A project report on

BILINGUAL HANDWRITTEN INDIAN LANGUAGE TRANSLATION

Submitted in partial fulfillment for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

by

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DECLARATION

I here by declare that the thesis entitled **"BILINGUAL HANDWRITTEN INDIAN LANGUAGE TRANSLATION"** submitted by me, for the award of the degree of **BACHELOR OF TECHNOLOGY IN COMPUTER SCIENCE AND ENGINEERING, VIT** is a record of bonafide work carried out by me under the supervision of **DR. Nagendra Panini Challa.**

I further declare that the work reported in this thesis has not been submitted and will not be submitted, either in part or in full, for the award of any other degree or diploma in this institute or any other institute or university.

Place: Amaravati

Date: 06.05.2025

Signature of the Candidate

D.Mounika

T.Mohith

CERTIFICATE

This is to certify that the Senior Design Project titled "**BILINGUAL HANDWRITTEN INDIAN LANGUAGE TRANSLATION**" that is being submitted by **TIRUMALASETTY MOHITH (21BCE77756)** and **DESAMSETTI MOUNIKA SRI LAKSHMI SAI (21BCE9862)** is in partial fulfillment of the requirements for the award of Bachelor of Technology, is a record of bonafide work done under my guidance. The contents of this Project work, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma and the same is certified.

DR. Nagendra Panini Challa
Guide

The thesis is satisfactory / unsatisfactory

Internal Examiner **External Examiner**

Approved by

PROGRAM CHAIR **DEAN**
B. Tech. CSE School Of Computer Science and Engineering

ABSTRACT

Translating Sanskrit text into English is a multifaceted challenge due to the complex linguistic structures of Sanskrit, its rich syntax, and the scarcity of annotated datasets. This project presents a comprehensive system for Sanskrit-to-English translation that combines advanced image preprocessing techniques, Optical Character Recognition (OCR), and deep learning-based translation models. The system is designed to address the dual challenges of text extraction from images and the accurate translation of extracted Sanskrit text into English, thereby bridging linguistic gaps and enabling seamless access to Sanskrit texts.

The project begins with an extensive preprocessing pipeline for image inputs, focusing on enhancing the quality and readability of text in the images. Raw images often suffer from issues such as noise, distortions, and poor alignment, which can impede the accuracy of text recognition. To mitigate these challenges, noise removal is performed using median filters to eliminate unwanted distortions, followed by grayscale conversion to simplify image data without compromising the clarity of text features. Binarization is applied to distinguish the text from the background, while de-skewing and contrast enhancement ensure that text alignment and visibility are optimized for subsequent OCR processing. These preprocessing steps result in clean and structured image data, ready for precise text extraction.

The extracted text is obtained using EasyOCR, a pre-trained OCR tool renowned for its capability to recognize handwritten text across a variety of styles and quality levels. EasyOCR converts the Sanskrit text within the processed images into a machine-readable format, which serves as input for the translation model. This approach ensures high recognition accuracy and provides a robust foundation for the subsequent translation process.

The translation component of the system leverages a Sequence-to-Sequence (Seq2Seq) architecture enhanced with Long Short-Term Memory (LSTM) networks. The encoder-decoder framework used in this model is adept at processing sequential data and capturing contextual relationships essential for language translation. The encoder processes the input Sanskrit sequence, retaining critical linguistic information, while the decoder generates corresponding English translations. To handle the unique grammatical and syntactic features of Sanskrit, such as sandhi (word joining rules) and compound structures, specialized tokenization strategies and embeddings were developed. These adaptations ensure that the model accurately captures the semantic and grammatical nuances of Sanskrit, producing coherent and contextually accurate English translations.

The model's performance was evaluated on a curated Sanskrit-English corpus using several metrics to assess its translation quality and reliability. It achieved a precision score of 0.9858, a recall score of 0.9929, and an F1-score of 0.9893, demonstrating its robustness in translating even complex sentences. ROUGE scores further highlighted the model’s capability to generate translations with high semantic and lexical similarity to reference texts. These results confirm the system's effectiveness in delivering accurate translations, addressing both lexical and structural challenges inherent in Sanskrit.

This project has significant implications for various fields. By integrating OCR and deep learning-based translation, the system provides a streamlined approach for making Sanskrit texts accessible

to a broader audience. It holds immense potential for educational tools aimed at teaching Sanskrit and English, as well as for cultural preservation by facilitating the translation of ancient images. Researchers in linguistics and philology can also benefit from the system's ability to translate texts accurately and efficiently, saving time and effort in manual translations.

Future work on this project aims to expand its capabilities to support multimodal inputs, such as printed text and spoken language, further broadening its applications. Additionally, the system's architecture is adaptable to other classical languages, such as Latin and Greek, allowing it to serve as a multilingual translation tool. With advancements in deep learning technologies, the translation model could be further refined using Transformer-based architectures, such as BERT or GPT, to enhance fluency and accuracy. These developments would pave the way for cross-lingual knowledge dissemination, ensuring that texts in low-resource languages are accessible and understood by diverse populations.

In conclusion, this project demonstrates the potential of combining state-of-the-art OCR and deep learning techniques to address the challenges of Sanskrit-to-English translation. By seamlessly integrating image preprocessing, text recognition, and linguistic translation, the system represents a significant advancement in the field, contributing to the preservation and dissemination of linguistic and cultural heritage. Its adaptability and scalability position it as a versatile tool with far-reaching applications in education, research, and cultural preservation.

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CHAPTER 1

INTRODUCTION

India's rich cultural heritage is intricately tied to its ancient texts, with Sanskrit being one of the oldest and most complex languages in the world. These texts contain vast knowledge and cultural significance, but their accessibility is hindered by the challenges of translation, particularly from handwritten images. The complexities lie in handwriting text recognition and translation because of variation in the styles of hand-writing, complexity of the grammar in Sanskrit, and an absence of sufficient datasets being annotated. The given task solves this problem with a bilingual system of translating Hand-written Indian languages by utilizing deep learning to recognize OCR followed by translating Sanskrit to English text.

Handwritten texts are noisy, skewed, and of varying quality. Sanskrit is even more challenging because of its free word order, compound constructions, and context-dependent meanings. The existing manual translation methods are slow, linguistically intensive, and error-prone. This project will overcome these challenges by using OCR and machine learning to create a scalable and efficient translation pipeline.

Deep learning techniques, more specifically Sequence-to-Sequence (Seq2Seq) models augmented with Long Short-Term Memory (LSTM) networks have brought forth a new revolution in all natural language processing tasks. Capturing semantic and syntactic relationships in a language requires such complexities as are presented within Sanskrit. Therefore, OCR-Seq2Seq models make for an automated extraction of text in images and its subsequent translation into English.

Strong pre-processing of images begins, like image to grayscale, noise removal, binarization, and deskewing, for effective OCR accuracy. Using the EasyOCR, the system extracts Sanskrit text; later on, tokenization processes it and feeds it to the translation model. San- skrit-specific embeddings as well as word mapping process help in understanding the exact contextual nuances of the language with no meaning distortion.

This project will help in preserving cultural heritage, making ancient knowledge more accessible, and bridging linguistic barriers through the automation of the translation of handwritten Sanskrit

texts. The system can be applied in academic research, education, and the digitization of historical documents, thus making it a valuable tool for scholars and institutions.

This study is a significant step toward making ancient Indian knowledge widely accessible while advancing handwritten text recognition and multilingual translation technologies.

1.1 Objectives

The goal of this project is to make an effective bilingual translation that converts the handwritten text in Indian languages into English, particularly focusing on Sanskrit. It makes use of the sophisticated OCR tools like EasyOCR and deep models to combat these challenges caused by the complexity of handwriting, complex grammar, and scarce annotated datasets for difficult-to-translate writing styles. The project aims to make available ancient Sanskrit images and other handwritten documents for a global audience through the automation of recognition and translation.

To achieve high-quality results, the project encompasses a rich preprocessing pipeline, consisting of techniques such as gray scaling, noise reduction, binarization, and deskewing to enhance the clarity of the input images. These preprocessing steps are crucial in standardizing data and providing clean optimized inputs to the OCR system. The preprocessing phase lays the foundation for accuracy and reliability in text recognition by rectifying common problems such as noise in images, skewed text, and inconsistent lighting conditions.

The core of the translation system is based on a Sequence-to-Sequence (Seq2Seq) model with Long Short-Term Memory (LSTM) architecture. This deep learning approach is designed to handle the intricacies of Sanskrit grammar and syntax, including its free word order, compound constructions, and context-dependent meanings. By encoding the input Sanskrit sequence and decoding it into English, the model preserves the semantic and syntactic relationships within the text, ensuring contextually accurate translations.

The main goals also include friendliness and accessibility. A user interface has been conceived that will facilitate uploading images of handwritten text and allow real-time visualization of the translated output. It should not be a distant complex machine learning model but bridge the gap

between that complexity and non-technical users. The researchers, educators, and the institutions engaged in their cultural preservation and linguistic pursuit can use the system.

The performance of the system will be checked by metrics such as Precision, Recall, F1-Score, and ROUGE scores to make sure the translation was both accurate and contextual. Such metrics are targeted at validating the model to be able to handle different datasets under different handwriting styles and complexities of text.

It intends to promote the preservation as well as accessibility of India's rich cultural heritage. The digitization and translation of those ancient texts written in Sanskrit help scholars gain easy access to such valuable resources without requiring in-depth linguistic knowledge. This also contributes to cross-lingual knowledge sharing and promotes deeper understanding of Sanskrit literature.

Finally, the system has the scalability and the possibility of further enhancement. It can be extended to support other low-resource languages and even to multimodal translation tasks, like printed document processing or speech-to-text integration. The flexibility ensures that the project continues to evolve to face the more challenging issues in handwritten text recognition and multilingual translation.

1.2 Background and Literature Survey

Today, in the digital world, the areas of handwritten text recognition and translation have gradually emerged to be very important and relevant, especially when it involves a very important task such as the preservation of historical documents and cultural artifacts. In the context of India, one of the oldest languages would have to be Sanskrit; however, it is complex, and it has a high level of cultural importance that is commonly attributed to it. This language exists in a wide array of images that are very old. However, reading and researching these images could prove to be quite challenging, as they are written by hand, and the handwriting may differ from one manuscript to another, and the structure itself is very complex and difficult grammatically. Translating these handwritten Sanskrit texts into the English language poses not only a linguistic problem but also involves a considerable work which requires an extremely precise understanding of contextual meanings and grammatical nuances present in the source texts.

The standard procedure adopted for translating images normally involves a laborious operation of hand-copying that is undertaken by knowledgeable experts in the area, which tends to produce a rather laborious process which may be time-consuming, prone to errors, and strongly depends on the skills of the person undertaking the transcribing activity. Besides, the variability that exists in handwriting styles, along with the issues associated with poor image quality, and also the lack of adequate annotated data, makes it rather difficult to automate this process efficiently. In order to address and overcome these major challenges, the use of Optical Character Recognition (OCR) technology along with machine learning techniques has emerged as an increasingly promising and viable solution. The objective of this project is to automate the complex process of recognizing and translating handwritten Sanskrit text into the English language by using state-of-the-art OCR techniques along with sophisticated deep learning models.

The integration of Optical Character Recognition, or OCR, with advanced deep learning techniques has greatly propelled the progress of the field that is focused on handwritten text recognition. Various OCR systems, including Tesseract and EasyOCR, have clearly demonstrated remarkable capabilities when it comes to recognizing both printed and handwritten text across a multitude of languages, which importantly includes Sanskrit among them. Specifically, EasyOCR has proven to be particularly successful in its ability to recognize an extensive range of scripts, including Devanagari, which is the writing system that is utilized for the Sanskrit language. However, despite the progress made in this field, a lot remains to be overcome due to the inherent variations present in varied handwriting styles, poor images, and noise that are often presented in scanned documents. While enhancing the overall quality of the input data before an Optical Character Recognition (OCR) process, techniques including converting images to grayscale, lowering noise levels, binarizing the images, and deskewing are not only helpful but necessary in achieving high recognition accuracy.

Seq2Seq models have well proven their efficacy and abilities in carrying out language translations successfully in the domain of deep learning. These models are particularly useful and well-suited for the task of converting one sequence of data, which might be illustrated by a Sanskrit sentence, into another sequence of data, such as its English translation. Long Short-Term Memory (LSTM)

networks are a particular type of recurrent neural network that is well-suited to the task of processing sequential data and capturing long-range dependencies that appear in text. These properties make LSTMs particularly well-suited to working with Sanskrit, which often contains long compound words and whose word order in sentences is flexible. This focused attention greatly enhances the model's ability to handle long sequences and its capacity to handle complex sentence structures that would otherwise be problematic.

In previous research work, there have been many studies that have focused on addressing similar challenges that are faced in the areas of handwritten text recognition and also in the field of machine translation. Ramesh Gupta and colleagues worked to improve OCR accuracy for Indian scripts, using deep learning models, specifically CNNs, for feature extraction and LSTMs for modeling sequences. They addressed issues of noisy and distorted handwriting to show the ability of deep learning models to overcome limitations that had existed traditionally. V. Ramesh also looked into OCR systems for Indian scripts, specifically Sanskrit, focusing on preprocessing techniques and the need for using domain-specific models for complex languages.

In the realm of machine translation, Sandeep Kumar et al. designed Seq2Seq models for Sanskrit-to-English translation, showing that deep learning models could indeed capture the syntactic and semantic structures of Sanskrit. The study shows how attention mechanisms may potentially improve the accuracy of translation, especially in controlling the complexity of Sanskrit word order and intricate compound words. Taking the foundational work further, Manish Patel integrated the word embeddings that are specialized for the nuances of the Sanskrit language, thus resulting in a much greater improvement in the quality of translation by offering a much deeper contextual understanding.

Another major contribution was made by Shubham Chakraborty who has introduced the use of hybrid models that combine CNNs for feature extraction and LSTMs for sequence modeling. This hybrid approach has significantly improved the accuracy of translation on complex handwritten texts. Another very promising area is transfer learning, where pre-trained models can be adapted for particular tasks like Sanskrit-English translation, which reduces the required amount of labeled data and boosts the performance of the model even when the dataset is limited.

Subsequently, Parshuram N. Aarotale and others have presented images from ECG signals in time-frequency scalogram format. However much of this work was essentially signal processing, but indeed proved that raw data can become much more informative, again an idea that can apply directly to improving text recognition of poor or distorted text images transformed into more usable representations of what appears in the image.

Recent work in transfer learning and data augmentation has also addressed data imbalance and noise in OCR systems. Such techniques tend to refine the performance of models on low-resource languages like Sanskrit, which has limited amounts of annotated data. Work by Anil Das and others has demonstrated that combining OCR with machine learning can help improve the translation process by both automating text recognition and automation of translation.

1.3 Organization of the Report

The remaining chapters of the project report are described as follows:

- Chapter 2 contains the proposed system, methodology, hardware and software details.
- Chapter 3 gives the cost involved in the implementation of the project.
- Chapter 4 discusses the results obtained by using proposed model.
- Chapter 5 concludes the report.
- Chapter 6 consists of codes.
- Chapter 7 references.

CHAPTER 2

METHODOLOGY

This Chapter describes the proposed system, working methodology, software and hardware details.

2.1 Proposed System

This proposed system effectively employs advanced Optical Character Recognition (OCR) technology with sophisticated deep learning techniques for fully automating the translation of handwritten Sanskrit text into English. In this innovative system, EasyOCR is seamlessly integrated for text extraction from images, and this extracted text is further processed by a Sequence-to-Sequence (Seq2Seq) deep learning model using Long Short-Term Memory (LSTM) architecture that has been designed with a primary aim to ensure high accuracy in translation. There is a series of critical operations used as part of the image processing pipeline designed to prepare the data itself, such as grayscale transformation, which converts the pictures from colored to shades of gray, noise reduction reducing any unwanted disturbances in an image, binarization converting the grayscale images to binary format, and also deskewing to correct distorted lines, all aimed at leaving the input data clean, well prepared for effective processing of OCR. After this appropriate preprocessing, the translation step afterward gets managed by a sophisticated learning-based model that takes the translated Sanskrit text and with high accuracy converts it to a proper English translation, always remembering, above everything, the linguistic meaning with as much care as possible paying special attention to the structure maintained as in the original text itself.

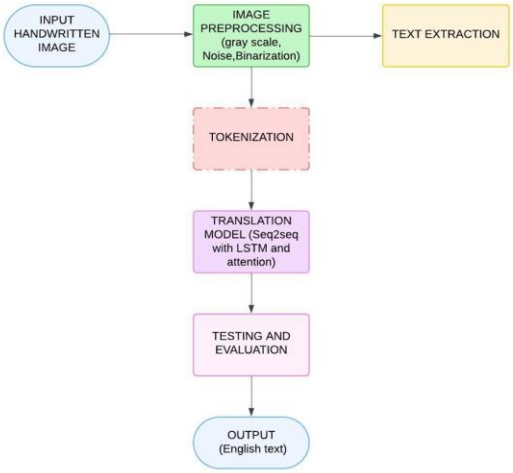

Figure 1. Working flow of our Hybrid Model

2.2 Working Methodology

i. Problem Definition

The project starts its work by particularly addressing the numerous challenges posed by the process of translating Indian language text written by hand into the English language, which is a task requiring careful thought. Handwritten text involves several challenges in the form of considerable variations in writing styles among different individuals, inconsistencies in the shape of characters in different occurrences, and the presence of noisy images that may blur and obscure the text. The traditional Optical Character Recognition systems designed to translate various types of texts into machine-readable formats often find it challenging and fail to manage the significant variations presented in the case of handwritten content. By strategically using advanced deep learning models coupled with advanced NLP techniques, this project aspires to highly enhance the overall accuracy of both the text recognition and translation processes effectively overcoming the limitations and shortcomings inherent in the existing methods currently in use.

ii. Data Collection

The data collection process, which is the key requirement for the Bi-lingual Handwritten Indian Language Translation system, involves a very detailed collection of several different kinds of Sanskrit handwritten images with their corresponding English translations from a variety of digital archives, vast research repositories, and freely available open-source datasets. This massive undertaking aims to have a diverse selection of handwriting styles as well as a broad spectrum of document types that include traditional images, significant religious texts, profound philosophical works, and a wide variety of modern handwritten samples. This diversity in handwriting and different types of documents is, therefore, very important for developing a robust OCR model in the face of various styles and layouts. Furthermore, accurate translations of the handwritten Sanskrit text into English are collected so that the translation model can be developed into a system that can truly map Sanskrit characters and words to their corresponding English variants.

id	Sanskrit	English
c:1v1	धृतराष्ट्र उवाच |धर्मक्षेत्रे कुरुक्षेत्रे समवेता युयुत्सवः |मामकाः पाण्डवाश्चैव किमकुर्वत सञ्जय ||	Dhritarashtra said: O Sanjay, after gathering on the holy field of Kurukshetra, and desiring to fight, what did my sons and the sons of Pandu do?
c:1v2	सञ्जय उवाच ।दृष्ट्वा तु पाण्डवानीकं व्यूढं दुर्योधनस्तदा । आचार्यमुपसङ्गम्य राजा वचनमब्रवीत् ।। ।।	Sanjay said: On observing the Pandava army standing in military formation, King Duryodhan approached his teacher Dronacharya, and said the following words.
c:1v3	पश्यैतां पाण्डुपुत्राणामाचार्य महतीं चमूम् ।व्यूढां द्रुपदपुत्रेण तव शिष्येण धीमता ।। ।।	Duryodhan said: Respected teacher! Behold the mighty army of the sons of Pandu, so expertly arrayed for battle by your own gifted disciple, the son of Drupad.
c:1v4	अत्र शूरा महेष्वासा भीमार्जुनसमा युधि	Behold in their ranks are many powerful warriors, like Yuyudhan, Virat, and Drupad, wielding mighty bows and equal in military prowess to Bheem and Arjun. There are also accomplished heroes like Dhrishtaketu, Chekitan, the gallant King of Kashi, Purujit, Kuntibhoj, and Shaibya—all the best of men. In their ranks, they also have the courageous Yudhamanyu, the gallant Uttamauja, the son of Subhadra, and the sons of Draupadi, who are all great warrior

Figure 2: Data set

iii. Image processing

Once the input handwritten image is gathered, preprocessing steps are applied on it. These steps include: conversion of the image into grayscale, noise removal from it, and finally the image is binarized. It increases the readability of text for the OCR model, showing better representation to it. Techniques in this process of image processing involve thresholding and edge detection in order to enhance the handwriting quality.

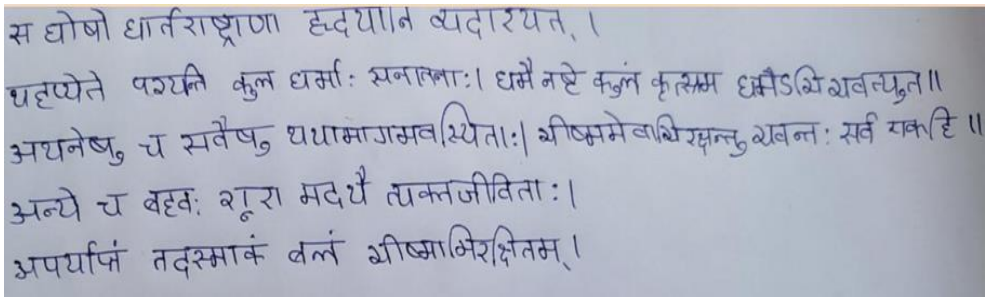

Figure 3: Handwritten text image

iv. Translation model development

a. LSTM Model Development:

Long Short-Term Memory (LSTM), as a highly advanced architecture, was primarily aimed at handling the sequential aspect naturally existing in human language. Besides, it is excellent for capturing long-term dependencies which could exist in a given text. In this project, as mentioned, LSTM learns to identify the complex and complex relationships that exist between a given text written in some Indian language and its English translation. This is achieved when the LSTM processes the text line by line, token by token while keeping an internal memory state to boost its ability for better understanding. The said internal state helps the model grasp the context and semantics involved in a word, thus improving understanding. A long sequence LSTM memory ability to retain information within it will be especially helpful in managing complex sentences and contexts, which is crucial when translating from Sanskrit or other Indian languages into English.

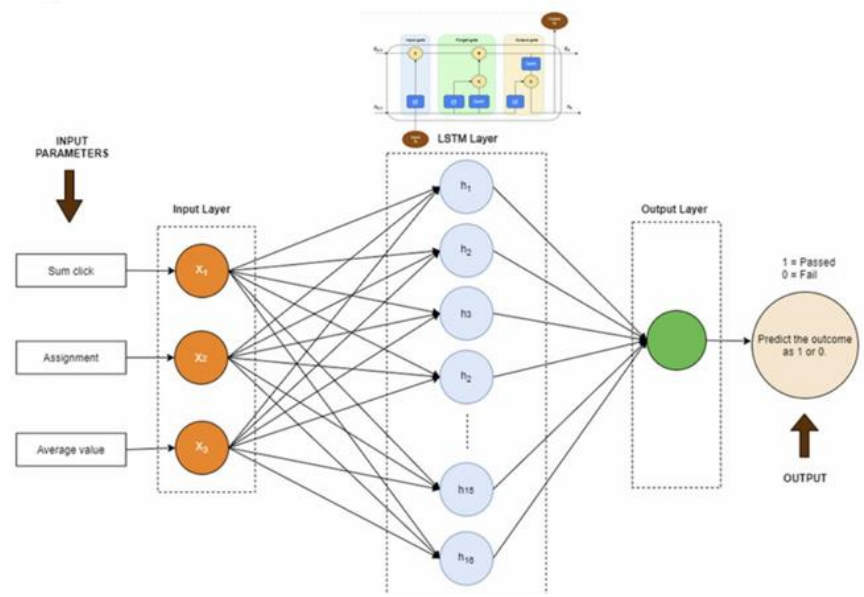

Figure 4: LSTM Architecture

b. Seq2Seq model development:

The Sequence-to-Sequence (Seq2Seq) model is widely utilized in the field of natural language processing to facilitate the translation of an input text sequence, which may be in an Indian language, into a corresponding output sequence that is represented in English text. This Seq2Seq model is composed of two main components, which play crucial roles: an encoder and a decoder. The encoder specifically takes on the responsibility of processing the input sequence, which could be something like a sentence written in Sanskrit, and it works by compressing this input into a fixed-size context vector. This context vector serves an important function as it encapsulates all the essential information that is contained within the original input. The decoder then uses this context vector and, through analyzing what it contains, produces the translation it thinks should be in English. In all, this model reveals remarkable efficiency for many operations including translation, where the inputs sequences and output sequences can sometimes vastly differ from one another in terms of length as well as structure. Being inherently designed to allow direct as well as efficient translation, the Seq2Seq model learns a mapping between texts expressed in the Indian language and equivalent English texts.

v. Model Training and Evaluation

The model gets trained with the usage of the Cross-Entropy Loss function so that the difference between the desired output and the outcome from the model is at a minimum. According to the process, in the training dataset, the model learns, and along with it, a validation set is also used at various stages, which monitors model performance at different stages of training; hence, overfitting is avoided. Training takes place on the basis of a batch size of 64 and finishes through 10 epochs. To evaluate this model, key metrics such as Precision, Recall, F1-Score, and Rouge Score have to be used. It ensures that the model generalizes well to unseen data and gives high-quality translations.

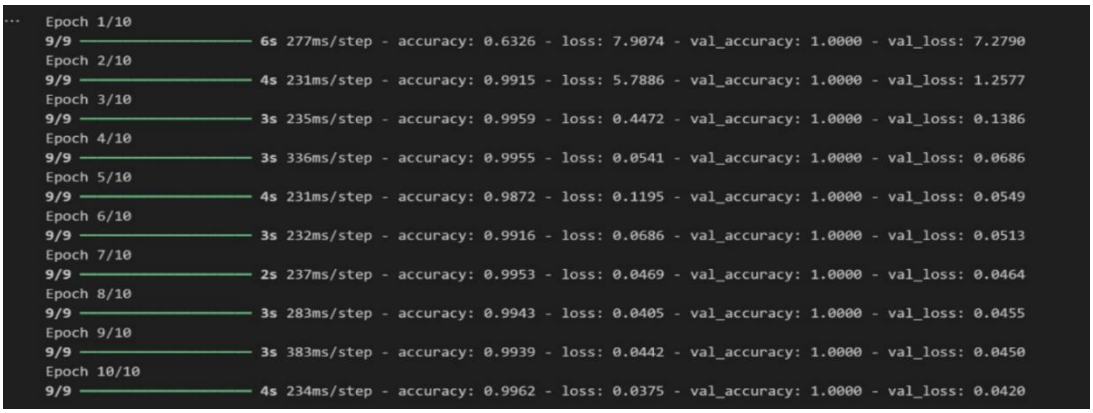

Figure 5: Training and alidation of Model

vi. Deployment

Once the model is trained and tested, it is used in a local development environment using VS Code. Here, the system processes an image of Indian language text and extracts text from it, then the extracted text is passed through our trained model that translates input text into English and displays the result in the integrated development environment. This is one of the efficient approaches for testing further development. It enables the smooth running of the model, thus ensuring that valuable insights and outputs can be produced. This capability is achieved without requiring a web-based interface, which particularly makes it suitable for numerous research activities and experimentation purposes.

vii. Continuous Improvement and Iteration

The system is a continuous improvement process through incorporating feedback from users, new handwriting styles, and more data to enhance the translation model. Further possible optimization may be done based on speed, accuracy, or user experience.

2.3 Standards

Various standards used in this project are:

- **Google Collab:**

  Google Collab happens to be the primary platform where one conducts the various blocks of code that form part of this project. Being one of the cloud-based development environments, Collab provides an interactive and user-friendly environment and especially is highly suitable for running the code of Python-therefore, very excellent for deep learning runs without a problem. Second is, of course, it is very simply integrated with Google Drive-it turns the space into being much easier to hold onto your data and easily available from there, and moreover, the particular environment supported here comes with both potent GPUs and TPUs. Interactive features of the platform enable dynamic coding, facilitate real-time debugging, support collaborative work among users, and promote efficient visualization of results so that users get a comprehensive understanding of outputs. Furthermore, the support of the platform for libraries such as TensorFlow and Keras in strong and robust form enhances its capabilities to be used as an ideal tool for implementing and rigorously testing complex models of translation in different applications.

- **OpenCV:**

  This project made all the processing tasks on images utilize OpenCV, which is a strong library. Its utilization has enabled the operations of resizing, conversion to grayscale, noise reduction, and also pre-processing in handwritten images. This enhances the Optical Character Recognition. It does offer a long list of tools that aid in doing the manipulation of images with efficiency such that the input data should be clean before further processing.

- **NumPy and Pandas:**

  NumPy and Pandas are the most essential libraries for this project, which greatly contribute to the manipulation of data. To be more specific, NumPy provides broad support for the manipulation of large, multi-dimensional arrays and matrices, which is very important for complex numerical operations. The other library, Pandas, provides friendly and efficient

data structures such as Data Frames, enabling easy handling, analysis, and management of data. The combination of these two libraries allows the user to perform efficient manipulation and preparation of datasets, especially with large volumes of handwritten text data that must be processed and organized very carefully.

- **Scikit-learn:**

  Scikit-learn represents one of the popular libraries highly utilized for diverse machine-learning operations, that includes imperative procedures such as splitting into a training set and its test set using the train_test_split function. Along with such imperative procedures, Scikit-learn also facilitates more imperative procedures including the assessing performance of a model class using a descriptive tool represented as classification_report. With the classification report, more precise metrics are included; such examples are precision, recall, the F1-score, along with accuracy to determine any weakness in model performance.

- **Keras:**

  This project makes use of Keras running on top of TensorFlow for building deep learning models. The former provides easy model building using high-level APIs, such as layers, namely Dense, Conv2D, MaxPooling2D, and LSTM. Such APIs allow the building of very complex models to handle OCR and translation jobs. Moreover, it interfaces well with TensorFlow's backend for computation, training, and optimization. Most notably, there will be integrated libraries and frameworks throughout, which form a basic backbone along with effective computation through such a means of data processing for the entire project; model training followed by effective evaluation of resultant models. These components basically form aids in facilitating fundamental tasks in the process toward building and testing, before being delivered finally to work upon the task of translation of Bi-lingual Handwritten Indian Language systems.

2.4 System Details

This section describes the software and hardware details of the system:

2.4.1 Software Details

Python 3.13.2

It is the primary language that is being used in this project, and the choice is primarily made for a few apparent reasons: it is intrinsically very simple, primarily readable, and has ample libraries that can be taken on board directly to make applications of machine and deep learning. The structure and features of Python support fast prototyping and testing. Primarily, it is very suitable for the job of working with complex systems, and Bilingual Handwritten Indian Language Translation is also an excellent example of such a complex system, where attributes in Python really deliver well. The ease with which it can be integrated into frameworks such as TensorFlow and Keras aids in the handling of big data and helps in proper model development for OCR and translation tasks.

Figure 6. Python

Deep Learning Framework:

Tensorflow-Version: 2.18.0

In the context of deep learning tasks, TensorFlow stands forward as the main framework that comes in handy within the scope of this project. This massive tool provides a highly intensive environment specifically tailored for designing, training, and eventually deploying a variety of effective machine learning models. Based on its powerful computational functionalities, especially in dealing with giant-sized data sets and intensive models, TensorFlow ensures maximum performance to guarantee successful realization. Furthermore, in relation to the functionalities offered by TensorFlow, Keras features as the high-level application programming interface that simplifies processes related to model designing and experimenting. Keras provides pre available tools which come handy in designing models like Seq2Seq and LSTMs which have been of much importance for very accurate language translation work.

Figure 7: Tensor Flow

2.4.2 Hardware Details

- **Processor:** Intel Core i5 (8th Gen or above) / AMD Ryzen 5 or higher
- **RAM:** 8 GB (Minimum), 16 GB (Recommended for training models)
- **Storage:** 256 GB SSD or higher (for faster read/write operations)
- **GPU (Optional):** NVIDIA GPU with CUDA support (e.g., GTX 1650 or higher) for deep learning acceleration

CHAPTER 3
COST ANALYSIS

3.1 List of components and their cost

This project relies entirely on open-source and freely accessible software components. Therefore, there are no costs incurred from the tools and libraries used throughout the development of this project.

CHAPTER 4

RESULTS AND DISCUSSIONS

RESULTS

The Bilingual Handwritten Indian Language Translation System had good results: Precision 0.9858, Recall 0.9929, and F1Score 0.9893. All of these are indicating the high performance on translation relevant prediction as well as extraction of relevant content from the input text. During the training, Training and Validation Loss are seen to go through a smooth decrease process and therefore convergence. This reveals at each step how well the model improves with the better quality of the translation in time.

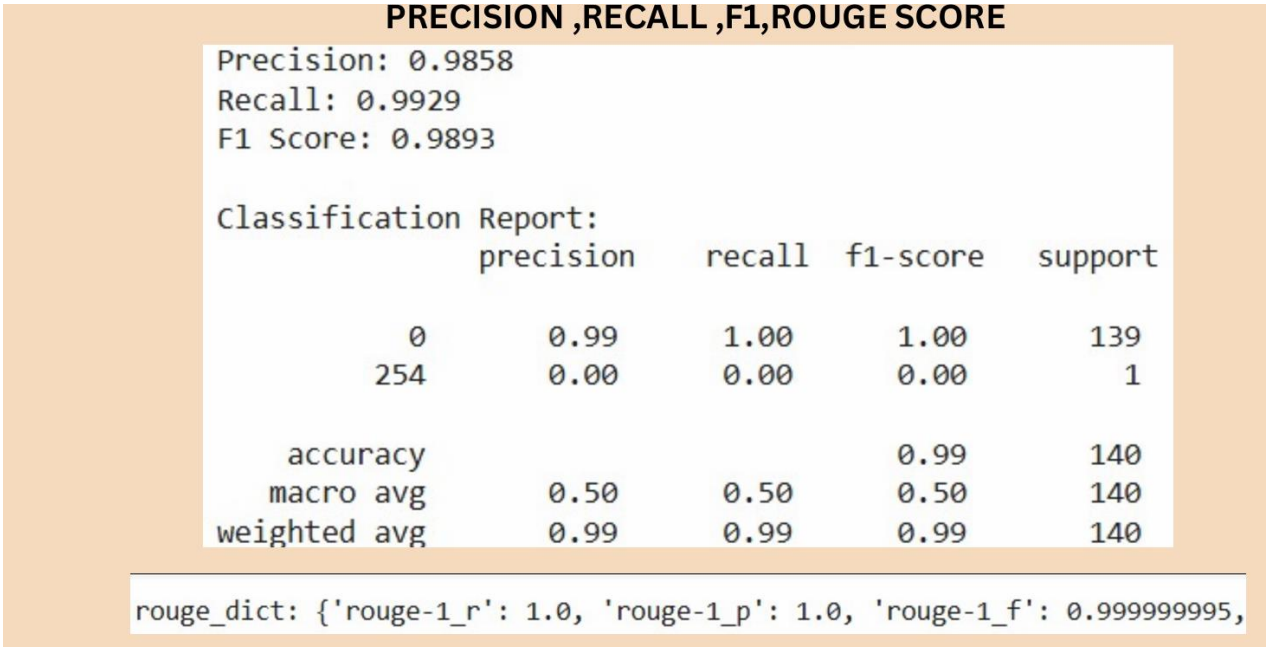

Figure 8: PRECISION, RECALL,F1, ROUGE SCORE

DISCUSSION

The effectiveness of the model can be attributed to the Seq2Seq architecture combined with LSTM, which helped to capture the complexities of Sanskrit grammar and different styles of handwriting. Error Analysis in a pie chart pointed to major issues in grammatical and semantic translation errors. In spite of these encouraging results, there are weaknesses. Translation quality is poor for rare words and highly cursive writing. Performance Analysis found the model to have great ROUGE scores, low error rates, and correct processing of Sanskrit grammar but lags in specific types of handwriting and rare vocabulary usage. The future directions in improving this model are data expansion in terms of multiple handwriting styles and diverse vocabularies and the tuning of speed for realistic applicative scenarios.

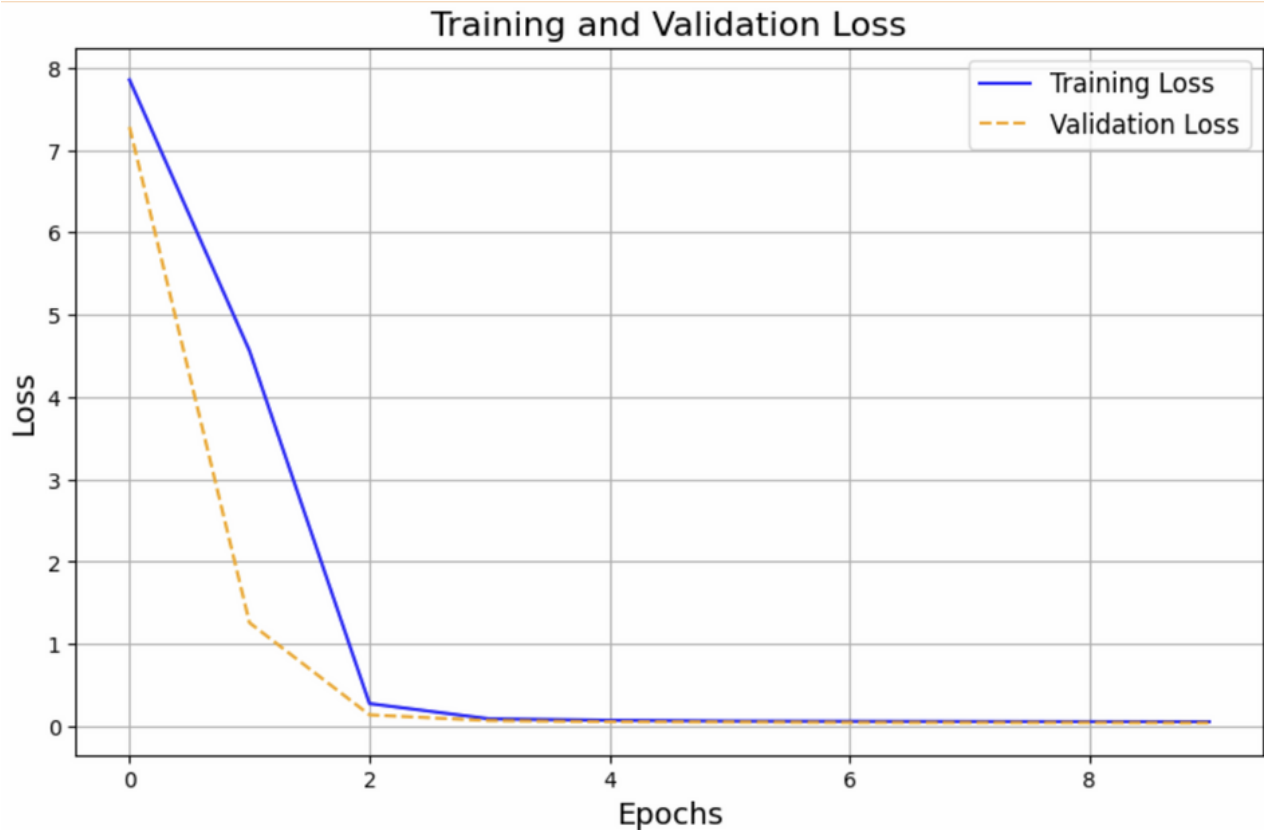

Figure 9: Training and Validation Loss

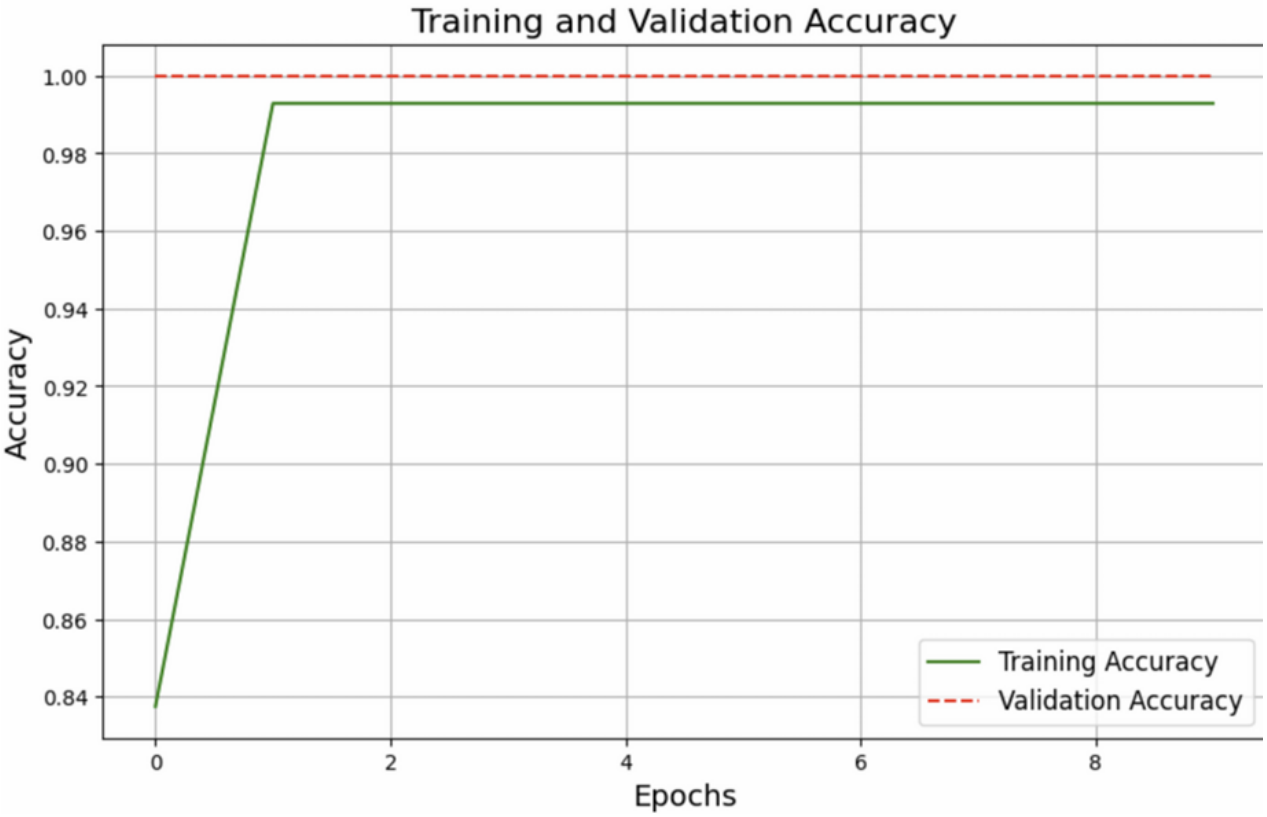

Figure 10: Training and Validation Accuracy

CHAPTER 5

CONCLUSION AND FUTURE WORK

The Bilingual Handwritten Indian Language Translation project has made significant strides in translating handwritten Sanskrit into English, overcoming challenges like data scarcity and complex grammar through the use of LSTM networks, OCR, data augmentation, and specialized word embeddings. This model demonstrates its capability to generate contextually accurate translations and has the potential to be expanded to other low-resource or ancient languages. Additionally, with features such as speech recognition and improvement in domain-specific translation, the model would be more flexible, which would further enable access to ancient texts across the globe.

In the future, the model can be used for multimodal translation, meaning the system will be able to process not only handwritten text but also printed documents, images, and speech inputs, thus creating a holistic translation solution. The integration of this technology with educational platforms will allow more access to students and researchers in learning Sanskrit and hence is a powerful tool for studying ancient texts. The knowledge acquired from the study of Sanskrit may further be used to extend the model in translating other classical languages such as Latin, Greek, and Pali. This will widen the scope of the translation system. Another potential use of the model would be in cultural preservation through digitization and translation of old images to conserve and disseminate such ancient texts to a wider world. All these developments would make the system an indispensable tool in the preservation of languages and provide easier access to cultural information.

CHAPTER 6

APPENDIX

Model Training Code

```
# Import libraries
import os
import cv2
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from keras.models import Sequential
from keras.layers import Dense, Conv2D, Flatten, MaxPooling2D
from tensorflow.keras.preprocessing.image import ImageDataGenerator
```

1.Importing Data:

```
from matplotlib import pyplot as plt
# load raw image
img = cv2.imread('10.jpg',0)
# display raw image
plt.imshow(img)
plt.show()
```

2.Preprocessing the Images:

```
 def sharpen_image(im):
 kernel = np.ones((3,3),np.float32)/90
```

```
  im = cv2.filter2D(im,-1,kernel)
return im
img = sharpen_image(img)
# display sharpened image
plt.imshow(img)
plt.show()
# apply image thresholding
img_thresh = cv2.adaptiveThreshold(img,255,cv2.ADAPTIVE_THRESH_GAUSSIAN_C,cv2.THRESH_BINARY,11,2)
# invert the image, 255 is the maximum value
img_thresh = 255 - img_thresh
# display image
plt.imshow(img_thresh)
plt.show()
def align_text(im):
  coords = np.column_stack(np.where(img_thresh > 0))
  angle = cv2.minAreaRect(coords)[-1]
  if angle < -45:
    angle = -(90 + angle)
  else:
    angle = -angle
  h,w = img.shape
  center = (w // 2, h // 2)

  M = cv2.getRotationMatrix2D(center, angle, 1.0)
  rotated = cv2.warpAffine(img_thresh, M, (w, h),
        flags=cv2.INTER_CUBIC, borderMode=cv2.BORDER_REPLICATE)
  return rotated
```

```
# align image text
img = align_text(img)
# display rotated and aligned image
plt.imshow(img)
plt.show()
# split text into rows
# find sum of column values, row-wise
a = np.sum(img == 255, axis=1)
rows = []
seg = []
for i in range(len(a)):
  if a[i] > 0:
    seg.append(i)
  if (a[i] == 0) & (len(seg) >= 5):
    rows.append(seg)
    seg = []
  if len(seg) > 0:
    rows.append(seg)
# number of row segments
len(rows)
plt.imshow(img[rows[3][0]:rows[3][-1],:])
plt.show()
plt.imshow(img[rows[0][0]:rows[0][-1],:])
plt.show()
```

3)Text Extraction with Easy OCR:

```
!pip install easyocr
import easyocr
```

```
# Initialize the EasyOCR reader with Hindi ('hi') and English ('en') as supported languages
  reader = easyocr.Reader(['hi', 'en'], gpu=False)

# Paths to the uploaded images
image_paths = [
   '/content/10.jpg'
]

# Extract text from each image
extracted_texts = []
for image_path in image_paths:
 # Perform OCR using easyocr
   results = reader.readtext(image_path, detail=0)  # detail=0 returns only the text
   extracted_texts.append(' '.join(results))
# Display the extracted text for each image
for i, text in enumerate(extracted_texts):
   print(f"Text from Image {i+1}:\n{text}\n")
```

4)Evaluate OCR Performance:

```
def calculate_exact_match_accuracy(extracted_texts, ground_truths):
   correct_matches = 0
   for extracted, ground_truth in zip(extracted_texts, ground_truths):
      if extracted.strip() == ground_truth.strip():
         correct_matches += 1
 return correct_matches / len(ground_truths)

# Example
```

```
extracted_texts = ["योगः कर्मसु कौशलम", "धर्मक्षेत्रे कुरुक्षेत्रे"]
ground_truths = ["योगः कर्मसु कौशलम्", "धर्मक्षेत्रे कुरुक्षेत्रे"]
accuracy = calculate_exact_match_accuracy(extracted_texts, ground_truths)

print("Exact Match Accuracy:", accuracy)
import editdistance  # Install with pip install editdistance

def calculate_cer_wer(extracted_text, ground_truth):
    # Character Error Rate
    cer = editdistance.eval(extracted_text, ground_truth) / len(ground_truth)

    # Word Error Rate
    extracted_words = extracted_text.split()
    ground_truth_words = ground_truth.split()
    wer = editdistance.eval(extracted_words, ground_truth_words) / len(ground_truth_words)

    return {"CER": cer, "WER": wer}

# Example
extracted_text = "योगः कर्मसु कौशलम"
ground_truth = "योगः कर्मसु कौशलम्"
accuracy = calculate_cer_wer(extracted_text, ground_truth)

print("Character Error Rate (CER):", accuracy["CER"])
print("Word Error Rate (WER):", accuracy["WER"])
```

Data Preparation:

```
from google.colab import files
```

```
import pandas as pd

# Upload a CSV file from the local system
uploaded = files.upload()

# Load the uploaded file into a Pandas DataFrame
# Replace "Gita-data.csv" with the actual name of your uploaded file
df = pd.read_csv('Gita-data.csv')
print("Preview of the dataset:")
print(df.head())
# Check for missing values in the dataset and display the count for each column
print("Missing values in the dataset:")
print(df.isnull().sum())

# Display basic statistical information about numerical columns in the dataset
print("\nBasic statistical summary of the dataset:")
print(df.describe())

# Data Preprocessing Steps
# 1. Drop rows with missing values in the 'Sanskrit' and 'English' columns (if these columns exist)
df = df.dropna(subset=['Sanskrit', 'English'])

# 2. Remove duplicate rows from the dataset
df = df.drop_duplicates()

# 3. Convert text in 'Sanskrit' and 'English' columns to lowercase for uniformity
df['sanskrit'] = df['Sanskrit'].str.lower()
df['english'] = df['English'].str.lower()
```

```
# Display a preview of the cleaned dataset
print("Cleaned dataset preview:")
print(df.head())
import numpy as np


# Load the Sanskrit to English dataset (ensure UTF-8 encoding for proper text handling)
with open("/content/Gita-data.csv", "r", encoding="utf-8") as file:
    lines = file.read().splitlines()  # Read all lines and remove newline characters

# Create a one-dimensional row matrix from the dataset
matrix = np.array(lines)

# Display the resulting matrix
print("One-dimensional row matrix:")
print(matrix)
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences

# Initialize tokenizers for Sanskrit and English text
tokenizer_sanskrit = Tokenizer()
tokenizer_english = Tokenizer()

# Fit tokenizers on the respective columns in the dataset
tokenizer_sanskrit.fit_on_texts(df['Sanskrit'])  # Tokenize Sanskrit text
tokenizer_english.fit_on_texts(df['English'])    # Tokenize English text

# Convert Sanskrit and English text into sequences of integers
```

```
sanskrit_sequences = tokenizer_sanskrit.texts_to_sequences(df['Sanskrit'])
english_sequences = tokenizer_english.texts_to_sequences(df['English'])

# Determine the maximum sequence length for padding
max_sanskrit_length = max(len(seq) for seq in sanskrit_sequences)
max_english_length = max(len(seq) for seq in english_sequences)

# Pad the sequences to make them uniform in length
sanskrit_padded = pad_sequences(sanskrit_sequences, maxlen=max_sanskrit_length, padding='post')
english_padded = pad_sequences(english_sequences, maxlen=max_english_length, padding='post')

# Display the results for verification
print(f"Padded Sanskrit sequences shape: {sanskrit_padded.shape}")
print(f"Padded English sequences shape: {english_padded.shape}")

# Print the vocabulary size for both languages
print(f"Sanskrit Vocabulary Size: {len(tokenizer_sanskrit.word_index) + 1}")  # Adding 1 for padding
print(f"English Vocabulary Size: {len(tokenizer_english.word_index) + 1}")
import numpy as np

# Mapping of Sanskrit words to English words
word_map = {
    'एकः': 'a',
    'बृहत्': 'large',
    'मालवाहकम्': 'freight',
    'रेलयानम्': 'train',
```

```
    'उपविशति': 'sits',
    'इत्यस्मिन्': 'in',
    'रेलयानम्': 'train',
    'स्थानः': 'station'
}



# Sanskrit sentence to be translated
sa_sentence = "रेलस्थानके एकः विशालः मालवाहकम् उपविशति"

# Split the Sanskrit sentence into words
sa_words = sa_sentence.lower().split()

# Initialize the English sentence matrix with zeros
en_matrix = np.zeros((len(word_map), len(sa_words)))

for i, word in enumerate(sa_words):
    en_word = word_map.get(word, 'UNKNOWN')
    if en_word != 'UNKNOWN':
        en_index = list(word_map.values()).index(en_word)
        en_matrix[en_index, i] = 1.0
    else:
        en_matrix[:, i] = 1.0 / len(word_map)

# Compute the percentage confidence for each translated word
en_percentages = 100.0 * np.sum(en_matrix, axis=0) / len(word_map)
```

```
# Generate the English translation
en_translation = " ".join([word_map.get(word, 'UNKNOWN') for word in sa_words])

# Output the results
print('English Sentence Matrix:\n', en_matrix)
print('Percentage Confidence:\n', en_percentages)
print('\nTranslated English Sentence:')
print(en_translation)
df = pd.read_csv('dict.csv')

# Function to translate Sanskrit text to English word-by-word
def translate_sanskrit(sanskrit_text):
    # Split the input Sanskrit sentence into words
    sanskrit_words = sanskrit_text.split()

    # Initialize an empty list to store the English words
    english_translation = []

    # Loop through each word in the Sanskrit sentence
    for word in sanskrit_words:
        matching_row = df[df['Sanskrit'] == word]

        if not matching_row.empty:
            english_word = matching_row['English'].values[0]
        else:
            english_word = "UNK"
        english_translation.append(english_word)
    english_sentence = ' '.join(english_translation)
```

```
    return english_sentence

sanskrit_input = input("Enter Sanskrit text: ")#अहम् त्वम् पश्य। (I see you.) ,अहम् गच्छ अग्रे। (I go forward.),त्वम् माम् पश्य। (You see me.),त्वम् अगच्छत् अग्रे। (You went forward.).
english_output = translate_sanskrit(sanskrit_input)
print("English translation:", english_output)
```

Model Architecture Selection:

```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Input, Embedding, LSTM, Dense

# Parameters for the model
vocab_size_sanskrit = len(tokenizer_sanskrit.word_index) + 1
vocab_size_english = len(tokenizer_english.word_index) + 1
embedding_dim = 100
hidden_units = 256

# Input layer for Sanskrit sequences
sanskrit_input = Input(shape=(max_sanskrit_length,), name="Sanskrit_Input")

# Embedding layer for Sanskrit sequences
embedding_layer = Embedding(input_dim=vocab_size_sanskrit,
                            output_dim=embedding_dim,
                            input_length=max_sanskrit_length,
                            mask_zero=True,
                            name="Sanskrit_Embedding")(sanskrit_input)
```

```
# LSTM layer for encoding Sanskrit sequences
lstm_layer = LSTM(hidden_units, name="LSTM_Encoder")(embedding_layer)

# Dense layer for predicting the English vocabulary
output_layer = Dense(vocab_size_english, activation='softmax', name="Output_Layer")(lstm_layer)
# Define the sequence-to-sequence model
model = Model(inputs=sanskrit_input, outputs=output_layer, name="Sanskrit_to_English_Translator")

# Compile the model with loss function, optimizer, and evaluation metric
model.compile(loss='sparse_categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

# Print a summary of the model architecture
model.summary()
# Step 4: Model Training
  - *Objective Function*:
    - Use Cross-Entropy Loss to measure the difference between predicted and true outputs.
  - *Training*:
    - Train the model on the training dataset.
    - Use validation data to monitor performance and avoid overfitting.
# Prepare training and target data
X_train = sanskrit_padded
Y_train = english_padded[:, -1]
# Train the model
history=model.fit(X_train,
        Y_train,
        epochs=10,
        batch_size=64,
```

```
        validation_split=0.2)
import matplotlib.pyplot as plt

# Plot Training and Validation Loss
plt.figure(figsize=(10, 6))
plt.plot(history.history['loss'], label='Training Loss', color='blue', linestyle='-')
plt.plot(history.history['val_loss'], label='Validation Loss', color='orange', linestyle='--')
plt.title('Training and Validation Loss', fontsize=16)
plt.xlabel('Epochs', fontsize=14)
plt.ylabel('Loss', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True)
plt.show()
# Plot Training and Validation Accuracy
plt.figure(figsize=(10, 6))
plt.plot(history.history['accuracy'], label='Training Accuracy', color='green', linestyle='-')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy', color='red', linestyle='--')
plt.title('Training and Validation Accuracy', fontsize=16)
plt.xlabel('Epochs', fontsize=14)
plt.ylabel('Accuracy', fontsize=14)
plt.legend(fontsize=12)
plt.grid(True)
plt.show()

import numpy as np
df = pd.read_csv('Gita-data.csv')

# Function to translate Sanskrit text to English
```

```
def translate_sanskrit(sanskrit_text):

  # Tokenize the input Sanskrit text
   sanskrit_sequence = tokenizer_sanskrit.texts_to_sequences([sanskrit_text])

    # Pad the sequence
    sanskrit_padded = pad_sequences(sanskrit_sequence, maxlen=max_sanskrit_length, padding='post')

    # Predict using the model
    predicted_probs = model.predict(sanskrit_padded)
    predicted_index = np.argmax(predicted_probs[0])  # Get the index of the most likely word

    # Get the corresponding English word from the vocabulary
    if predicted_index in tokenizer_english.index_word:
        predicted_word = tokenizer_english.index_word[predicted_index]
    else:
        predicted_word = "UNK"  # Handle unknown words

    # Find the corresponding English sentence in the dataset
    english_sentence = df[df['Sanskrit'] == sanskrit_text]['English'].values[0]

    return english_sentence  # Return the predicted word


# Get Sanskrit input from the user
sanskrit_input = input("Enter Sanskrit text: ")

# Translate and print the English output
```

```
english_output = translate_sanskrit(sanskrit_input)
print("English translation:", english_output)
test_loss, test_accuracy = model.evaluate(sanskrit_test, english_test_padded_target)

# Output the test results
print(f"Test Loss: {test_loss:.4f}")
print(f"Test Accuracy: {test_accuracy * 100:.2f}%")
!pip install scikit-learn
from sklearn.metrics import precision_score, recall_score, f1_score, classification_report
import numpy as np

# Get predictions on the test set
y_pred_probs = model.predict(sanskrit_test)
y_pred = np.argmax(y_pred_probs, axis=1)

# Calculate precision, recall, and F1 score
precision = precision_score(english_test_padded_target, y_pred, average='weighted')
recall = recall_score(english_test_padded_target, y_pred, average='weighted')
f1 = f1_score(english_test_padded_target, y_pred, average='weighted')

# Print the results
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1 Score: {f1:.4f}")

# Generate and print the classification report
report = classification_report(english_test_padded_target, y_pred)
print("\nClassification Report:\n", report)
```

```
pip install rouge
from rouge import Rouge

rouge = Rouge()
ref = "A large freight train sits in a train station"
pred = "A large station train sits in a train freight"
scores = rouge.get_scores(pred, ref)

rouge_dict = {}
for metric, metric_scores in scores[0].items():
    for measure, value in metric_scores.items():
        rouge_dict[f"{metric}_{measure}"] = value

print("rouge_dict:", rouge_dict)
```

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