Sanskrit Audio-To-Text Transcription

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***Abstract*—The primary objective of this project is to create a sophisticated deep learning model that can precisely convert spoken Sanskrit language into written Sanskrit text. The main aim is to solve the existing lack of advanced technology tools for processing the ancient Sanskrit language, given its tremendous historical and religious importance. The main objective is to develop a resilient system capable of effectively transforming spoken Sanskrit into its written format, while overcoming the complex phonetic and linguistic features of the language.**

In order to accomplish this goal, the state-of-art Wave2Vec 2.0 model was employed, which is renowned for its exceptional performance in voice recognition tasks. This model excels at catching and comprehending the complex patterns included in audio data. The project entails prepping the Sanskrit audio data, which includes tasks such as loading and merging the audio files and their related transcripts, transforming the data into a Hugging Face Dataset, and applying several padding techniques to maintain consistency among the samples.

The efficiency of the technique is evaluated by setting up initial performance baselines and progressively enhancing the system using the Wave2Vec 2.0 model. The primary metrics monitored during the training and evaluation procedure encompass Training Loss, Validation Loss, and Word Error Rate (WER).

This initiative has the capacity to improve the accessibility and conservation of Sanskrit literature, offering a vital resource for scholars and aficionados of this ancient language. Moreover, the knowledge acquired from this research can make a valuable contribution to the wider domain of speech recognition for languages with limited resources. It sheds light on the difficulties and possibilities involved in creating precise transcription models for linguistic traditions that are not well-represented.

I. Introduction

The precise transcription of Sanskrit speech into its written form presents a substantial difficulty in the domain of deep learning. Sanskrit, an old language of great historical and cultural importance, frequently lacks the technology resources required for its proper preservation and study, especially for those who are not fluent in Sanskrit and the wider academic community. Existing speech-to-text algorithms are mostly designed for widely spoken languages and have difficulties in accurately transcribing Sanskrit due to its intricate phonetic and linguistic characteristics, leading to less than optimal transcription accuracy. Prior studies have predominantly concentrated on commonly used languages, resulting in a significant deficiency in technological advancements and assistance for ancient languages such as Sanskrit. Several existing models are inadequate because they lack training data specifically tailored for Sanskrit and do not have models that have been fine-tuned to its distinct phonetics, syntax, and script.

The primary research of this project is whether a deep learning model, specifically tailored and trained on Sanskrit speech data, can effectively transcribe Sanskrit audio into Sanskrit text, beyond the constraints of existing speech recognition systems. In order to address this question, the study was conducted utilizing the Wav2Vec 2.0 model, which is widely recognized for its efficacy in voice recognition endeavors. This project utilizes the advantages of Wav2Vec 2.0 to effectively deal with the complexities of Sanskrit phonetics and linguistic structure, instead than using conventional methods that may involve a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs).

II. Related Work

The challenge of precise speech transcription and translation, particularly for languages with limited resources such as Sanskrit, has received considerable interest in the domain of deep learning. Multiple researchers have investigated the possibility of utilizing pre-trained language models for machine translation jobs, demonstrating their ability to adapt to different languages and fields. In their study, Han et al. [1] showcased the efficacy of fine-tuning Massive Multilingual Pre-Trained Language Models (MMPLMs) for translating clinical domain texts. They highlighted how these models effectively expand translation capabilities to language pairs that were previously unexplored. In a similar manner, Sartipi et al. [2] performed a thorough assessment of Persian-English translation datasets using transformer models, providing insights into how the quality and quantity of the dataset affect translation accuracy. Lankford et al. [3] presented adaptMLLM, demonstrating its ability to improve translation accuracy for languages with limited resources, such as Irish and Marathi. These findings emphasize the significant influence of pre-trained models in overcoming language barriers, closely coinciding with the our goal of translating Sanskrit audio into text.

Moreover, the progress in deep learning methods for speech recognition provides valuable knowledge. Kumar et al. [4], Jia et al. [5], and Alinejad and Sarkar [6] have investigated different methodologies, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), for the purpose of speech recognition tasks. Methods like SpecAugment [7] and ContextNet [8] have shown substantial enhancements in the accuracy of speech recognition, highlighting the capability of CNN-based models to achieve cutting-edge performance. Furthermore, recent research conducted by

Chiu et al. [9], Schneider et al. [10], and Zhang et al. [11] has investigated different methods, such as attention processes and unsupervised pre-training, to improve the ability of speech recognition systems to perform well in noisy situations.

Numerous researchers have also explored the difficulties presented by languages with limited resources and emphasized the significance of safeguarding and ensuring their accessibility. Nguyen and Chiang [12] investigated methods for neural machine translation in situations where resources are limited. They highlighted the importance of employing effective tactics for data augmentation and transfer learning. Birch et al. [13] introduced a technique for adjusting language models that are well-supplied with resources to languages that lack resources. They demonstrated the efficacy of this approach in enhancing the quality of translation. Vania et al. [14] examined the issue of safeguarding low-resource languages in the era of digital technology, emphasizing the significance of creating language technologies to avert language extinction.

Besacier et al. [15] investigated many methods, such as transfer learning and data augmentation, to enhance the performance of speech recognition systems for languages with limited resources. Dalmia et al. [16] introduced a framework that utilizes data augmentation and semi-supervised learning techniques to enhance low-resource voice recognition. In their study, Bansal et al. [17] examined the difficulties associated with developing speech recognition systems for low-resource Indian languages. They emphasized the importance of employing customized methods to effectively tackle the distinctive features of these languages.

These studies collectively establish a basis for applying sophisticated speech recognition and translation methods in the context of low-resource languages such as Sanskrit. This aligns with the goals of this project to precisely transcribe and translate Sanskrit audio into text, thereby supporting the preservation and accessibility of this ancient language.

III. Methodology

A. Dataset Description

1) Data Collection: For this project, we utilize the "Sanskrit Speech Recognition" dataset hosted on Kaggle [18]. This dataset is sourced from the News Services Division of All India Radio and contains approximately 27 hours of audio data in WAV format with a 16 kHz sample rate. The audio files are organized by news bulletins, with each file named according to a sentence ID, such as 'sent_1.wav', facilitating the linking of spoken content to its written form. The dataset is tailored for immediate use with the Fairseq framework [19], providing a couple of accompanying files to support model training and evaluation:

- train.tsv: A file mapping audio paths to their corresponding frames.
- train.wrd: A file containing word-level transcripts of the audio data.

To ensure no data leakage and maintain a consistent class ratio across training, validation, and testing sets, we employ a stratified split approach. This method ensures that the distribution of classes (in our case, the sentences) is preserved in each split, preventing any potential bias or skew in the data. Specifically, we first sort the dataset by the sentence IDs, ensuring a consistent ordering across all accompanying files (train.tsv, train.wrd). Then, we divide the sorted data into three stratified subsets: training, validation, and testing. The stratification is based on the sentence IDs, ensuring that sentences from the same news bulletin are not split across different subsets. By adhering to this stratified split approach, we maintain a representative distribution of the Sanskrit language and audio characteristics across all three subsets. This stratification helps prevent data leakage, where information from the training set could inadvertently "leak" into the testing sets, leading to an overestimation of model performance. The resulting dataset splits are as follows:

- Training set: 80% of the dataset, used for model training
- Testing set: 20% of the dataset, used for evaluating the final model performance.

This dataset, with its unique focus on Sanskrit speech recognition and the accompanying files tailored for the Fairseq framework, provides a robust foundation for developing and evaluating our deep learning models for transcribing and translating Sanskrit audio into text.

2) Data Pre-processing: To ensure the dataset was appropriately prepared for training the deep learning model, we implemented several preprocessing steps. First, we loaded the audio file paths and frame information from a .tsv file, and the corresponding transcripts from a .wrd file. We then combined these datasets into a single dataframe for ease of manipulation.

Next, we converted the combined dataframe into a Hugging Face Dataset object to leverage the efficient dataset handling capabilities of the datasets library. We then processed the audio files and transcripts. Specifically, we loaded the audio files using torchaudio and converted them to arrays, extracting and storing the sample rates alongside the audio data. We also created tokenized labels from the transcripts using the Wav2Vec2CTCTokenizer. Fig. 1 shows a snippet of a few sanskrit transcripts that have been tokenized into Sanskrit characters. Fig. 2 shows a snippet of a Custom vocab for the assigning Label IDs to each tokenized character.

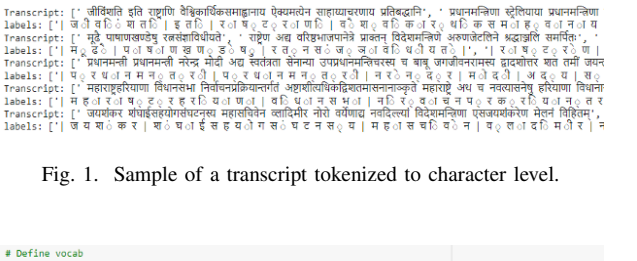

Fig. 1. Sample of a transcript tokenized to character level.

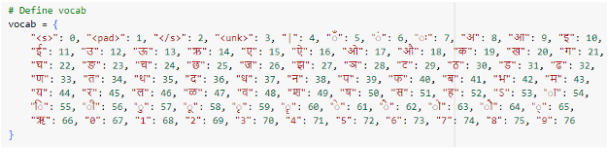

Fig. 2. Custom label IDs for Sanskrit tokens

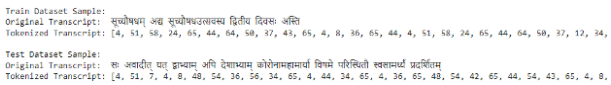

Fig. 3. Sample of original transcripts and their respective tokens

Fig. 3 shows a sample snippet of the sanskrit labels entirely converted to the tokens. We then assigned IDs for each tokenized transcript label based on a custom vocabulary created for this project. To ensure uniformity across the samples, we implemented padding techniques. For the audio data, we padded shorter samples with zeros to match the length of the longest sample. Similarly, for the labels, we padded shorter transcripts to the maximum length in the batch. Fig. 4 shows a sample audio which has been padded with silence.

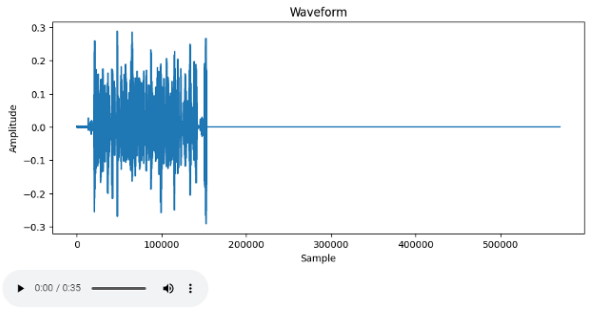

Fig. 4. Sample of waveform of an audio with padding.

Finally, we split the dataset into training and test sets using an 80/20 split. We converted the input values (audio data) and labels to tensors for compatibility with PyTorch, and mapped and converted the processed dataset into a DatasetDict for structured handling during training. These comprehensive preprocessing steps ensured the dataset was clean, consistent, and formatted correctly for training the Wav2Vec2 model.

3) Data Augmentation: For this project, explicit data augmentation techniques were not applied. The focus was on ensuring the dataset was correctly preprocessed and structured to leverage the capabilities of the Wav2Vec2 model effectively. The inherent noise and variability in the speech dataset provided a natural form of data augmentation, helping the model generalize better to unseen data.

If future improvements are sought, data augmentation techniques such as adding background noise, varying the speed and pitch of the audio, and applying random shifts could be considered to further enhance the model's robustness and performance.

B. Wave2Vec2 Model Architecture

The Wav2Vec2ForCTC model from the Hugging Face transformers library was employed for the task of automatic speech recognition (ASR) on Sanskrit audio data. The Wav2Vec2.0 model is well-suited for this task as it is designed to handle raw audio inputs and convert them into textual transcriptions using a series of convolutional and transformer layers optimized for speech processing. The overall architecture of the

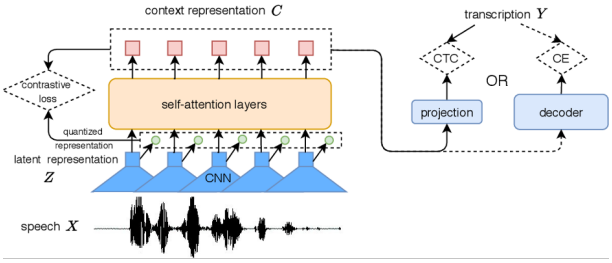

Fig. 5. Architecture of Wave2vec2 model.

Wav2Vec2ForCTC model can be visualized in the Fig. 5.

The model takes the raw audio waveform (X) as input and applies a Convolutional Neural Network (CNN) to extract latent representations (Z). The latent representations are converted into discrete representations using quantization, which serves to decrease redundancy and capture the most pertinent characteristics of the audio stream. The quantized representations undergo self-attention layers, which acquire contextual representations (C) by focusing on various segments of the input sequence. This enables the model to comprehend distant connections and associations within the audio data. During the training process, a contrastive loss function is utilized to compare the latent representation (Z) with the context representation (C). This helps to enhance the learning of reliable representations by effectively differentiating between genuine and counterfeit audio samples.

The context representation (C) is subsequently transformed to produce the ultimate transcription (Y) using either Connectionist Temporal Classification (CTC) or Cross-Entropy (CE) methodologies. The model's output is the transcription (Y), which is the anticipated text that corresponds to the input speech. The Wav2Vec2 model architecture is particularly efficient for Automatic Speech Recognition (ASR) applications. It utilizes self-supervised learning and self-attention layers to comprehend the audio environment, hence enhancing transcription accuracy. The model is very flexible, able to handle a wide range of speech tasks and easily adaptable to multiple languages and datasets.

C. Model Architecture Used in the Project

The key components of the Wav2Vec2ForCTC model architecture include a Feature Extractor, Positional Encoding, Transformer Encoder, Projection Layer, and CTC Loss Layer. The Feature Extractor is a Convolutional Neural Network (CNN) comprising 7 convolutional layers with varying kernel and stride sizes, responsible for extracting latent representations from the raw audio waveform inputs. To maintain the temporal coherence of the speech representations, convolutional positional encodings are employed, which add information about the position of each frame to the extracted features. The processed features from the CNN are then passed through a Transformer Encoder, which consists of 12 transformer blocks. Each transformer block has a hidden size of 768, 12 attention heads, and a feedforward layer size of 3072. Dropout

of 0.1 is applied at various stages to prevent overfitting. The transformer encoder is designed to model long-range dependencies in the audio data.

The final step is a Projection Layer, which is a fully connected layer that projects the hidden states from the transformer encoder to the vocabulary size for Connectionist Temporal Classification (CTC) decoding. The CTC Loss Layer uses the CTC loss function to calculate the loss between the predicted sequences and the target transcriptions, allowing the model to learn without requiring pre-segmented training data.

The diagram Fig. 6 illustrates the flow of the model, starting from the raw audio input, passing through the convolutional feature extractor, positional encoding, transformer encoder, projection layer, and finally, the CTC loss layer to produce the predicted transcription.

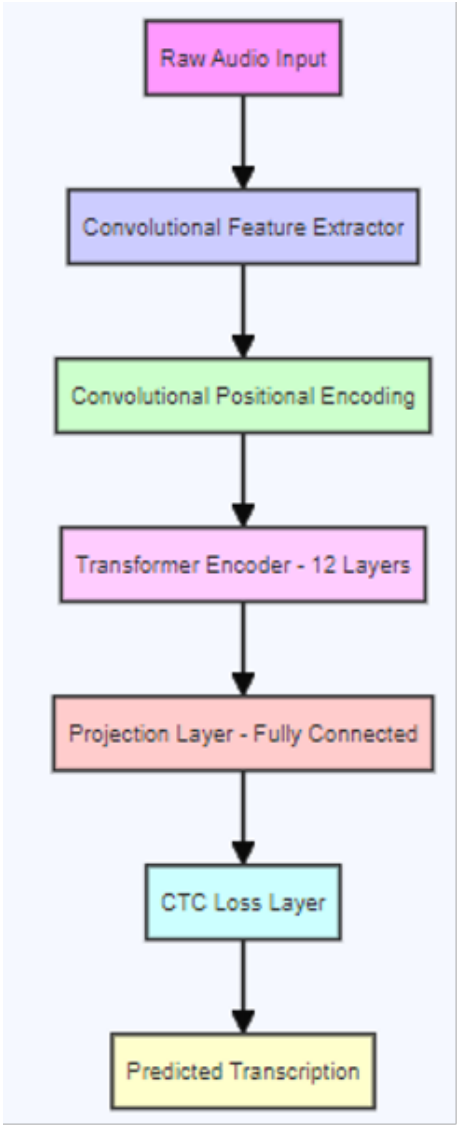

Fig. 6. Flow diagram.

The design choices for this architecture include the use of convolutional layers for effective feature extraction from the raw audio signal, the transformer-based encoder for modeling long-range dependencies, and the CTC loss function to handle the alignment between the audio frames and the target transcriptions. This comprehensive model architecture allows the Wav2Vec2ForCTC model to accurately transcribe spoken Sanskrit into written text, leveraging the power of deep learning and transformer-based models for high-quality automatic speech recognition.

D. Experimental Setup

TABLE I
HYPERPARAMETERS AND OPTIMIZATION

Hyperparameter	Value
Learning Rate	1e-5
Batch Size	2 per device
Gradient Accumulation Steps	8
Warmup Steps	200
Max Steps	20,000
Dropout	0.1
Activation Function	GELU
Normalization	Layer normalization with epsilon 1e-5
Evaluation Strategy	Steps
Per Device Eval Batch Size	2
Save Steps	250
Eval Steps	250
Logging Steps	250
Gradient Checkpointing	True
FP16	True
Load Best Model at End	True
Metric for Best Model	WER (Word Error Rate)
Greater is Better	False
Optimization Algorithm	AdamW Optimizer

The hyperparameters used in our experiments were carefully selected based on empirical evidence from similar automatic speech recognition (ASR) tasks and further fine-tuned to ensure stable convergence during the training process.

The learning rate was set to 1e-5, chosen to balance between effective optimization and stable convergence. The batch size was set to 2 per device, which allowed for efficient GPU utilization while considering memory constraints. To further improve gradient estimates without exceeding memory limits, we employed gradient accumulation with 8 steps.

To stabilize the initial training phase, we utilized a warm-up period of 200 steps, gradually increasing the learning rate. The maximum number of training steps was set to 20,000, ensuring the model had sufficient time to capture the complex patterns in the data.

To prevent overfitting, a dropout rate of 0.1 was applied at various stages of the model. The smooth activation curve of the Gaussian Error Linear Unit (GELU) made it an excellent choice for the activation function since it promotes improved gradient flow and model convergence. By normalizing the activations of each layer, layer normalization with an epsilon of 1e-5 was utilized to preserve the model's stability.

The evaluation strategy involved assessing the model's performance at specified steps during training to monitor progress. The per-device evaluation batch size was set to 2 to manage memory usage during validation. Model checkpoints were

saved every 250 steps, and the model was evaluated at the same interval to track its performance. Training progress was logged every 250 steps for monitoring and debugging purposes.

To further optimize memory usage, we enabled gradient checkpointing, which saves memory during training by allowing intermediate activations to be recomputed. Additionally, we utilized mixed-precision training (FP16) to speed up training and reduce memory usage.

By keeping the weights from getting too big, the AdamW optimizer—a version of the Adam optimizer with weight decay correction—was used to improve generalization.

Word Error Rate (WER) was the main parameter used to assess the model's performance and choose the best model; a lower WER denotes better transcription accuracy.

TABLE II
HARDWARE RESOURCES

Hardware	Specification
Processor	High-performance processors in Google Colab Pro
Memory	83.5 GB RAM
Graphics Card	NVIDIA A100 GPU with 40 GB GPU RAM
Disk	200 GB

TABLE III
SOFTWARE LIBRARIES AND PURPOSE

Software	Purpose
Pandas	Data manipulation and handling dataframes
Torchaudio	Loading and processing audio files
PyTorch	Core deep learning framework for model training and inference
Transformers (Hugging Face)	Model architecture, tokenizer, and feature extractor
Datasets (Hugging Face)	Handling and processing datasets
Scikit-learn	Train-test split
IPython	Displaying audio during the notebook environment
Numpy	Numerical computations and data manipulation
Editdistance	Calculating the word error rate (WER) metric

IV. RESULTS

A. Evaluation Metrics

The primary metric used to evaluate the performance of the model is the Word Error Rate (WER). WER is a common metric in speech recognition that measures the number of errors in the transcriptions produced by the model.

Fig. 7 shows how WER is calculated based on the model output and the ground truth.

It is mathematically calculated as shown in Fig. 8.

The results of the experiments were evaluated at regular intervals throughout the training process, specifically at every 250 steps up to a total of 20000 steps. The key metrics tracked were Training Loss, Validation Loss, and Word Error Rate (WER). The following table summarizes these metrics at each evaluation step are shown in table IV.

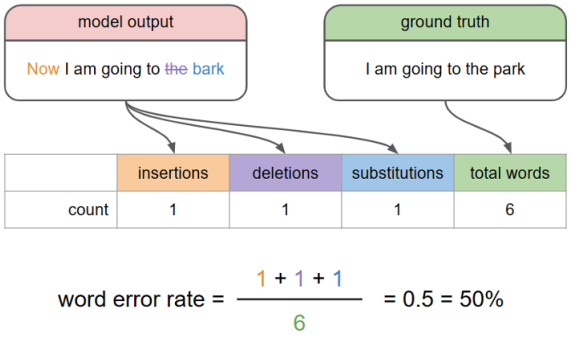

Fig. 7. Example of a Word Error rate calculation.

$$\text{WER} = \frac{\text{Substitutions+Insertions+Deletions}}{\text{Total Words in Reference}}$$

Fig. 8. Formula of Word Error Rate

B. Results Analysis

The model is learning and getting better at both the training and validation sets, as seen by the declining trends in the training and validation losses across the steps. The model appears to be generalizing well to the validation data and is not overfitting considerably, as evidenced by the small difference between the training and validation losses.

As training went on, the Word Error Rate (WER) readings gradually dropped from their high starting point (which was near to 1.0). Nonetheless, the WER values persisted in being comparatively high, suggesting that the transcription accuracy of the model was subpar. The small variations in WER across evaluation phases imply that additional architectural or hyperparameter tweaking may be required to improve performance.

The preprocessing pipeline ensures consistency and compatibility with the needs of the model by efficiently preparing the dataset. Using the Wav2Vec2 architecture makes use of cutting-edge voice recognition methods, giving precise transcriptions a solid base. Frequent evaluations throughout training provide ongoing performance monitoring of the model, enabling prompt interventions when necessary.

The limited processing power available during training is the main cause of the high WER. Due to memory limitations, a small batch size has to be used, which hinders the model's ability to generalize well across the dataset and results in less than ideal performance and a higher WER. Furthermore, a large amount of computational resources are needed for the model's training with a large batch size and the lengthy preprocessing stages, which may not be available to all users.

C. Future Improvements

A higher batch size would be possible with more computing power, which is anticipated to greatly enhance the model's generalization capacity and lower the WER. Additional adjustments to hyperparameters like learning rate, batch size, and dropout rates may also aid in enhancing the model's

TABLE IV
EVALUATION METRICS AT DIFFERENT TRAINING STEPS

Step	Training Loss	Validation Loss	WER
250	3.273500	3.256672	0.999579
500	3.252100	3.239619	1.000000
750	3.199500	3.156237	0.999813
1000	3.133800	3.084471	0.999673
1250	3.097200	3.050990	1.003555
1500	3.069300	3.022552	0.999953
1750	3.045800	3.000278	1.000187
2000	3.032900	2.990549	0.999953

functionality. More data collection (such as 50–60 hours of audio data) can have a big influence on the model's capacity to generalize and improve WER for jobs involving speech recognition.

V. CONCLUSION

The objective of this project was to create a cutting-edge speech recognition model for the Sanskrit language utilizing the advanced Wav2Vec2 architecture. This work has made significant contributions in several areas. Firstly, a strong preprocessing pipeline has been developed to effectively handle the raw audio data and corresponding transcripts. Secondly, the Wav2Vec2 model has been successfully implemented for transcribing the Sanskrit language, which lacks technological help. Lastly, the training process has been closely evaluated, with tracking of metrics such as Training Loss, Validation Loss, and Word Error Rate (WER). This has provided valuable insights into the model's ability to learn and generalize. The importance of this research rests in its capacity to close the current disparity in ASR technologies for the Sanskrit language, facilitating a more accessible and precise conversion of Sanskrit speech into written form. This effort also contributes to the conservation and broader distribution of historic manuscripts and literature. This project has the capacity to significantly influence educational and cultural preservation efforts by utilizing advanced technology to improve the accessibility of this historically and linguistically significant language.

The outcomes of this study, albeit demonstrating a decline in training and validation losses, revealed somewhat elevated WER values. The reason for this result might be ascribed to the constraints in computational power, as the model was trained using a limited batch size due to limitations in memory. Nevertheless, the Wav2Vec2 model has shown its capacity to handle and acquire knowledge from Sanskrit speech data, indicating its potential efficacy given sufficient computer resources. These findings highlight the need for additional optimization of hyperparameters, augmentation of data, and potentially more sophisticated architectural modifications to improve the model's performance.

In order to further develop this study, future efforts could concentrate on ensuring access to enhanced computational resources. This would enable the utilization of bigger batch sizes and perhaps more intricate models, resulting in improved performance and reduced Word Error Rate (WER). In addition, doing thorough hyperparameter tuning experiments can aid in determining the ideal configurations for the learning rate, batch size, and other parameters to enhance the accuracy and dependability of the Sanskrit voice recognition model.

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