# Sanskrit Audio-To-Text Transcription

#### **Team Members:**

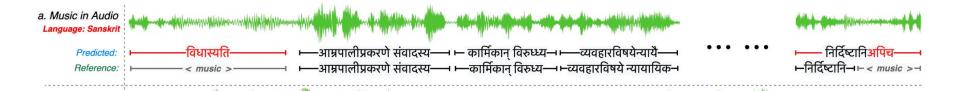
Venu Anupati, Mounika Vempalli Sai Saran Parasa

### Problem Statement

- Taking one step forward to bridge the gap between ancient Sanskrit and modern English
- Addressing the challenge of limited technological support for Sanskrit
- Make Sanskrit's rich heritage accessible in today's world
- Developing a deep learning system for accurate Sanskrit Audio to text transcription

### Dataset Collection

- Audio data from the News Services Division of All India Radio.
- Total duration of 27 hours with over 9700 samples with each audio ranging from 3 seconds to 35 seconds.
- Utilizing a subset of data from a study on mining audio and text pairs from public sources to improve Automatic Speech Recognition (ASR) systems for low-resource languages.



# Data Understanding

#### **Audio Data:**

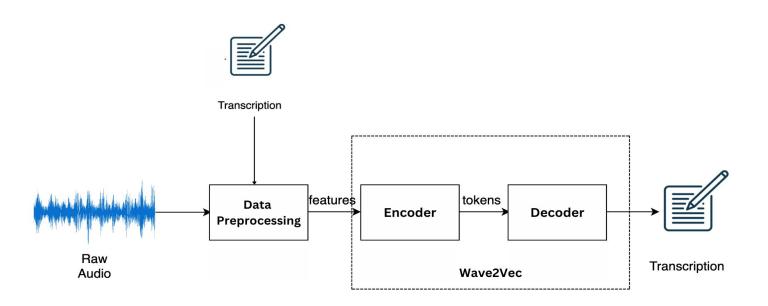
- Audio files are stored in separate folders, each corresponding to a news bulletin.
- The audio files are in wav format with a sampling rate of 16KHz.
- Filenames are structured with sentence IDs, such as sent\_1.wav, for easy reference to their transcripts.

# Data Understanding

#### **Transcripts:**

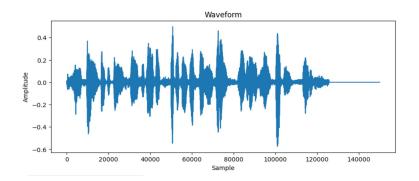
- Audio paths and Transcripts are stored in train.tsv, train.wrd
- The train.tsv file contains the relative path to an audio file and the number of frames in the audio, with an absolute path header.
- Train.wrd contains the word-level transcriptions corresponding to the audio files in train.tsv.

## Architecture



# Data Preprocessing

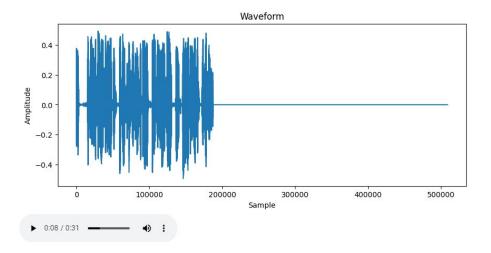
- Audio Loading: Loaded audio files and extract speech arrays and sample rates to prepare for analysis.
- Transcript Tokenization: Tokenized transcripts to convert them into input IDs for model processing..



Transcript: [' जीविंशित इति राष्ट्राणि वैश्विकार्थिकसमाह्णाय ऐक्यमत्येन साहाय्याचरणाय प्रतिबद्धानि', ' प्रधानमन्त्रिणा स्ट्रेलियाया प्रधानमन्त्रिणा स्कटमिरिसनवर्येण साकमिप वार्ताकृता यत्र क्रीडाखनन प्रौद्योगिकीरक्षासमुद्रस् labels: [' ज ी व ि ं श त ि | इ त ि | र ा ष ् ट ् र ा ण ि | व े श ् व ि क ा र ् थ ि क स म ा ह ् व ा न ा य | ऐ क ् य म त ् य े न | स ा ह ा य ् य ा च र ण ा य | ए Transcript: [' मूढे पाषाणखण्डेषु रत्ससंज्ञाविधीयते', ' राष्ट्रणा अद्यान विदेशमन्त्रिणे अरुणजेटलिने अद्धाञ्जलि समर्पितः', ' तस्मै अन्तिम अद्धाञ्जलि प्रदातुं दलस्य नेतारः कार्यकर्ताश्च उपस्थिता अवर्तन्त् labels: [' मूढ ढे | प ा ष ा ण ख ण ् ड े ष ु | र त ् न स ं ज ् ञ ा व ि ध ी य त े |', ' | र ा ष ् ट ् र े ण | अ द ् य | व र ि ष ् ठ भ ा ज प ा न े त ् र े | प ् र ा Transcript: [' प्रधानमन्त्री प्रधानमन्त्री नरेन्द्र मोदी अद्य स्वतंत्रता सेनान्या उपप्रधानमन्त्रिचरस्य च बाबू जगजीवनरामस्य द्वादशोत्तर शत तमीं जयन्तीम् उपलक्ष्य तस्मै अद्धाञ्जलि समापर्यत्', ' कोविडनवदशाख्यं महामारीं 1 labels: [' प ् र ध ा न म न ् त ् र ी | प ् र ध ा न म न त त र ी | प र ध ा न म न त त र र व ा म न र व ए य ए र ध ा न म रात्राक्षराम्पत्रियाणा विधानसभा निर्वाचनप्रक्रियान्तर्गतं अष्टाशीत्यधिकद्विशतमासनानाञ्कृते महाराष्ट्रे अथ च नवत्यासनेषु हरियाणा विधानसभानिर्वाचनेभ्यो सोमवासरे मतदानं अनुष्ठितमासीत्', ' जम्मू जम्मूकश्मीरे labels: [' म ह ा र ा ष ् ट ् र ह र ि य ा ण ा | व ि ध ा न स भ ा | न ि र ् व ा च न प र र क र र ि य ा न ् त र ए य ल व द श व विधियतुं शंघाई सहयोग संघटनियोश हितानेष्ठ सहयोग संघटन सहयोग सहयोग संघटन सहयोग संघटन सहयोग सहयोग सहयोग सहयोग सहयोग

# Data Preprocessing

- Audio Padding: Padded audio samples to a specified maximum length to ensure uniformity in the dataset
- Label Padding: Padded labels to a specified maximum label length for consistency in model training.
- **Tensor Conversion:** Converted input values to tensors needed for compatibility with deep learning frameworks.
- Dataset Preparation: Input values and labels are correctly formatted and ready for model training.



## Wav2Vec2 Model

Model Type: Wav2Vec2ForCTC, based on the wav2vec framework developed by Facebook

**Advanced Architecture:** Utilizes a robust convolutional neural network to process raw audio data, extracting rich, contextual features without the need for manual feature engineering.

**CTC for Alignment:** Employs Connectionist Temporal Classification (CTC) to align speech inputs with their corresponding textual outputs, enabling effective transcription without requiring frame-wise alignment.

**Self-Supervised Learning:** Leverages self-supervised pre-training on vast amounts of unlabelled audio data, followed by fine-tuning on smaller annotated datasets, enhancing its ability to generalize across diverse linguistic contexts.

**Optimized Performance:** Designed with attention mechanisms and dropout strategies to enhance focus on relevant audio features and prevent overfitting, making it highly efficient for real-world applications.

# Model Training

#### **Training Configuration**

- Directory: Outputs and models saved to "/content/drive/MyDrive/sanskrit/ABC"
- Batch Size: 2 per device during training and evaluation (Kept it 2 based on the resource available)
- Learning Rate: Starts at 1e-5, with warmup over 200 steps

#### **Optimization Techniques**

- Gradient Accumulation: 8 steps to effectively handle larger batch sizes
- Gradient Checkpointing: Enabled for memory efficiency
- Precision Training: FP16 enabled to accelerate computations

## Model Training

#### Checkpointing

- Save Interval: Model and checkpoints saved every 250 steps
- Load Best Model: Automatically reloads the best model at the end of training

#### **Training Execution**

- Max Steps: Limited to 20000 to constrain the training period
- Trainer Setup: Utilizes Hugging Face's Trainer class for streamlined workflow
  - train\_dataset for training
  - eval\_dataset for validation

# Hyperparameter Tuning

Batch size (per\_device\_train\_batch\_size, per\_device\_eval\_batch\_size): 2 (Kept as 2 to fit in with the resources available)

Learning rate: 1e-5

Training iterations: warmup\_steps=200, max\_steps =20000

Hardware optimization settings: gradient\_checkpointing= Enabled

#### Evaluation settings:

- Evaluation\_strategy: Steps = Steps determines that the evaluation will be performed at regular intervals based on the number of steps
- save\_steps = 250
- Eval\_steps = 250
- Load\_best\_model\_at\_end
- Metric\_for\_best\_model: greater\_wer\_is\_better=False

### Model Evaluation

Evaluation Strategy: Conduct evaluations at regular steps

Metrics: Word Error Rate (WER) as the key metric

Best Model Criteria: Select model with lowest WER

As of now the WER is very high, meaning the predictions are not as per expectations.

#### Challenges:-

- High computational powered resources
- Limited Labeled Data
- Unique Phonetics or Distinct Sounds
- Language Structure (Grammar, Syntax etc)
- Computational Resources
- Language-Specific Adaptations

### Future Work

- Try with batch size of 16 or 32 by putting high end resources, which can help the model to generalize better and give good predictions.
- This project can be expanded to transcribe from Sanskrit Audio to English text.
- Expanding the model to transcribe other less common languages, using insights from Sanskrit-to-English transcription to create a more versatile system.
- Create a system for live events or speech-to-text applications that transcribes speech in real-time for non english languages.

## Conclusion

Our project is not just about transcribing ancient words into modern text, it's about preserving a language's legacy and making it accessible to generations to come

## Thank You