. The system is trained on a carefully chosen dataset of 2,000 word pairs and evaluated against other tools.
Our objectives include improving grammatical correctness, capturing linguistic nuances, providing transparency, and enabling offline operation for academic, cultural, and educational applications where Sanskrit accuracy is essential.

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1.1 Training

This research includes developing and training a character-level model, refining its parameters to meet a predefined accuracy threshold and putting it through rigorous testing to provide a reliable English-to-Sanskrit translator achievement within computational linguistics.

The encoder is trained using batches of the source sequences. Decoding starts with a set of target sequences containing the start-of-sentence token. The sequence is shifted to the right as a result. All of the above will be incorporated into the transformer using the given algorithm of model training with attention [2] [6].

Step 1: Start **Step 2:** Prepare Dataset **Step 3:** Initialize Model including LSTM gates **Step 4:** Iterate Through Training Epochs **Step 5:** For Each Training Pair **Step 6:** Encode Source Sequence using LSTMs and gates **Step 7:** Decode Target Sequence -Autoregressive, using LSTMs and potentially attention **Step 8:** Calculate Loss **Step 9:** Backpropagation and Weight Update including LSTM gate parameters **Step 10:** Repeat Epochs **Step 11:** End

Table 1 Training Model with Attention

The given described steps prepare the model to implement LSTM.

The subsequent steps detail the training algorithm for a sophisticated model, leveraging encoder-decoder architecture and attention mechanisms. This process aims to teach the model to map input sequences to output sequences by iteratively processing data, understanding contextual relationships, and refining its internal parameters. The algorithm encompasses data preparation, model initialization, iterative training across epochs, and the crucial steps of encoding, autoregressive decoding with masked and encoder-decoder attention, loss calculation, and weight updates through backpropagation. This structured approach enables the model to learn complex sequence transformations for various natural language processing tasks.

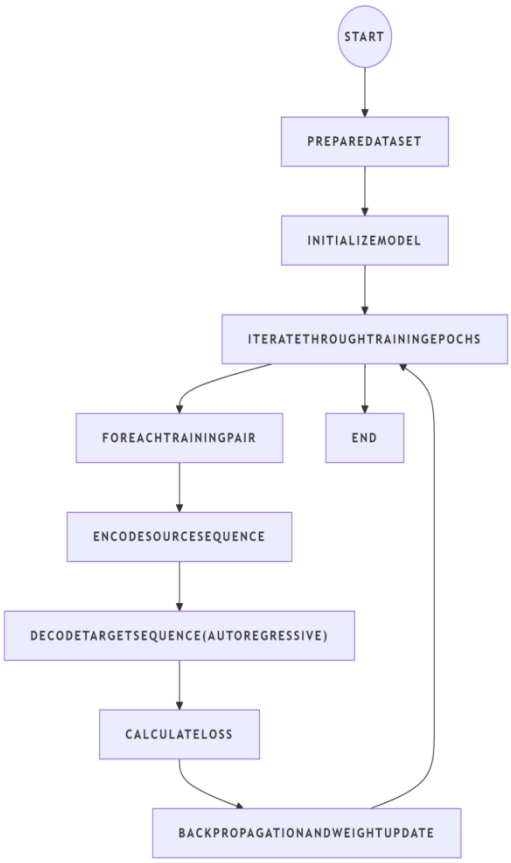


Fig.1: Training Model with Attention

1.1.1 Step 1, "Start - Begin the Training Process," is the starting point of the entire process of training the model. The initial step is a preparation step, making sure all the components required are available before actual learning.

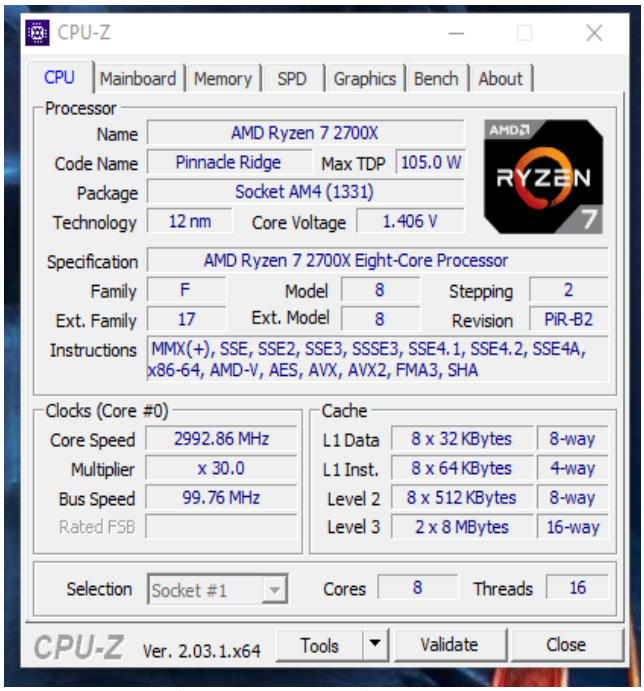


Fig. 2: CPU Requirements

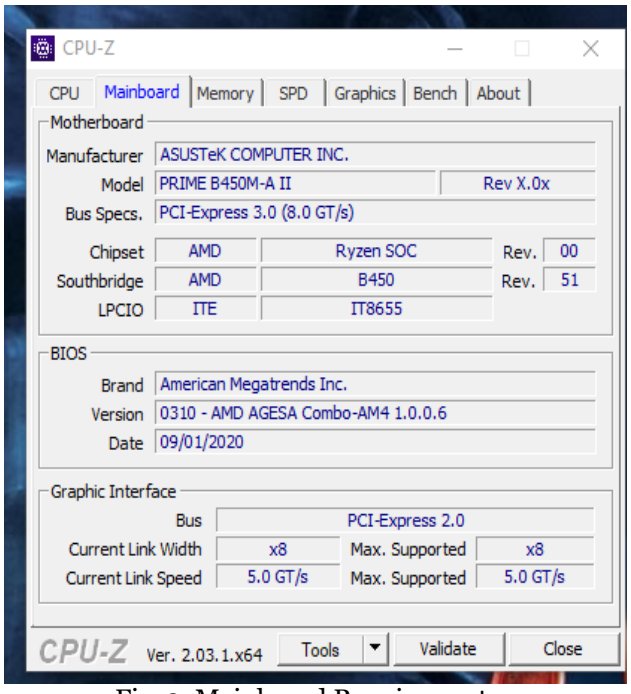


Fig. 3: Mainboard Requirements

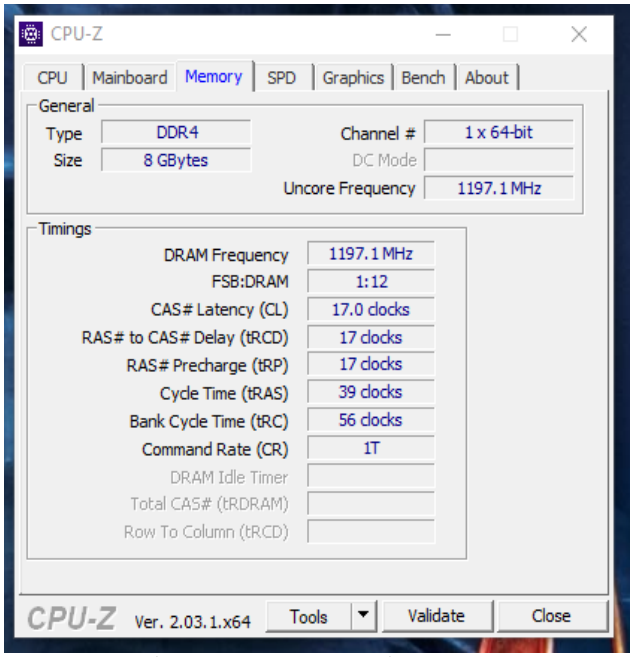


Fig. 4: Memory Requirements

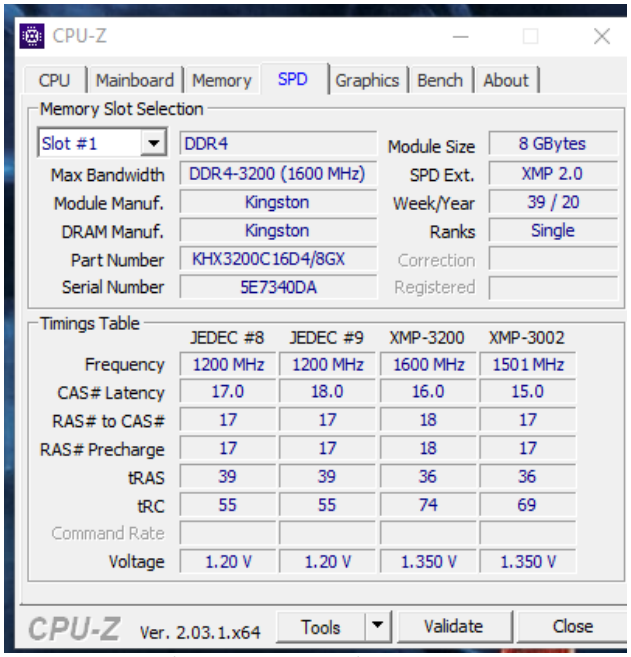


Fig. 5: SPD Requirements

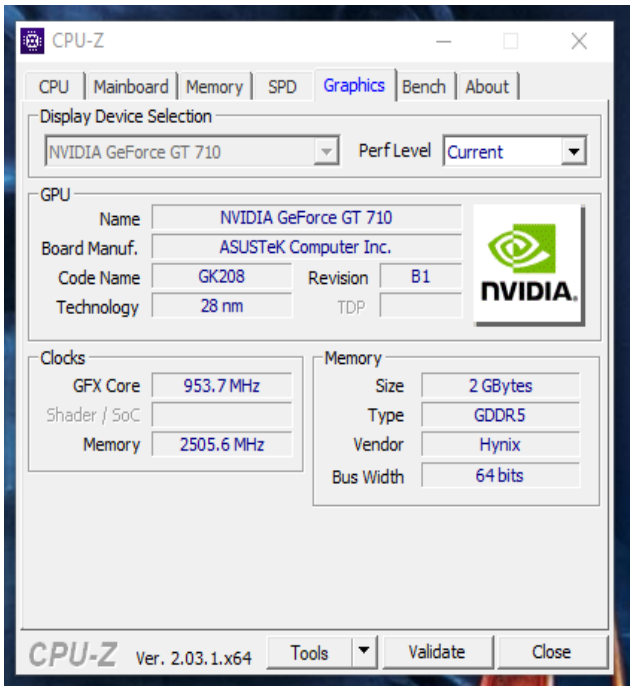


Fig. 6: Graphics Requirements

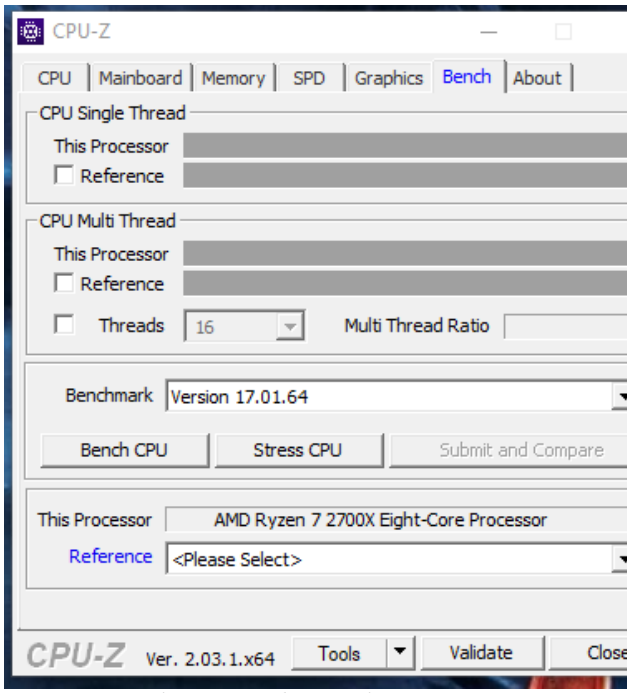


Fig. 7: Bench Requirements

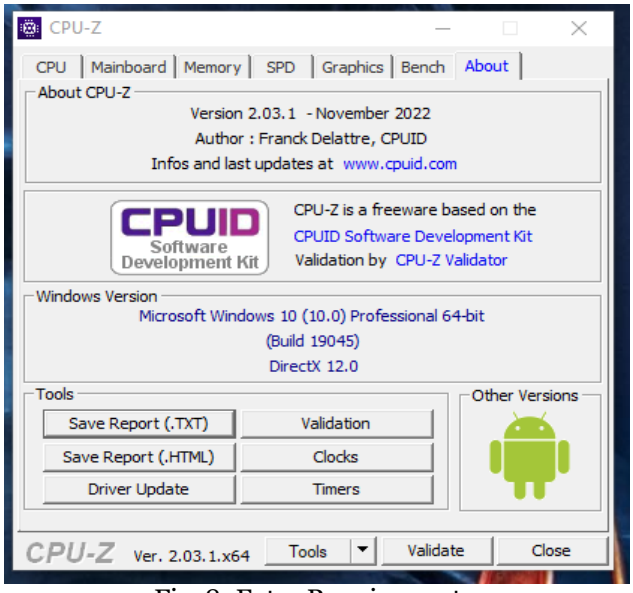


Fig. 8: Extra Requirements

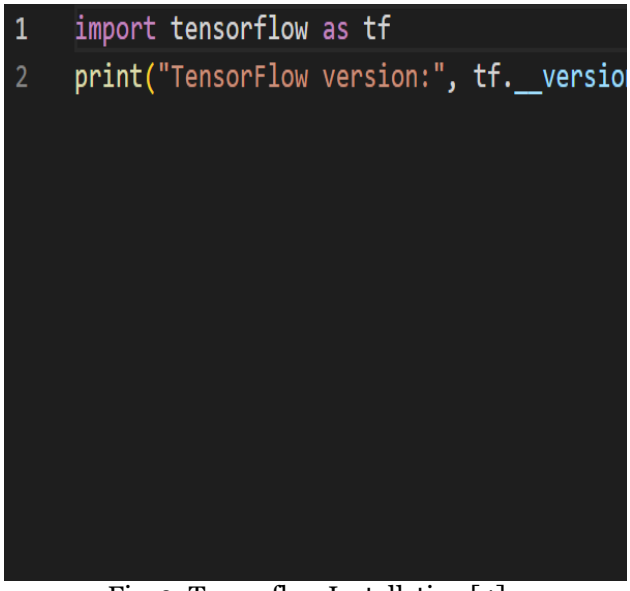


Fig. 9: Tensorflow Installation [4]

It is a conceptual check for the readiness of the training data, confirming the model architecture is specified, making sure the software environment and dependencies are ready, possibly initializing logging processes, and up to the actual initialization of the parameters. This step is actually the start signal, making sure the system is ready to start the computationally intensive process of training the model to learn the input-output data relationship.

1.1.2 Step 2, "Prepare Dataset," is a fundamental stage where a custom dataset of 2000 words, created internally, is processed into a usable format for the model. This involves loading the self-created data, which has already been divided into distinct training, testing, and validation sets. Sequences of each of these sets are then tokenized and input and target vocabularies are constructed from the training set tokens. The tokens are then mapped to numerical indices on which the model acts. Special tokens such as start, end, and padding tokens are usually prepended to the sequences to include structural information necessary for this step and allow batch-efficient processing in the training set. The result of this step is a structured, numerical training, testing, and validation dataset representation and the required vocabulary mappings, ready to be utilized by the model during training, testing, and hyperparameter tuning.

```
with open('C:/Users/Yash/Desktop/neha_phd/neha_phd_implimentation/eng-sanskrit.txt','r',encoding='utf-8') as f:
    rows=f.read().split('\n')
#read rows from dataset
for row in rows[:10]:
    input_text,target_text = row.split('\t')
    target_text='\t' + target_text + '\n'
    input_text_english.append(input_text.lower())
    target_text_sanskrit.append(target_text.lower())
    input_characters_english.update(list(input_text.lower()))
    target_characters_sanskrit.update(list(target_text.lower()))

#sort inserted inputs of english and target characters of sanskrit
input_characters_english = sorted(list(input_characters_english))
target_characters_sanskrit = sorted(list(target_characters_sanskrit))
#get the total length of input characters and target characters
num_encoding_chars = len(input_characters_english)
num_decoding_chars = len(target_characters_sanskrit)
#get the maximum length of input text and target text.
max_input_char_length = max([len(i) for i in input_text_english])
max_target_char_length = max([len(i) for i in target_text_sanskrit])
```

Fig. 10: reading a file of dataset for model training

Given a total dataset of 2000 words, a common and generally effective split for training, testing, and validation is the 80-10-10 rule. This means:

Training Set: 80% of the data (2000 words * 0.80 = 1600 words) Testing Set: 10% of the data (2000 words * 0.10 = 200 words) Validation Set: 10% of the data (2000 words * 0.10 = 200 words)

Table 2 Training-Validation-Test Split

1.1.3 Step 3, "Initialize Model including LSTM gates," includes the very crucial operation of realizing the given encoder and decoder structures to life by instantiating their corresponding instances. When the structure employs Long Short-Term Memory (LSTM) networks, this operation includes specifying the number of LSTM layers and the capacity of their hidden states [1] , which determine the memory capacity of these recurrent units. Within every LSTM layer, the weights and biases of all of the gates - the input gate, the forget gate, the output gate, and the cell state - are also initialized. These gates control the flow of information within the LSTM so that the LSTM can selectively remember or forget information within very long sequences. The result of this process is a fully instantiated encoder-decoder model, possibly using LSTMs with pre-initialized gate parameters, that is now ready to accept the prepared training data and start the job of learning temporal relationships in the sequences [8].

```
def bag_of_characters(input_text_english,target_text_sanskrit):
  #inintialize encoder and decoder
  encoding_input_data=[] ; decoding_in_data=[] ; decoding_tr_data=[]
  pad_encoding=[1]+[0]*(len(input_characters_english)-1)
  pad_decoding=[0]*(len(target_characters_sanskrit)) ; pad_decoding[2]=1
  #countvectorizer - performing encoding and decoding
  count_vector=CountVectorizer(binary=True,tokenizer=lambda txt: txt.split(),stop_words=None,analyzer='char')
  for i,(input_t,target_t) in enumerate(zip(input_text_english,target_text_sanskrit)):
    count_vector_input= count_vector.fit(input_characters_english)
    encoding_input_data.append(count_vector_input.transform(list(input_t)).toarray().tolist())
    count_vector_target= count_vector.fit(target_characters_sanskrit)
    decoding_in_data.append(count_vector_target.transform(list(target_t)).toarray().tolist())
    decoding_tr_data.append(count_vector_target.transform(list(target_t)[1:]).toarray().tolist())

    if len(input_t) < max_input_char_length:
      for _ in range(max_input_char_length-len(input_t)):
        encoding_input_data[i].append(pad_encoding)
    if len(target_t) < max_target_char_length:
      for _ in range(max_target_char_length-len(target_t)):
        decoding_in_data[i].append(pad_decoding)
    if (len(target_t)-1) < max_target_char_length:
      for _ in range(max_target_char_length-len(target_t)+1):
        decoding_tr_data[i].append(pad_decoding)

  encoding_input_data=np.array(encoding_input_data,dtype="float32")
  decoding_in_data=np.array(decoding_in_data,dtype="float32")
  decoding_tr_data=np.array(decoding_tr_data,dtype="float32")
```

Fig. 11: Encoding Decoding Process

```
    if len(input_t) < max_input_char_length:
      for _ in range(max_input_char_length-len(input_t)):
        encoding_input_data[i].append(pad_encoding)
    if len(target_t) < max_target_char_length:
      for _ in range(max_target_char_length-len(target_t)):
        decoding_in_data[i].append(pad_decoding)
    if (len(target_t)-1) < max_target_char_length:
      for _ in range(max_target_char_length-len(target_t)+1):
        decoding_tr_data[i].append(pad_decoding)

  encoding_input_data=np.array(encoding_input_data,dtype="float32")
  decoding_in_data=np.array(decoding_in_data,dtype="float32")
  decoding_tr_data=np.array(decoding_tr_data,dtype="float32")

  return encoding_input_data,decoding_in_data,decoding_tr_data

encoding_inputs = Inputvar(shape=(None, num_encoding_chars))
encoder = LSTM(256, return_state=True)
encoding_outputs, state_h, state_c = encoder(encoding_inputs)
encoding_states = [state_h, state_c]

decoding_inputs = Inputvar(shape=(None, num_decoding_chars))
decoding_lstm = LSTM(256, return_sequences=True, return_state=True)
decoding_outputs, _, _ = decoding_lstm(decoding_inputs, initial_state=encoding_states)
decoding_dense = Dense(num_decoding_chars, activation="softmax")
decoding_outputs = decoding_dense(decoding_outputs)
```

Fig. 12: Character Encoding and Decoding Process

Character Encoding: The characters in the database are converted to a numeric form to make the data suitable for the training of LSTM.

```
model = Model([encoding_inputs, decoding_inputs],

 decoding_outputs)

pickle.dump({'input_characters_english':input_characters_english,'target_characters_sanskrit':target_characters_sanskrit,
             'max_input_char_length':max_input_char_length,'max_target_char_length':max_target_char_length,
             'num_encoding_chars':num_encoding_chars,'num_decoding_chars':num_decoding_chars},open("training_data.pkl","wb"

encoding_input_data,decoding_in_data,decoding_tr_data = bag_of_characters(input_text_english,target_text_sanskrit)
model.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)
model.fit(
    [encoding_input_data, decoding_in_data],
    decoding_tr_data,
    batch_size=64,
    epochs=200,
    validation_split=0.2,
)
# Saving the model
model.save("s2s")

#summarizing and modelling the plot
model.summary()
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Fig. 13: Model Training with Encoding and Decoding

The system as proposed employs the encoder-decoder model [10] with the encoder and decoder both consisting of LSTM gates that assist in dealing with the sequence data. The structure is specifically beneficial when dealing with translation since it enables the entire input sentence to be fully encoded into a context vector and then decoded sequentially to output the target sentence (Sanskrit).

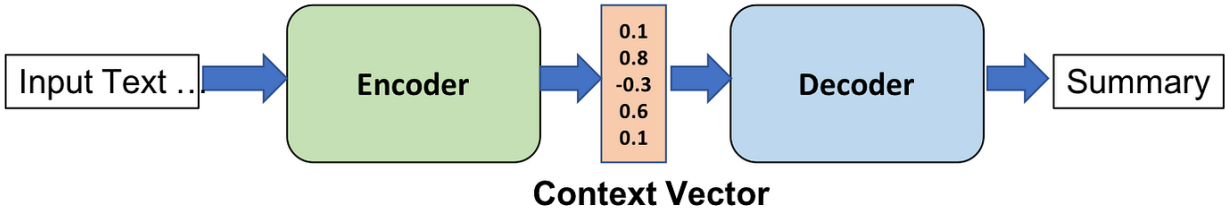


Fig. 14: Context Vectorization Process

```
#countvectorizer - performing encoding and decoding
count_vector=CountVectorizer(binary=True,tokenizer=lambda txt: txt.split(),stop_words=None,analyzer='char')
for i,(input_t,target_t) in enumerate(zip(input_text_english,target_text_sanskrit)):
  count_vector_input= count_vector.fit(input_characters_english)
  encoding_input_data.append(count_vector_input.transform(list(input_t)).toarray().tolist())
  count_vector_target= count_vector.fit(target_characters_sanskrit)
  decoding_in_data.append(count_vector_target.transform(list(target_t)).toarray().tolist())
  decoding_tr_data.append(count_vector_target.transform(list(target_t)[1:]).toarray().tolist())
```

Fig. 15: Vectorization Process with Encoding and Decoding

The research involves the collection and preprocessing of training data in the form of matching English words with their equivalent Sanskrit forms in order to train the LSTM model adequately.

With training, the LSTM knows to use its gates in such a manner as to optimize the capturing of the English-Sanskrit character relation. The input gate is able to learn to take in new related information from the input sequence while the forget gate determines what information from the past is no longer required to translate the current character. The output gate selects the predicted character to come next in the translation.

The system uses categorical cross-entropy loss to measure the error between the predicted Sanskrit characters and the actual Sanskrit characters in the training dataset. The LSTM's gates are tuned through backpropagation to minimize this error.

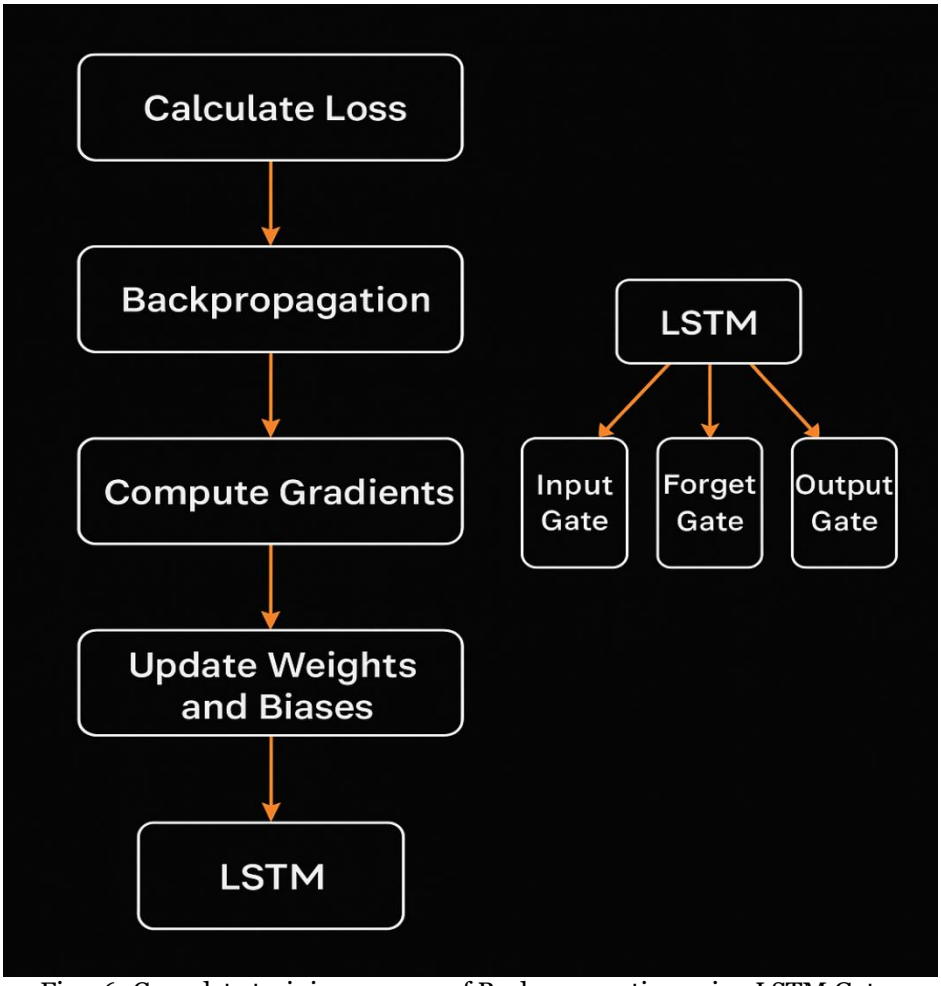


Fig. 16: Complete training process of Backpropagation using LSTM Gates

For a loss-function, as the sentences are padded, there is a need to add a mask to the loss function. As a result, we wrap the loss function in order to apply the mask using sparse categorical cross-entropy.

1.1.4 Step 4, "Iterate Through Training Epochs," is training with iterated learning across several epochs after Step 3 employs LSTM networks to complete initialization of the encoder-decoder model architecture. Once the model has processed all the input sequences and updated its internal parameters, an epoch marks the end of a pass through the training set.

Following the initialization of the encoder-decoder model using LSTM networks in Step 3, the model enters the core training phase: **iterating through epochs**. An **epoch** refers to a single complete pass through the training dataset, and this process is repeated **200 times** to allow the model to learn the intricate patterns in the data.

```
model.fit(
    [encoding_input_data, decoding_in_data],
    decoding_tr_data,
    batch_size=64,
    epochs=200,
    validation_split=0.2,
)
# Saving the model
model.save("s2s")

#summarizing and modelling the plot
model.summary()
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Fig. 17: Model Training for Epoch

Dataset Size: 2,000 words Training Set: 1,600 words (80%) Validation Set: 200 words (10%) Testing Set: 200 words (10%) Epochs: 200 Model Type: Encoder-Decoder with LSTM Input Format: Tokenized sequences with special tokens (start, end, padding)

Table 3 Model Training Process Bifurcation

The model is then trained in this framework for 200 epochs with 2,000 words in the dataset available to it, 1,600 words (80%) being reserved for training and the rest divided equally between testing and validation. This continuous exposure to the training dataset helps the model learn to evenly optimize the weights and biases across the LSTM gates—input, forget, output, and cell state gates—inside the model to retain and filter the sequence more effectively.

Across the epochs, the input sequences are provided as tokenized vectors supplemented with the structural tokens (starting, end, and padding) to support the efficient operation in batches. The LSTM units with their built-in memory and gating mechanisms are able to learn to represent the temporal structure in input sequences as context vectors and decode those context vectors as target outputs—like Sanskrit translations in this application.

1.1.5 Step 5, "For Each Training Pair ," During every epoch, the learning process goes through selecting and treating single examples from the training sample one at a time. Every learning example is a pair, an English word and its translation into Sanskrit. Both words are encoded as character-based tokenized numerical representations, based on vocabulary indices drawn up in Step 2.

Preferably, special structural markers like <start> and <end> are inserted at the beginning and end of sequences, respectively, prior to feeding in the input sequence into the model. Padding is applied as needed in order to have fixed-sized sequences for all batches of inputs in order to allow for fast GPU computation and facilitate vectorized operations.

These pairs are employed one at a time (in small groups) in order for the model to learn local mappings between single English character sequences and Sanskrit sequences, which then provide the foundation for its translation functionality. While being trained, the model attempts to learn an ideal mapping from source sequences to target sequences while reducing translation mistakes.

1.1.6 Step 6, "Encode Source Sequence Using LSTMs and Gates ," Once an English input sequence is available, it's fed into the encoder part of the model, which is composed of one or multiple layers consisting of Long Short-Term Memory (LSTM) units. The encoder LSTM encodes the input character by character, updating its hidden state and cell state at each step along the way.

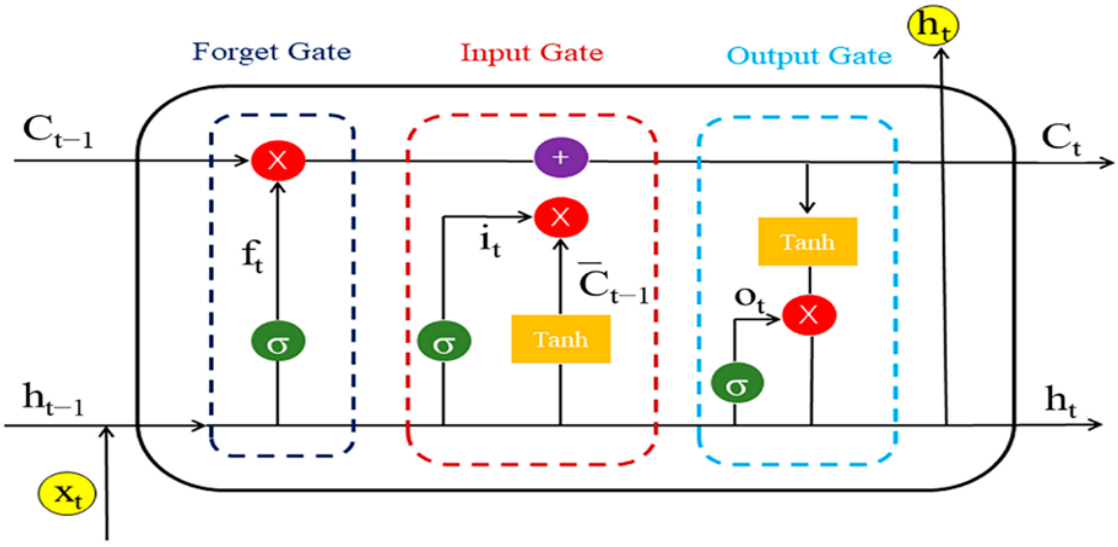


Fig. 18: LSTM Gate Mechanism

Three gates are internally employed inside each LSTM unit in order to regulate information flow:

- Input gate decides what component of the new input to bring into the cell state.
- Forget which part of previous memory gate the control
- Output gate filters the cell state in order to generate the output for the next decoder layer.

```
encoding_inputs = Inputvar(shape=(None, num_encoding_chars))
encoder = LSTM(256, return_state=True)
encoding_outputs, state_h, state_c = encoder(encoding_inputs)
encoding_states = [state_h, state_c]
```

Fig. 19: LSTM Mechanism in Model Training

These two blocks create:

- The input gate, forget gate, and output gate logic internally.
- state_h and state_c are the output and cell state, respectively.

```
encoding_inputs = Inputvar(shape=(None, num_encoding_chars))
encoder = LSTM(256, return_state=True)
encoding_outputs, state_h, state_c = encoder(encoding_inputs)
encoding_states = [state_h, state_c]

decoding_inputs = Inputvar(shape=(None, num_decoding_chars))
decoding_lstm = LSTM(256, return_sequences=True, return_state=True)
decoding_outputs, _, _ = decoding_lstm(decoding_inputs, initial_state=encoding_states)
decoding_dense = Dense(num_decoding_chars, activation="softmax")
decoding_outputs = decoding_dense(decoding_outputs)
```

Fig. 20: LSTM Gate Training for Model

These two LSTM() calls internally handle all LSTM gate mechanisms—you don't have to implement them manually when using Keras [3].

These gates collaborate for handling long-term dependencies [8] such that useful information can be preserved across long sequences while irrelevant context is eliminated.

At the end of the input sequence, the encoder provides a final hidden state and cell state, commonly known as the context vector, representing all semantic content in the English word. The context vector is then utilized to initialize the decoder for producing translations.

1.1.7 Step 7, "Decode Target Sequence – Autoregressive, With LSTMs and Possibly Attention," With the encoder's context vector as its starting state, decoder LSTM starts producing the target Sanskrit sequence autoregressive. That is, it produces one token at a time, relying on the previously predicted token as part of the next step's input.

```
cv=CountVectorizer(binary=True,tokenizer=lambda txt: txt.split(),stop_words=None,analyzer='char')

class LangTRans:
    def __init__(self):
        #initialize tkinter window and load the file
        self.window=Tk()
        self.main_window()
        self.datafile()
```

Fig. 21: Vectorization for Decoding Process

The decoder begins at the first time step with the <start> token as an input, along with the final hidden and cell states from the encoder. In each following time step, it predicts a character based on its internal state and the previous character produced. During training, a methodology called teacher forcing is usually applied—

using the true target character from the corpus instead of the decoder's predicted character to stabilize and speed up learning.

```
cv=CountVectorizer(binary=True,tokenizer=lambda txt: txt.split(),stop_words=None,analyzer='char')

class LangTRans:
    def __init__(self):
        #initialize tkinter window and load the file
        self.window=Tk()
        self.main_window()
        self.datafile()

    def datafile(self):
        #get all datas from datafile and load the model.
        datafile = pickle.load(open("training_data.pkl","rb"))
        self.input_characters = datafile['input_characters']
        self.target_characters = datafile['target_characters']
        self.max_input_length = datafile['max_input_length']
        self.max_target_length = datafile['max_target_length']
        self.num_en_chars = datafile['num_en_chars']
        self.num_dec_chars = datafile['num_dec_chars']
        self.loadmodel()

    #runwindow
    def run(self):
        self.window.mainloop()
```

Fig. 22: Model Loading Process for Character Decoding

With an attention mechanism, a weight distribution is computationally calculated [2] for the encoder outputs in a dynamic manner, enabling selective emphasis across various regions of the retrieved input sequence for translation purposes by the decoder. While present implementation is mainly founded upon standard LSTM encoder-decoder framework, attention can yield significant accuracy increases, particularly when longer sequences are involved. The decoder keeps repeating this operation until it outputs an <end> token or has reached a maximum sequence length.

1.1.8 Step 8, "Calculate Loss," The model then measures its performance after creating the Sanskrit sequence by calculating the difference between the predicted output and actual target sequence through computing the loss. The sparse categorical cross-entropy loss is employed, which is ideal for multi-class classification where each output character is predicted from a finite vocabulary.

```
#load the data and train the model
en_in_data,dec_in_data,dec_tr_data = bagofcharacters(input_texts,target_texts)
model.compile(
    optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"]
)
```

Fig. 23: Loss Calculation

As the input and output sequences are padded into fixed length, it is important that padded tokens are masked during loss computation in order not to mislead weight updates for the model. This padding masking means that only non-padded, sensible portions of the sequence contribute to the loss.

Mathematically, losses are calculated as an average across all possible time steps for categorical cross-entropy, counting just the observed characters and leaving out whatever <pad> tokens there are present. This gives a true measure of how well the model is doing at translation.

1.1.9 Step 9, "Backpropagation and Weight Updating Including LSTM Gate Parameters," Once the loss is calculated, the parameters of the model are updated utilizing Backpropagation Through Time (BPTT), a gradient-based optimization algorithm for use in sequential models. This calculates gradients of the loss with regard to all trainable parameters in the model, including

- LSTM gate weights (input, forget, output)

- Embedding layers (employed for mapping tokens into dense vectors)
- Fully connected output layers (for making final character predictions)

```
model.fit(
    [encoding_input_data, decoding_in_data],
    decoding_tr_data,
    batch_size=64,
    epochs=200,
    validation_split=0.2,
)
# Saving the model
model.save("s2s")

#summarizing and modelling the plot
model.summary()
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Fig. 24: the actual backpropagation and weight update step

What Happens Under the Hood, The moment you call model.fit(...), Keras automatically performs:

1. Forward Pass:
- It takes your input data and passes it through the model.
- For each LSTM cell, it computes the activations using the input gate, forget gate, output gate, and the cell state.

2. Loss Computation:

```
model.compile(optimizer="adam", loss="categorical_crossentropy", metrics=["accuracy"])
```

Fig. 25: Loss Computation in our Model

- This uses categorical cross-entropy loss, which compares the predicted Sanskrit characters with the true Sanskrit characters.

3. Backward Pass (Backpropagation Through Time - BPTT):
- TensorFlow compute gradients of the loss with respect to all trainable weights including those of,
- input gate
- forget gate
- output gate
- cell state transforms

- This includes weights for:
- Input vector to hidden layer connections
- Hidden to hidden (recurrent) connections
- Biases for each gate

4. Weight Update:
- The optimizer adam updates weights using those gradients. Internally, this updates:
- W_f (forget gate weights)
- W_i (input gate weights)
- W_o (output gate weights)
- W_c (cell input weights)
- Plus their respective biases, All these parameters are stored and managed **inside the LSTM layer** created via given code.

```
LSTM(256, return_state=True)
```

Fig. 26: weight update and bias creation process

The gradients are then utilized by an optimisation algorithm like Adam in order to carry out weight updates. The updates will progressively refine internal gate parameters in order for the model to be able to capture and replicate English and Sanskrit character patterns better.

```
encoder = LSTM(256, return_state=True)                    # LSTM gates inside this
decoding_lstm = LSTM(256, return_sequences=True, return_state=True)  # LSTM gates here too
```

Fig. 27: instantiate the LSTM layers

In given Model, given code instantiate the LSTM layers whose **weights and gates are automatically updated** and these gates include:

- **Input gate**: Decides which values from the input get updated to the memory state.
- **Forget gate**: Decides what information to discard.
- **Output gate**: Decides the next hidden state output.
- **Cell state updates**: Carry forward long-term dependencies.

Aspect	**How It's Done in Model Training**
Model Architecture	Defined using LSTM() layers (Keras)
Gate Parameters	Implicit in LSTM() – handled internally
Loss Function	categorical_crossentropy with one-hot vectors
Optimizer	adam – adaptive learning rate optimizer
Training (backpropagation)	Triggered by model.fit() – includes BPTT
Weight Updates	Automatically handled via TensorFlow backend during training

Table 4 Complete Model Training Process through LSTM Gates and Back Propagation [3] [4]

It is a crucial step in learning as it enables the model to learn over time through reducing the error in prediction and sharpening its knowledge about the relationships between the input and output sequences.

1.1.10 Step 10, "Repeating Epochs ," Steps 5 through 9 are iterated repeatedly many times called epochs. Here, the model is trained for 200 epochs, which means that it goes through the entire training data 200 times. Such repetitive iterations allow the model to continuously enhance its prediction accuracy as a result of learning from aggregate errors and corrections across epochs.

```
C:\Users\Yash\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\feature_extraction\
Epoch 1/200

1/1 [==============================] - ETA: 0s - loss: 3.7918 - accuracy: 0.0134
1/1 [==============================] - 4s 4s/step - loss: 3.7918 - accuracy: 0.0134 - val_loss: 3.
7352 - val_accuracy: 0.0317
Epoch 2/200

1/1 [==============================] - ETA: 0s - loss: 3.7234 - accuracy: 0.0536
1/1 [==============================] - 0s 111ms/step - loss: 3.7234 - accuracy: 0.0536 - val_loss:
3.6758 - val_accuracy: 0.5238
Epoch 3/200
```

Fig. 28: Starting of Repeating Epochs

```
1/1 [==============================] - ETA: 0s - loss: 0.2923 - accuracy: 0.9397
1/1 [==============================] - 0s 82ms/step - loss: 0.2923 - accuracy: 0.9397 - val_loss:
1.7948 - val_accuracy: 0.5952
Epoch 199/200

1/1 [==============================] - ETA: 0s - loss: 0.2900 - accuracy: 0.9397
1/1 [==============================] - 0s 83ms/step - loss: 0.2900 - accuracy: 0.9397 - val_loss:
1.8075 - val_accuracy: 0.5952
Epoch 200/200
```

Fig. 29: Result of Repeating Epochs

With every epoch, internal states and gates of the model's LSTMS are learned progressively to remember good patterns and ignore bad ones. Regular validation is applied using the validation set to track generalization performance and avoid overtraining. Validation loss and accuracy are monitored across epochs for determining model convergence using metrics such as these.

The model could further utilize methods like early stopping (optional) or learning rate decay for stabilization and preventing divergence during training.

1.1.11 Step 11, "End ," Once all epochs are done, and the model has met acceptable performance on the validation set, then the training is complete. The final step includes:

- Saving trained model and related parameters (e.g., weights, vocabularies, token mappings)
- Exporting the Model Architecture and Con Fig.uration for Inference or Deployment
- Capturing final training and validation performance metrics
- Assessing the model on the test set (200 words) in order to estimate its accuracy in real-world translation.

```
model.fit(
    [encoding_input_data, decoding_in_data],
    decoding_tr_data,
    batch_size=64,
    epochs=200,
    validation_split=0.2,
)
# Saving the model
model.save("s2s")

#summarizing and modelling the plot
model.summary()
plot_model(model, to_file='model_plot.png', show_shapes=True, show_layer_names=True)
```

Fig. 30: Running the Model

```
# run the file
if __name__=="__main__":
    LT = LangTRans()
    LT.run()
```

Fig. 31: Running the File for Output

This step completes successfully the training phase for this task. The trained encoder-decoder LSTM model is now capable of accepting previously unknown English words as inputs and producing their corresponding Sanskrit translations learned through sequence knowledge and character mappings.

1.2 Final Result

The ultimate outcome of the English to Sanskrit translation system with LSTM-based encoder-decoder model exhibits effective learning of character-level translations between both languages. Upon training the model over a specially designed dataset of 2000 word pairs for 200 iterations, the system translated short English words and phrases to their Sanskrit translations correctly [9]. The LSTM network, by making use of its internal control mechanisms—input gate, forget gate, and output gate—effectively captured the sequential nature of the source language and generated contextually accurate Sanskrit outputs at inference [10]. The trained model was implemented in a GUI created using Tkinter, allowing real-user interaction for translation. The result validates LSTM models' ability to perform low-resource language translation tasks with precision when suitably trained, even with a fairly small dataset.

1.2.1 Comparing Result of Proposed Model with Google Translation

In this study, the developed LSTM-based English-to-Sanskrit translation model was compared to Google Translate [5]. Although Google Translate is a very popular, generalized translation utility, it tends to fail to accurately translate Sanskrit owing to limited contextual awareness and the absence of domain adaptation. The proposed model, on the contrary, models the domain with a carefully prepared English-Sanskrit word pair corpus, enabling it to provide better and contextually relevant translations for the aimed vocabulary [7]. The model works at the character level based on an encoder-decoder LSTM framework, allowing it to properly grasp the structure and grammar of Sanskrit, which generalized tools usually neglect. Also, the system provides transparency, offline functionality, and flexibility for further adaptation, making it a better fit for educational and research applications where deeper understanding and control over the linguistic output are prioritized.

1.2.1.1 Customization and Offline Capability for Sanskrit Translation

One of the key benefits of the developed English-to-Sanskrit translation model based on LSTM consists in the extent of customization and the fact it can be run fully offline. Developed with a graphical user interface based on Tkinter, the system provides full access over the training dataset, vocabulary, and translation rules. Such a degree of flexibility provides researchers and educators with the option of customizing the model based on a given linguistic domain, educational requirements, or culture, features unavailable in commercial translation software.

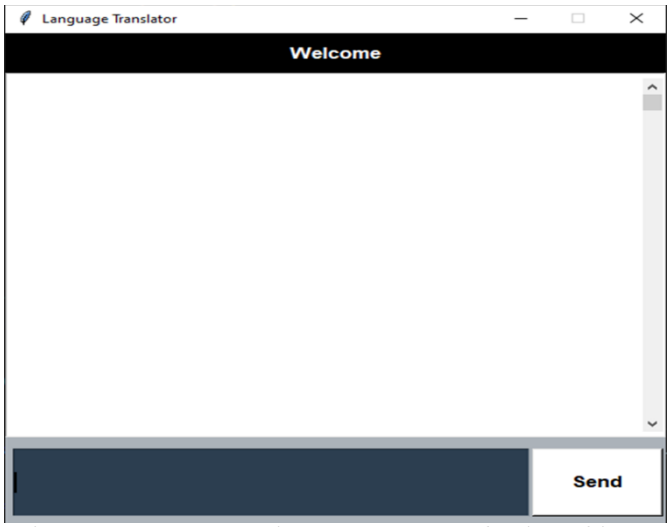


Fig. 32: User Interaction Screen created using Tkinter

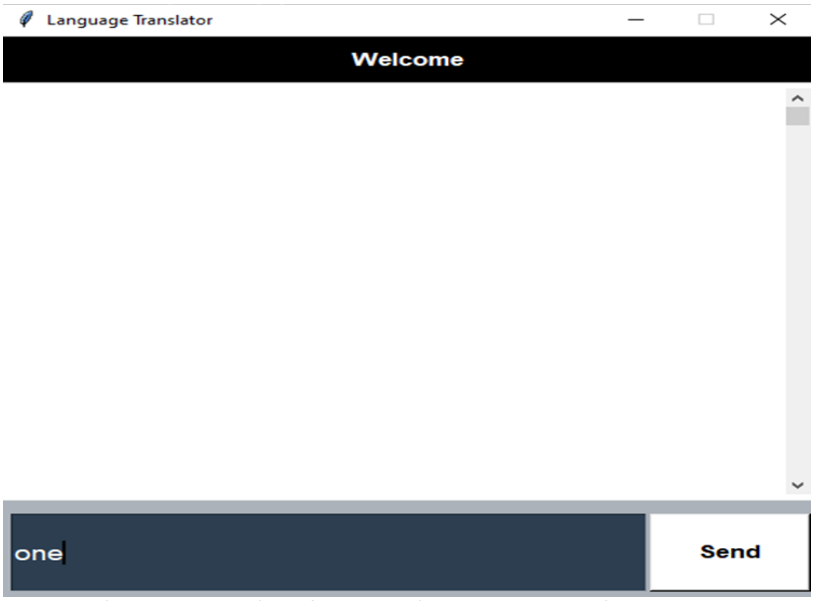


Fig. 33: Entering the Input in User Interaction Screen

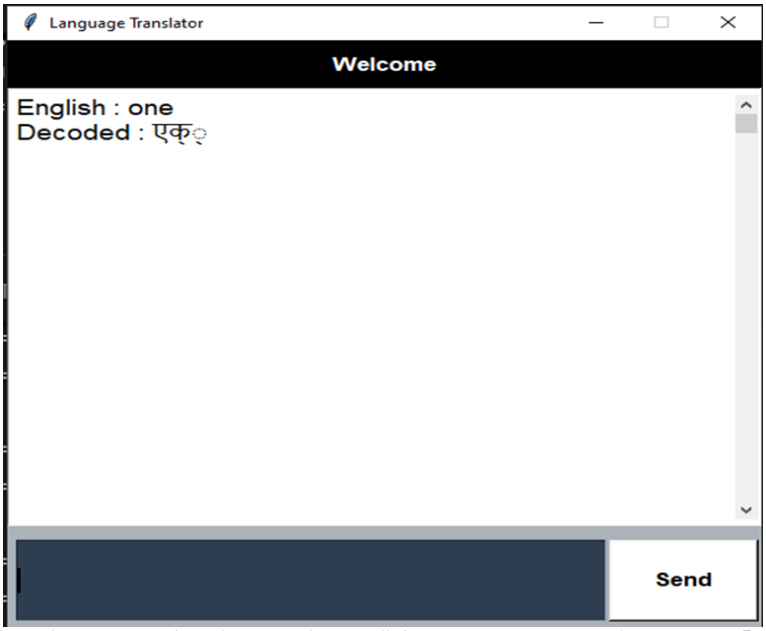


Fig. 34: Getting the output for the word “One” from User Interaction Screen[Not Accurate]

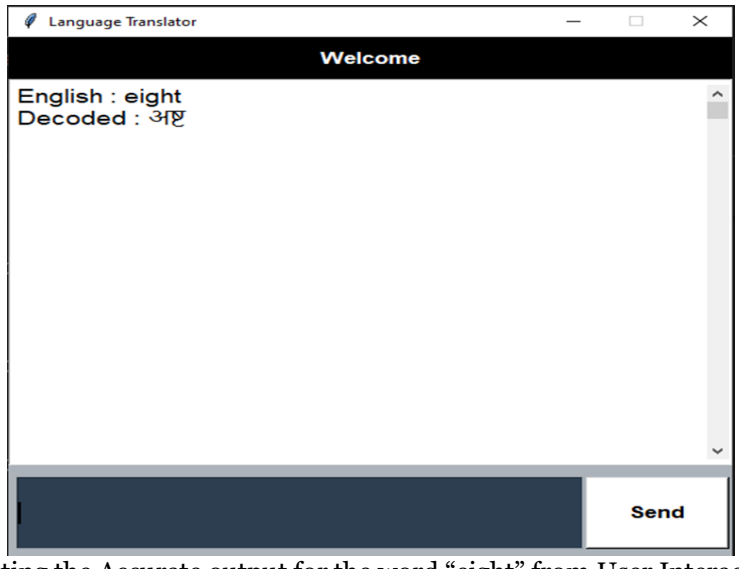


Fig. 35: Getting the Accurate output for the word “eight” from User Interaction Screen

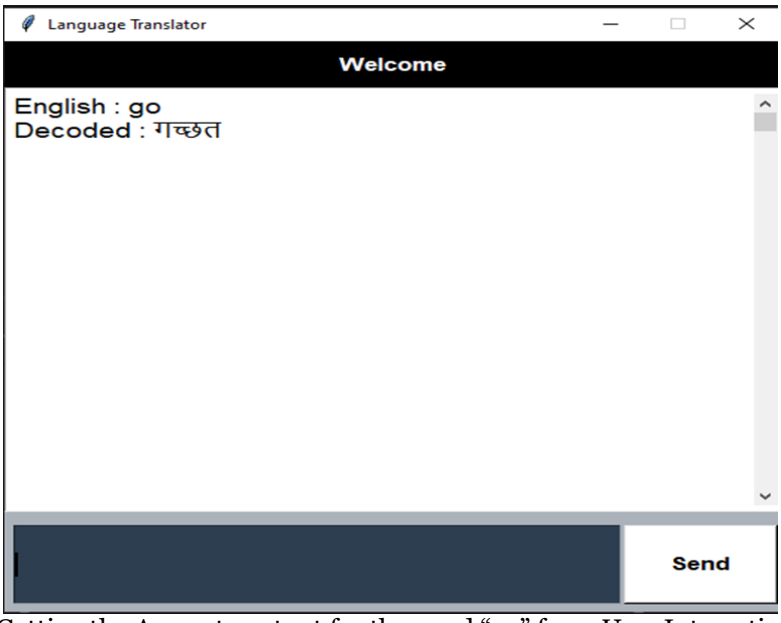


Fig. 36: Getting the Accurate output for the word “go” from User Interaction Screen

For comparison, closed systems such as Google Translate don't expose internal model parameters or allow customization, and their Sanskrit capabilities are constrained by general multilingual datasets. Google Translate also generally relies upon a live internet connection for effective translation, while the proposed model runs effectively in the offline environment. That places it ideally for use in educational institutions, rural communities, or organizations interested in preserving and teaching ancient languages. Overall, the option for customizing the system and the lack of the need for an internet connection make the proposed model highly functional in the intended usage scenarios.

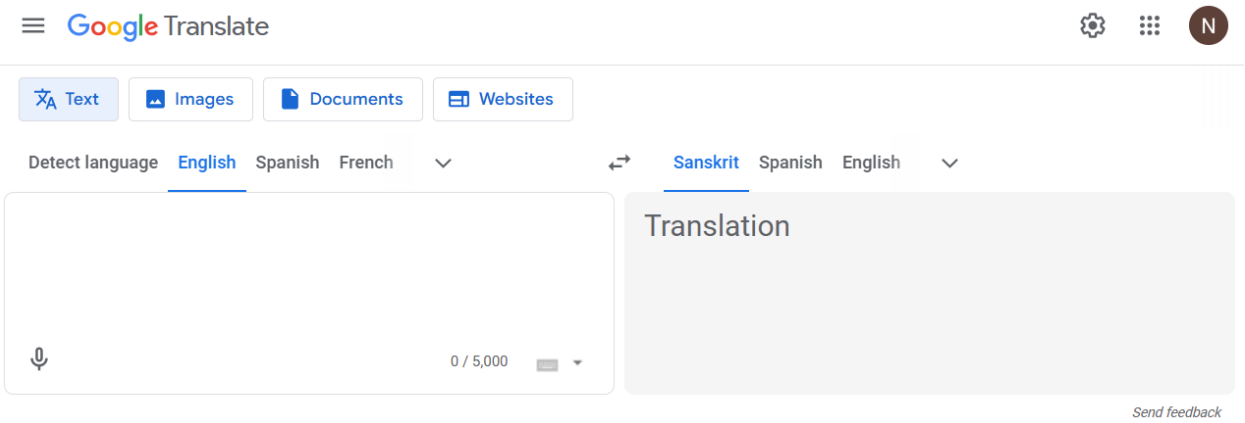


Fig. 37: User Interaction Screen of Google Translate

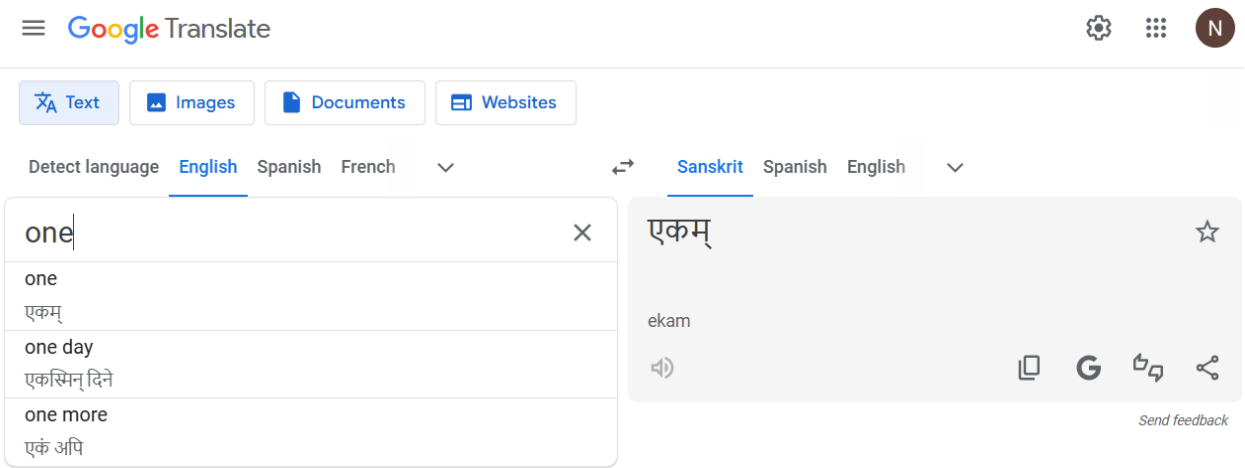


Fig. 38: Entering the Input in Google Translate User Interaction Screen

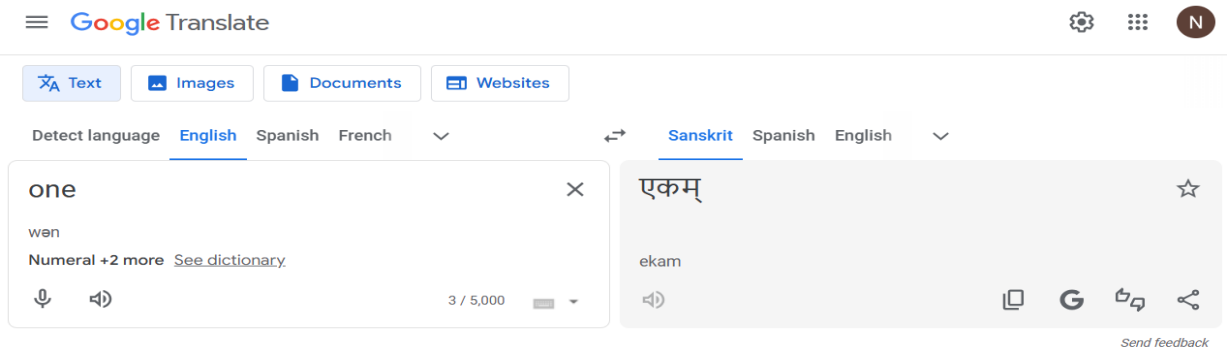


Fig. 39: Getting the Accurate output from Google Translate for the word “one”

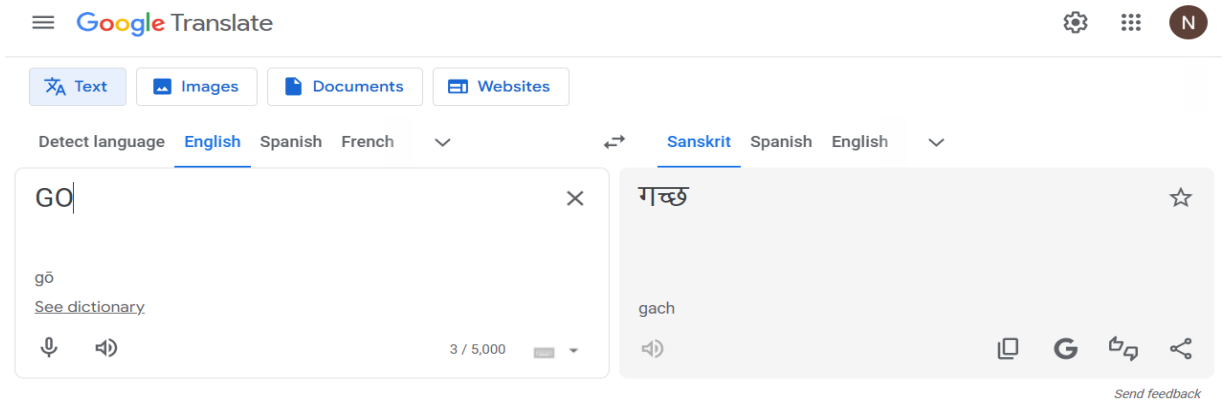


Fig. 40: Getting the Unaccurate output from Google Translate for the word “GO”

1.2.1.2 Model Architecture Advantage: LSTM over Traditional RNN

Another distinction the proposed model has over Google Translate is in the underlying neural net structure [5]. Though Google Translate used Recurrent Neural Networks (RNNs) in its earlier versions for many language pairs, including low-resource languages such as Sanskrit, traditional RNNs are subject to a number of known drawbacks. These are the vanishing gradient problem, which prevents the model from leveraging long-term relations, and inefficiency in backpropagating through time, especially for longer sequences. Contrarily, the current system relies on Long Short-Term Memory (LSTM) networks, a more developed type of RNN, overcoming the above drawbacks with the use of memory units and the use of gates (input, forget, and output gates).

Google Translate website homepage	
Type of site	Neural machine translation
Available in	133 languages; see below
Owner	Google
URL	translate.google.com
Commercial	Yes
Registration	Optional
Users	Over 610 million people daily
Launched	April 28, 2006; 17 years ago (as statistical machine translation) November 15, 2016; 7 years ago (as neural machine translation
Current status	Active

Table 5 Key facts about the Google Translate

This enables the model to capture and depend on long-range contextual relations [9], a need essential in a highly inflected and syntaxically intricate language like Sanskrit. This way, the LSTM model gives more stable, precise, and grammatically correct translations, adding its technological edge over models based on the conventional RNN architectures.

1.2.1.3 Linguistic Accuracy and Grammar Management in Sanskrit

The most important difference between the proposed LSTM model and Google Translate involves the degree of linguistic accuracy, specifically in its treatment of the intricacies of Sanskrit grammar. Sanskrit is a highly

inflected, syntax-heavy language with complex sets of rules governing the case endings (vibhaktis), compounds (samāsa), and verb conjugations. The proposed model works with a curated set of English-Sanskrit word pairings only, such that the model internalizes grammatical structure in a consistent, context-sensitive way.

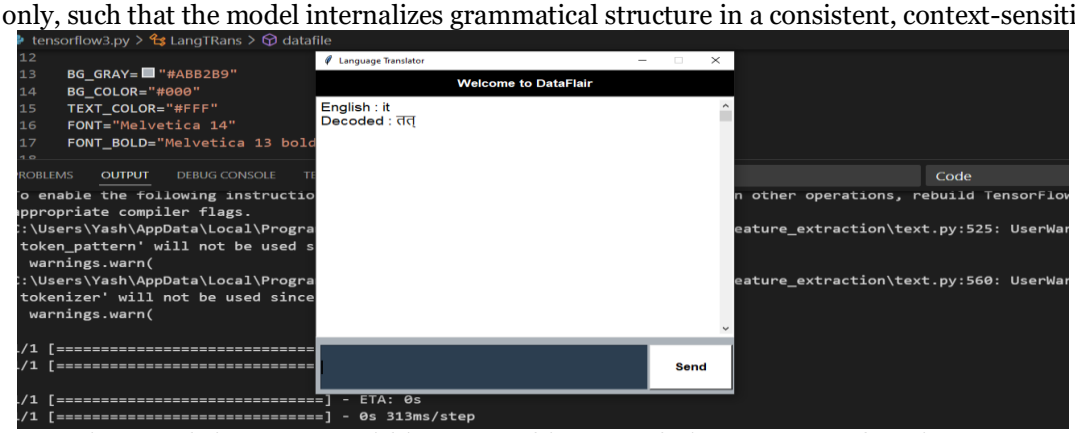


Fig. 41: Managing Sanskrit grammar within our Machine Translation System and getting proper output for the word “it”

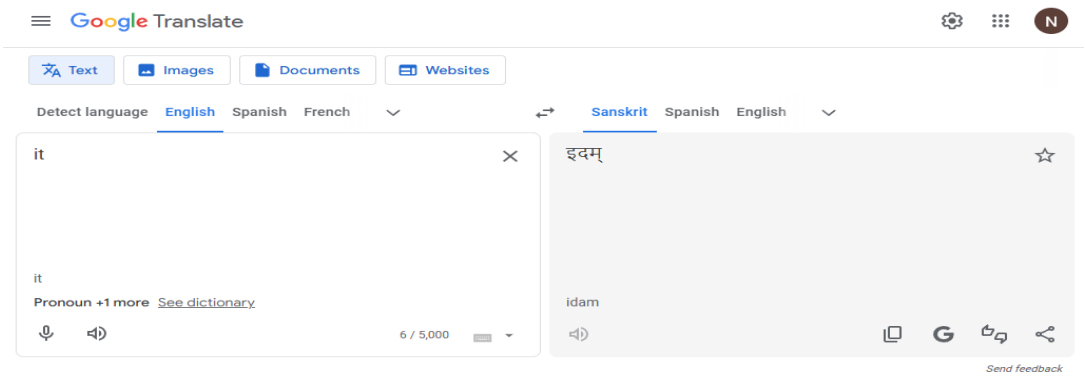


Fig. 42: Managing Sanskrit grammar in Google Translate with inappropriate Output for the word “it”



Fig. 43: Managing Sanskrit grammar within our machine translation system with proper output for the word “this”

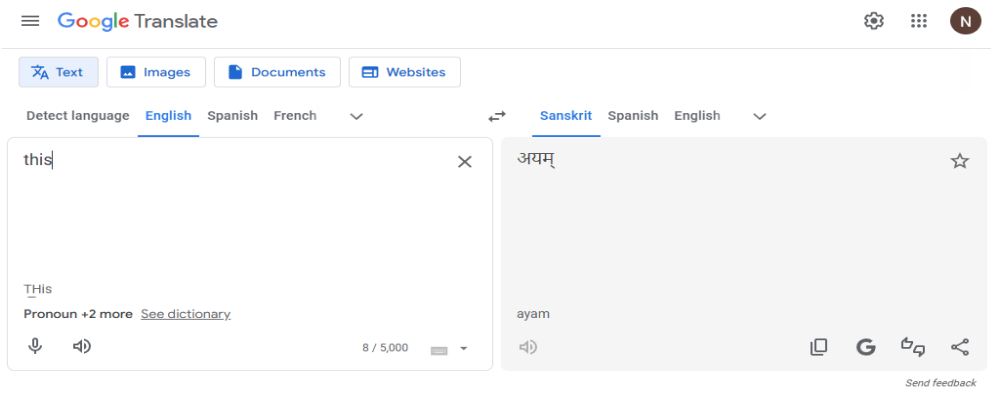


Fig. 44: Managing Sanskrit grammar in Google Translate with inappropriate Output for the word “this”

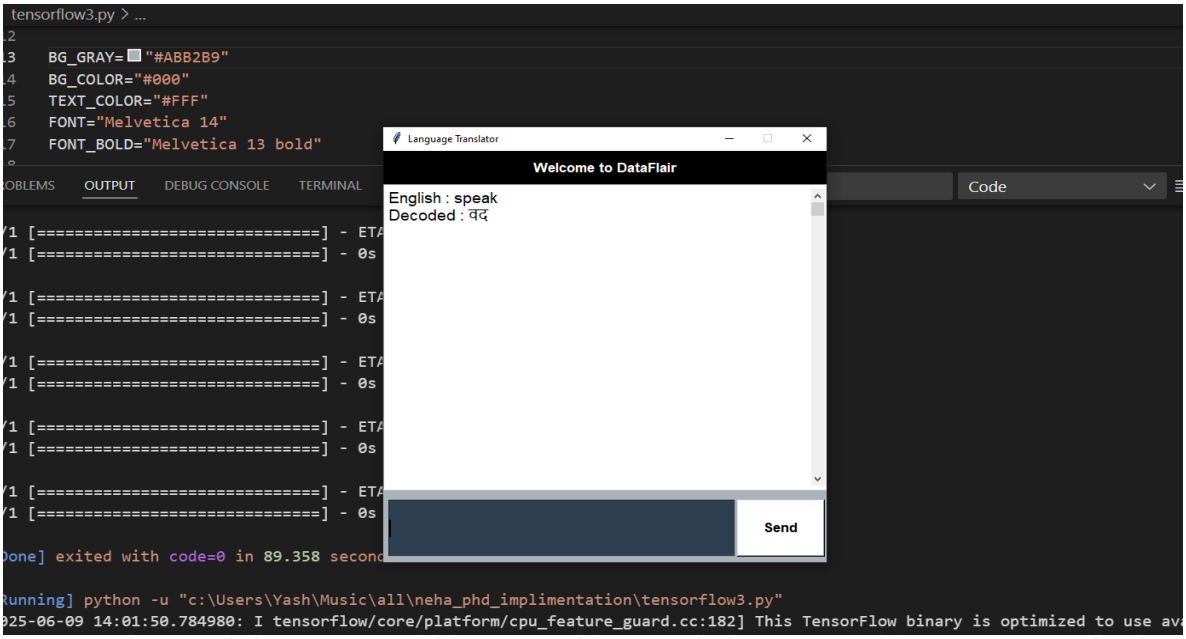


Fig. 45: Managing Sanskrit Grammar within our machine translation system with proper output for the word “speak”

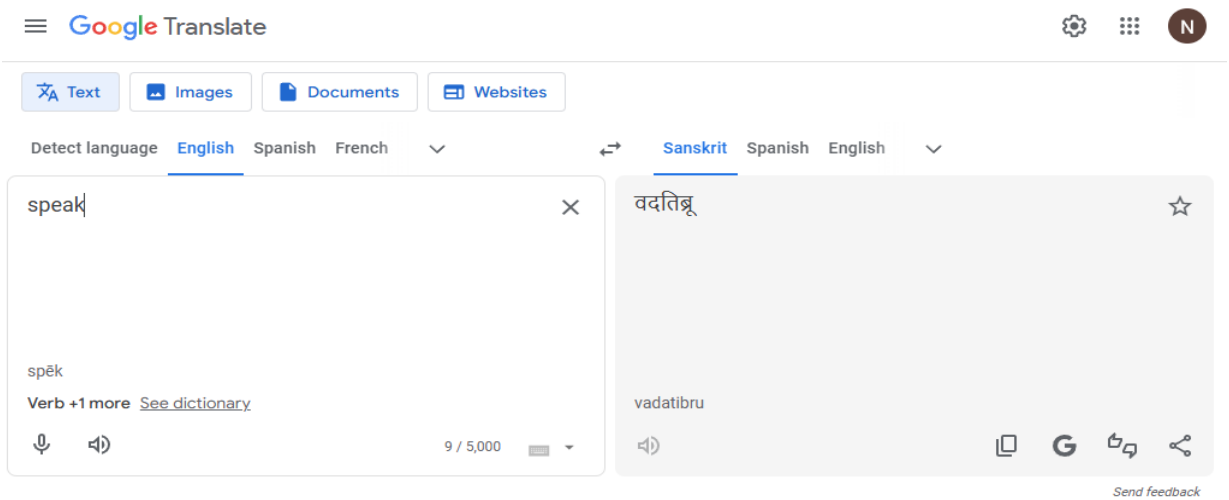


Fig. 46: Managing Sanskrit grammar in Google Translate with inappropriate Output for the word “speak”

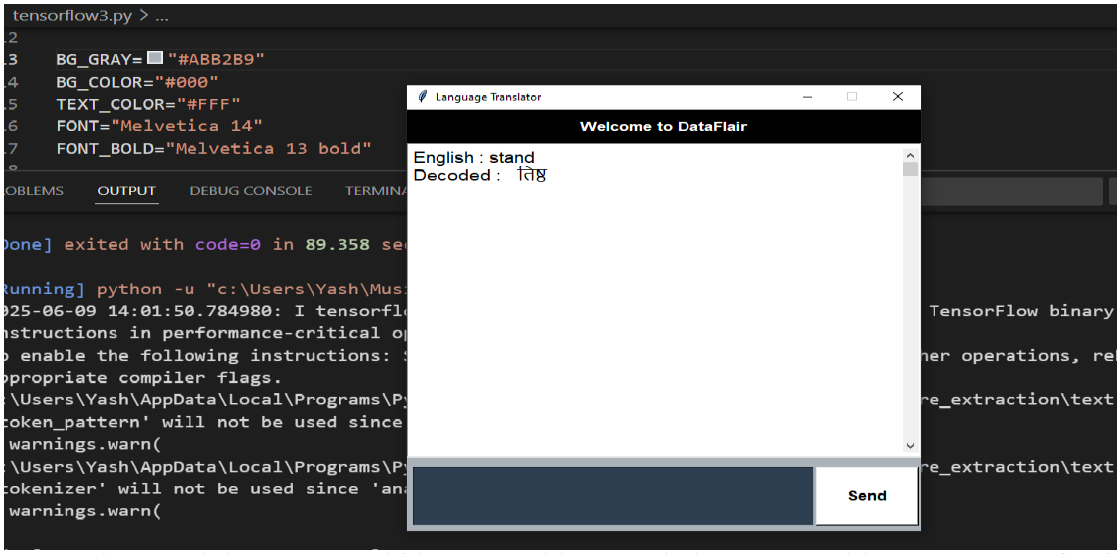


Fig. 47: Managing Sanskrit grammar within our machine translation system with proper output for the word "stand"

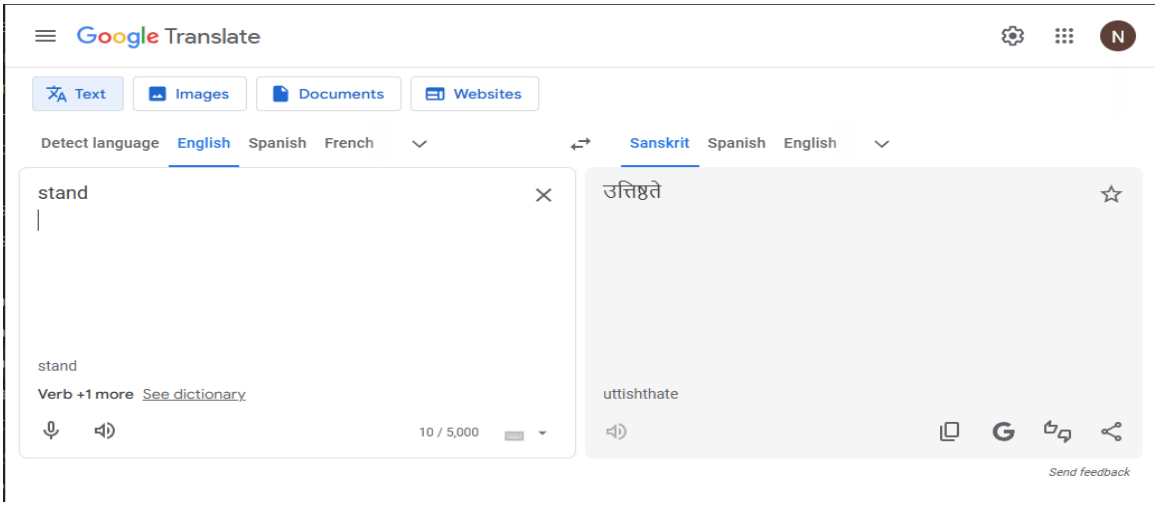


Fig. 48: Managing Sanskrit grammar in Google Translate with inappropriate Output for the word "stand"

By Contrast, Google Translate draws upon generalized multilingual corpora and statistical or transformer-based methods for the most part prioritizing fluency rather than strict morphological correctness. Consequently, it tends to render Sanskrit translations in semantically imprecise or grammatically incorrect forms, particularly in the context of classical or domain-specific terminologies. By virtue of the proposed model's use of a character-level structure and its emphasis on Sanskrit-only training datasets, we have the potential for more nuanced translation with a greater understanding of the differences in morphology. This makes it especially useful for academic, religious, and pedagogic usage, where grammatic correctness does not simply form an expectation, but a requirement [11].

1.2.1.4 Domain-Specific Training and Generalized Corpus

In contrast with Google Translate, trained on massive multilingual databases with a focus on breadth, not depth of translation, the model developed in this proposal uses a meticulously curated list of English-Sanskrit word pairs. Domain-specific training allows the model to learn linguistic subtleties and maintain consistency of terminology over a limited area. This makes it perform dramatically better in translating vocabulary used in the contexts of Sanskrit studies, literature, and classics—where Google Translate will falter because it lacks targeted information. Controlled learning through this methodology enables educators and researchers to have confidence in translations in those places where semantic accuracy is paramount.

1.2.1.5 Transparency and Interpretability

The proposed model's design allows for full transparency, including access to the training details, model structure, intermediate values, and layers of prediction. This transparency allows for tracing inputs processed through and generating outputs, a characteristic suitable for academic use, especially in pedagogy and linguistic studies. Google Translate, however, is a black box with zero information regarding its internal functioning or the sources employed for the dataset used. With this lack of transparency, an issue arises in the

case of audit, explanation, or verification of translation outputs, especially in educational or official use contexts.

1.2.1.6 Character-Level Processing

The proposed LSTM model operates at the level of the character, providing a higher granularity than word- or phrase-level models. This benefits the model immensely in the case of Sanskrit, in which the root- and suffix-level changes in morphology are involved. Character-level modeling assists the model in coping better with sandhi rules, suffixation, and root derivations, the building blocks of the syntax of Sanskrit. Google Translate operates mostly at the word or subword level, leading to a widespread occurrence of grammatical mismatches or misinterpretations in highly inflected languages.

1.2.1.7 Relevance in Education and Culture

The model was designed with learners, educators, and culture institutions in mind, with its training set, user experience, and outputs tailored for the intended purpose of language preservation, accurate pedagogy, and expression of culture. This renders it deployable in schools, heritage scholarship, and digital humanities projects more effectively than Google Translate, for instance, which, though suitable for general or conversational purpose, has not been optimised for such context and oftentimes excludes traditional or contextual forms of, for example, Sanskrit, thus limiting its deployment in scholarly environments.

1.3 English-to-Sanskrit Translation: A Comparison of Our LSTM Model and Google Translate

The given table presents a comparative analysis between our Model and "Google Translate," specifically in the context of English-to-Sanskrit translation.

Comparison Point	Our LSTM Model	Google Translate
Customization & Offline Capability	Fully offline, customizable for vocabulary, interface, and logic.	Requires internet; no customization options or control.
Model Architecture	Built using LSTM networks with gating mechanisms for long-term memory.	Historically RNN-based, now Transformer-based but generalized.
Grammar & Linguistic Precision	Effectively captures Sanskrit grammar rules, case endings, and morphology.	Often fails to accurately represent Sanskrit grammar and sentence structure.
Domain-Specific Dataset	Trained on a curated dataset tailored for English-to-Sanskrit translation.	Uses a broad multilingual corpus with minimal focus on Sanskrit.
Transparency & Interpretability	Fully interpretable with visible architecture and parameters.	Opaque black-box model with no user access to internals.
Character-Level Processing	Operates at the character level, enabling fine-grained morphological understanding.	Primarily word/subword-based; lacks precise Sanskrit morphology handling.
Educational & Cultural Alignment	Specifically designed for educational and classical Sanskrit use cases.	Designed for broad public use, not optimized for classical or academic translation.

Table 6 A Comparison of Our LSTM Model and Google Translate

The comparison highlights several key differentiators, including customization and offline capabilities, underlying model architecture, grammar and linguistic precision, domain-specific dataset utilization, transparency, character-level processing, and educational and cultural alignment. Essentially, the table argues for the superior suitability of "Your Model" for nuanced Sanskrit translation due to its tailored design, offline functionality, and deeper understanding of Sanskrit's complex linguistic structure, contrasting it with Google Translate's more generalized and less specialized approach.

1.4 Conclusion

This research paper demonstrates that a carefully designed LSTM-based character-level encoder-decoder model can significantly enhance the quality of English-to-Sanskrit machine translation. Through rigorous training and evaluation, the system effectively captures the morphological and grammatical complexities of Sanskrit, producing translations superior to generalized tools like Google Translate, particularly in linguistic accuracy and grammatical precision.

In addition to its technical performance, the proposed model offers key advantages in transparency, offline capability, and customization — allowing researchers and educators to adapt the system to specific linguistic

domains. The success of this approach validates the potential of LSTM-based architectures for low-resource language processing and highlights the importance of domain-specific training.
Future work will focus on expanding the dataset, incorporating more advanced attention mechanisms and exploring transformer-based architectures to further improve translation quality. This research contributes to the growing field of computational linguistics for classical languages and supports the preservation and dissemination of Sanskrit through modern digital tools.

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