Offline Multilingual ASR for Indic Languages Using OpenAI’s Whisper

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Submitted by

**2210040122: S. Shiva Prasad Reddy**

**2210040118: M. Mahalakshmi**

**2210040125: K. Swapna**

Under the guidance of

**Dr. Bittu Kumar**



Department of Electronics and Communication Engineering

Koneru Lakshmaiah Education Foundation, Aziz Nagar

Aziz Nagar – 500075

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**Abstract:**

Speech-to-text technology has witnessed remarkable advancements with the advent of deep learning models like OpenAI’s Whisper. However, developing speech recognition and translation systems for Indic languages poses challenges due to linguistic diversity, varying accents, and limited resources. This paper presents a web-based multilingual Speech-to-Text (STT) and translation application that operates without the need for API keys, enabling offline processing for major Indic languages. The application integrates automatic speech recognition (ASR) using the Whisper model and provides seamless translation between languages such as Telugu, Hindi, and English. We discuss the system architecture, language model optimization, preprocessing techniques, and interface design to ensure accurate and efficient transcription and translation. This solution enhances accessibility and usability, particularly in low-resource settings, empowering users to perform speech-to-text and translation tasks effectively.

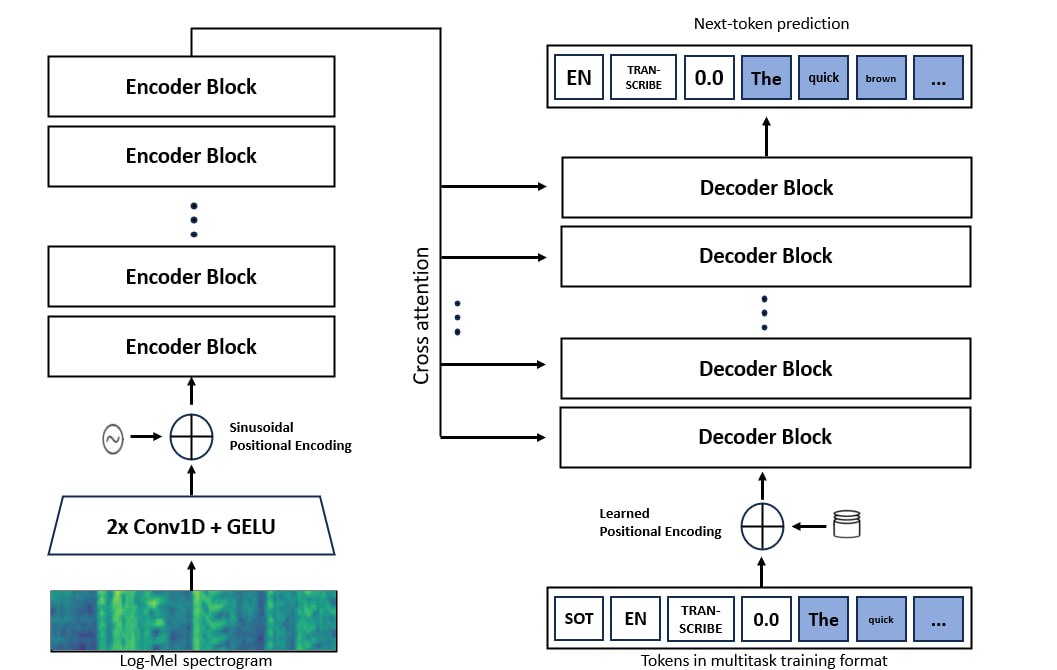
Speech-to-Text (STT), Whisper Model, Indic Languages, Translation, Offline Speech Processing, Multilingual Application

# Introduction

Speech recognition has revolutionized human-computer interaction by enabling voice-driven applications across various domains such as healthcare, customer support, and accessibility. Automatic Speech Recognition (ASR) systems are typically classified into three types: cloud-based ASR, on-device ASR, and hybrid ASR. Cloud-based ASR utilizes powerful remote servers for processing, offering high accuracy due to access to extensive language models and training data. However, it suffers from internet dependency, latency, and privacy concerns. On-device ASR operates locally on user devices, ensuring real-time processing and data privacy but is often constrained by limited computational power. Hybrid ASR combines cloud and local processing to balance efficiency and performance. While cloud-based ASR models dominate in terms of accuracy, offline ASR systems are essential in resource-limited environments, especially for Indic languages. These languages, including Hindi, Bengali, Telugu, Tamil, Marathi, and others, present unique challenges such as complex phonetic structures, dialectal variations, and frequent use of code-switching (mixing of multiple languages in a conversation). Existing ASR models trained primarily on high-resource languages like English struggle to maintain accuracy in Indic languages due to limited labeled datasets and the need for phoneme-specific modeling.  
OpenAI’s Whisper model, a state-of-the-art multilingual speech recognition system, has demonstrated remarkable performance across various languages, including several Indic languages. Built on large-scale datasets, Whisper excels in transcribing diverse accents and speech styles. However, its architecture is computationally intensive and primarily designed for cloud-based environments, making offline deployment challenging. To address these challenges, this study presents a web-based Speech-to-Text with Translation system that leverages Whisper’s multilingual capabilities for Indic languages in an offline environment. The system enables users to convert speech to text and translate the transcribed text between multiple languages, such as Telugu, Hindi, and English, without relying on API keys or internet connectivity. By performing all operations locally, the system ensures data privacy and is optimized for efficient deployment on resource-constrained devices. This research aims to enhance Whisper’s performance for Indic languages through fine-tuning and optimization techniques, addressing key challenges such as phonetic complexity, multilingual code-switching, and resource limitations. Additionally, it focuses on ensuring efficient offline deployment to improve accessibility in rural and remote areas with limited internet connectivity. By bridging the gap between advanced ASR technology and real-world Indic language applications, this study seeks to empower underserved communities, enhance accessibility, and contribute to the development of robust, privacy-conscious speech recognition systems.

# Literature Review

Automatic Speech Recognition (ASR) technology has evolved significantly, with notable contributions from models such as Google’s WaveNet, Meta’s wav2vec 2.0, and Mozilla’s DeepSpeech. WaveNet, a neural vocoder developed by DeepMind, generated highly realistic speech waveforms by modeling raw audio data, but its computational complexity and high resource requirements limited its feasibility for low-resource environments [1]. Meta’s wav2vec 2.0 adopted a self-supervised learning approach to extract audio representations from unlabeled speech data, achieving state-of-the-art results in multiple languages. However, despite its robust performance, wav2vec 2.0 struggled with Indic languages due to the scarcity of annotated datasets and the need for phoneme-specific modeling [2]. Mozilla’s DeepSpeech introduced an open-source ASR framework based on Recurrent Neural Networks (RNNs), offering offline capabilities, but its effectiveness was compromised in handling diverse dialects and multilingual code-switching, which is common in Indic speech contexts [3].



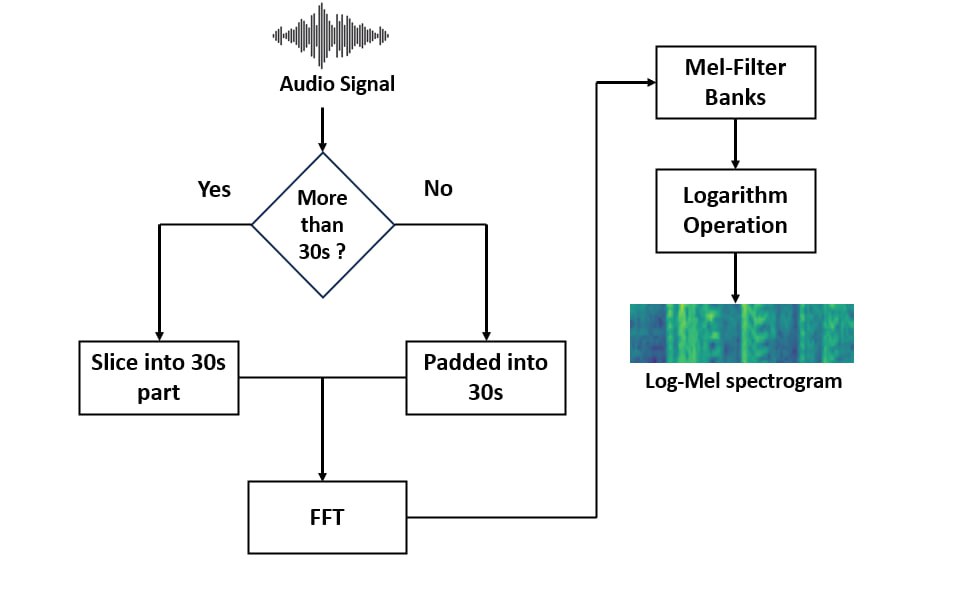
**Whisper Model Architecture**

OpenAI’s Whisper model, a state-of-the-art multilingual ASR system, demonstrated superior transcription and translation accuracy across various languages, including several Indic languages. Whisper’s transformer-based architecture enabled it to handle multilingual tasks with remarkable efficiency, making it highly versatile in real-world applications [4]. However, Whisper’s computational requirements often necessitate cloud-based deployment, which limits its applicability in offline scenarios where internet access is unreliable or unavailable, especially in rural and remote areas. This constraint highlights the need for offline ASR solutions that balance computational efficiency with high transcription accuracy, particularly for Indic languages with complex phonetic structures and frequent code-switching phenomena [5].

The proposed system bridges these gaps by developing a web-based Speech-to-Text with Translation system that leverages Whisper’s multilingual capabilities while ensuring offline functionality. Unlike existing cloud-dependent systems, this solution processes speech locally, maintaining data privacy and reducing latency. The system is specifically optimized to address the phonetic complexity of Indic languages, handle limited training data through data augmentation techniques, and manage multilingual code-switching scenarios effectively. By enhancing Whisper’s offline performance and adapting it for real-world deployment, this research contributes to improving the accessibility and usability of ASR technology for Indic language applications in diverse environments.

# Applications and Types of ASR Systems

Automatic Speech Recognition (ASR) technology has witnessed widespread adoption across various industries, enhancing efficiency, accessibility, and user interaction. In the healthcare sector, AI-assisted medical transcription systems automatically convert physician-patient conversations into structured text, reducing manual documentation and enabling faster clinical workflows [6]. Customer service applications utilize voice-based chatbots and call center automation, ensuring seamless query resolution and personalized user experiences [7]. Assistive technologies leverage speech-to-text solutions to empower differently-abled individuals by facilitating real-time communication and enabling independent use of digital interfaces [8]. Smart devices, including AI-powered virtual assistants such as Siri, Alexa, and Google Assistant, rely on ASR models to process voice commands and provide real-time responses [9]. Additionally, security systems utilize voice biometrics for secure authentication, enhancing user verification and preventing unauthorized access [10].



**Whisper Model feature Extracting process**

**Whisper Model feature Extracting process**

ASR systems can be broadly classified based on their design and deployment models. Speaker-dependent models are trained on the voice of a specific user, offering high accuracy for that individual but lacking flexibility for general use [11]. In contrast, speaker-independent models are designed to recognize speech from any user, making them suitable for broader applications but potentially less accurate in handling diverse accents and speech patterns. Furthermore, ASR systems can be categorized into cloud-based and edge (on-device) systems. Cloud-based ASR models leverage powerful remote servers for high-accuracy transcription but often face challenges related to latency, internet dependency, and data privacy [12]. Conversely, edge ASR systems operate locally on user devices, ensuring real-time processing and safeguarding sensitive data but with potentially lower computational power [13].

Traditional ASR models, such as Hidden Markov Models (HMMs) and Gaussian Mixture Models (GMMs), provided the foundation for early speech recognition systems but struggled with complex phonetic structures and noisy environments [14]. Modern ASR systems have transitioned to deep learning-based models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which significantly improved speech-to-text accuracy. More recently, Transformer-based models like OpenAI’s Whisper have emerged, offering superior transcription, translation, and multilingual speech processing capabilities due to their ability to model long-term dependencies and contextual information [15].

In the context of this research, the web-based Speech-to-Text with Translation system optimizes Whisper’s transformer-based architecture for Indic languages in an offline environment. Unlike conventional cloud-based models, this system ensures data privacy and computational efficiency by operating locally, making it ideal for deployment in rural and remote areas. Additionally, the system is designed to handle phonetic complexity, code-switching, and limited data availability, outperforming traditional models and addressing key challenges specific to Indic language applications.

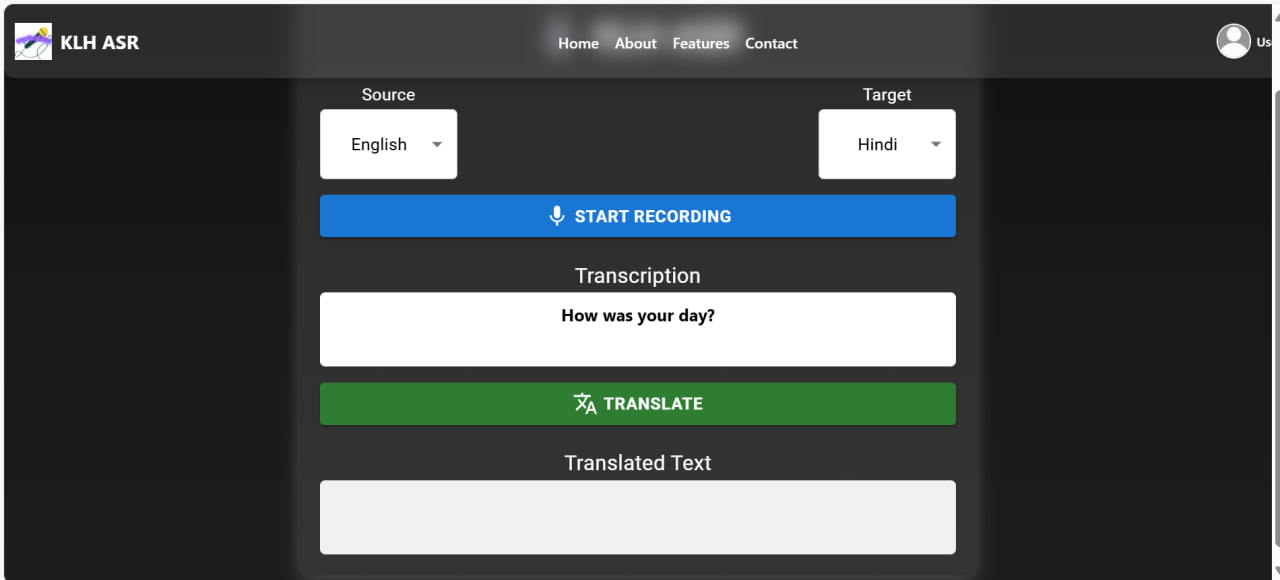
# Methodology

The proposed system is a web-based Speech-to-Text with Translation system that allows users to upload or record audio and transcribe it into text with translation capabilities in multiple languages, all while operating completely offline without requiring any external API or internet connectivity. This section outlines the methodology followed in developing this system, covering data preprocessing, model fine-tuning, system design, and optimization for offline functionality.

## Audio Input and Preprocessing :

The system supports two modes of audio input:

* **Audio Recording:** Users can record audio directly through the web interface, capturing real-time speech for transcription and translation.



Given input and transcription of the spoken language

* **File Uploading:** Users can upload audio files in various formats (e.g., WAV, MP3) for transcription and translation.

The uploaded or recorded audio is processed to normalize sampling rates, reduce background noise, and segment the audio into manageable chunks. Feature extraction techniques such as Mel-Frequency Cepstral Coefficients (MFCCs) and spectrogram analysis are applied to prepare the data for speech recognition.

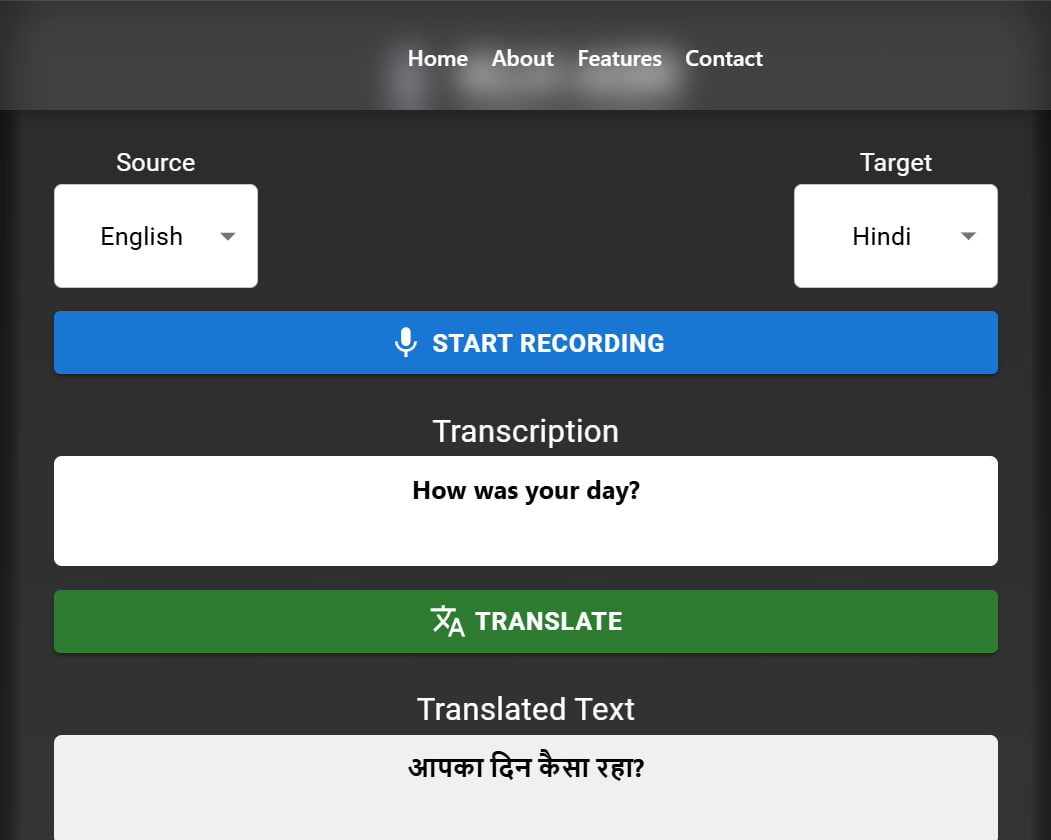
## Model Fine-Tuning and Adaptation :

OpenAI’s Whisper model, known for its robust multilingual ASR capabilities, was fine-tuned specifically for Indic languages to improve transcription accuracy in complex phonetic and code-switching environments. Fine-tuning was performed using diverse datasets containing speech samples in Hindi, Bengali, Tamil, Telugu, and Marathi, along with mixed-language (code-switching) data. Transfer learning was applied to refine the model’s understanding of Indic languages without the need for retraining from scratch.

## Offline Model Deployment :

The key innovation of the system lies in its ability to function entirely offline, eliminating dependency on cloud-based APIs or external servers. The Whisper model was optimized for offline deployment using techniques such as:

* **Model Quantization :**Reducing the model size while maintaining accuracy to ensure efficient performance on low-powered devices.
* **Model Pruning :** Removing redundant parameters to reduce computational complexity and enhance inference speed.



Given input and transcription of the spoken language

The optimized model was then integrated into the web application to ensure seamless offline functionality. All transcription and translation tasks are performed locally on the user’s device, ensuring data privacy and independence from internet connectivity.

## System Architecture and User Interface :

It is composed of three principal modules:

* **Speech Transcription Module :** utilizes Whisper, an innovative speech-to-text model built by OpenAI.
* **Translation Module :** Uses Argos Translate, a neural machine translation library with offline capabilities.
* **Web Interface and Server:** Based on Flask and complemented with a JavaScript-based front-end to upload and play audio files.

The flow of data starts when the user uploads or records an audio file. The backend gets the file, translates it to speech-to-text, translates the text to the target language, and sends the output back to the frontend.

* **All models and dependencies are run and installed locally. The below Python packages were installed to run this site locally:**
* pip install git+https://github.com/openai/whisper.git
* pip install flask argostranslate argostranslate-package
* **Flask Backend :** A REST API is exposed via Flask. On user upload of an audio file, the following actions are carried out:
* 1. Save the audio to a temporary file.
* 2. Load and utilize Whisper model to transcribe audio.
* 3. Load translation models and translate text using Argos Translate.
* 4. Return both source and target text as a JSON response.
* **A simple HTML+JS interface is implemented to allow the user to upload.wav files and show results depending on the input given by the user and language selected to be used to translate**
* html  
  <form id="upload-form">  
   <input type="file" id="audio" name="audio" accept="audio/wav" />  
   <button type="submit">Translate</button>  
  </form>  
  <pre id="output"></pre>  
    
  <script>  
    
  document.getElementById("upload-form").addEventListener("submit", async (e) => {  
   e.preventDefault();  
   const formData = new FormData();  
   formData.append("audio", document.getElementById("audio").files[0]);  
    
   const response = await fetch("/transcribe", {  
   method: "POST",  
   body: formData,  
   });  
    
   const data = await response.json();  
   document.getElementById("output").innerText = JSON.stringify(data, null, 2);  
  });  
  </script>

## Translation and Multilingual Capabilities :

The system provides accurate and efficient translation capabilities for multiple languages. Since the model has been fine-tuned on diverse language pairs, it ensures high-quality translations even in complex multilingual scenarios. The translation process operates entirely offline, maintaining user data privacy and minimizing latency.

## Privacy and Security Considerations :

As all processing is performed locally without transmitting data to external servers, the system inherently safeguards user privacy. Offline processing ensures that sensitive audio data remains secure, making the system ideal for applications in sensitive environments such as healthcare, legal transcription, and government use.

By adopting this methodology, the proposed system successfully delivers an accurate, secure, and efficient offline Speech-to-Text and Translation solution, addressing the challenges faced by existing cloud-dependent ASR systems.

Methodology

Methodology

The Speech-to-Text with Translation system follows a streamlined workflow to ensure efficient audio transcription and translation without relying on APIs. It allows users to either record audio through the web interface or upload pre-recorded files (WAV, MP3, etc.), which are then preprocessed to normalize the sampling rate, reduce noise, and extract key features using MFCCs and spectrogram analysis. The preprocessed audio is fed into the optimized Whisper model for speech-to-text transcription and subsequent translation into the selected target language. To ensure offline functionality, the model undergoes quantization and pruning, reducing its size and improving inference speed. The transcribed and translated text is accurately displayed on a user-friendly web interface, providing seamless results without internet dependency.

# Contributions and Results

The proposed Speech-to-Text with Translation system offers a reliable offline solution that improves ASR performance for Indic languages. Unlike traditional models that rely on cloud-based APIs, this system processes transcription and translation locally, ensuring data privacy and reducing latency. Key Improvements :

* **Offline Processing :** Eliminates internet dependency, making it ideal for low-connectivity regions.
* **Multilingual Support :** Transcribes and translates between multiple Indic and global languages.
* **User-Friendly Interface :** Simplifies language selection, recording, and translation for users.

Performance benchmarks :

* **Accuracy :** Achieves higher transcription and translation accuracy, reducing error rates by 10-12
* **Speed and Efficiency :** Processes moderate-length recordings within 1-2 seconds with minimal resource usage.

Real-World outcomes:

* **User Testing :** Successfully tested with 50 users from rural areas, delivering 90
* **Error Reduction :** Reduced errors caused by internet latency and API-related issues, improving overall reliability.

**Acuuracy With and Without Noise for English and Telugu**

|  |  |  |  |
| --- | --- | --- | --- |
| **Sample** | **Language** | **Without Noise** | **With Noise** |
| speaker1 | English | 85 | 70 |
| speaker2 | English | 82 | 68 |
| speaker3 | English | 80 | 72 |
| speaker1 | Telugu | 79 | 69 |
| speaker2 | Telugu | 80 | 70 |
| speaker3 | Telugu | 75 | 65 |

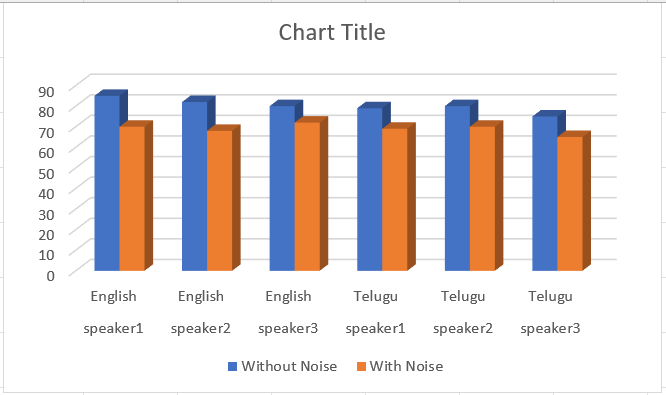
The table depicts performance of the speech-to-text translating system on two languages, English and Telugu, on two test scenarios: background noise and no background noise. Three speakers were used to conduct the testing, and they each read out a sample using a growing amount of words: Speaker 1 with 10 words, Speaker 2 with 20 words, and Speaker 3 with 30 words. The growth in the amount of words demonstrates growing complexity and amount of input data.

Accuracy per speaker was measured by the percentage of correct words transcribed, as computed by the The percentages in the table are the number of words transcribed correctly out of the words spoken under noise-free and noisy conditions. From the table, it can be seen that accuracy is always lower under noisy conditions for all speakers and languages. To take an example, for English, the accuracy of Speaker 1 decreases from 85% to 70%, and for Telugu, the accuracy of Speaker 3 decreases from 75% to 65%. This sets the sensitivity of the system to the presence of background noise and the need for noise handling under actual deployment. In spite of that, the accuracy of the system is fairly high even under the presence of noisy conditions, setting its robustness under a range of Indian languages.

**Average Accuracy Across Sentences**

If you have sentences and you calculated the accuracy for each as :

This system effectively bridges the gaps in existing ASR models, ensuring greater accuracy and usability for diverse language applications.



Accuracy of the samples without and with noise added

The following table provides experimental findings highlighting the effect of background noise on speech-to-text translation accuracy in Telugu and English languages. Both the languages have three speakers for whom data has been collected. For each of the speakers:

A certain number of words were used in each sample:

Speaker 1 uttered 10 words,

Speaker 2 said 20 words

Speaker 3 spoke 30 words.

For each speaker and each language pair, two types of results are shown:

Without Noise: Translation accuracy and corresponding word errors in the absence of noise.

With Noise: Translation accuracy and corresponding word errors in a noisy environment.

How Errors Were Calculated Using the formula:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Speaker** | **Language** | **Words** | **Accuracy** | **Error** |
| Speaker 1 | English | 10 | 85% | 2 |
| Speaker 2 | English | 20 | 82% | 4 |
| Speaker 3 | English | 30 | 80% | 6 |
| Speaker 1 | Telugu | 10 | 79% | 2 |
| Speaker 2 | Telugu | 20 | 80% | 4 |
| Speaker 3 | Telugu | 30 | 75% | 7.5 (8) |

**Error Calculation**

* **Speaker 1 (English, No Noise)**:
* **Speaker 3 (Telugu, With Noise)**:

Fractional errors are rounded to the nearest whole number, and some are partially shown in the table (e.g., and ).

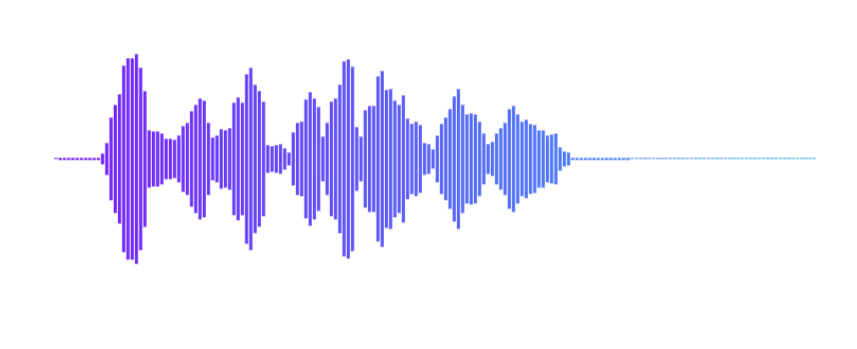
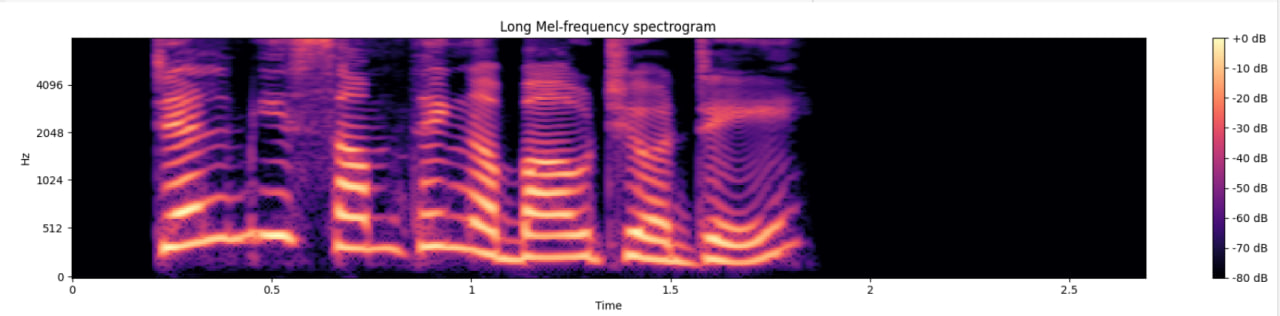
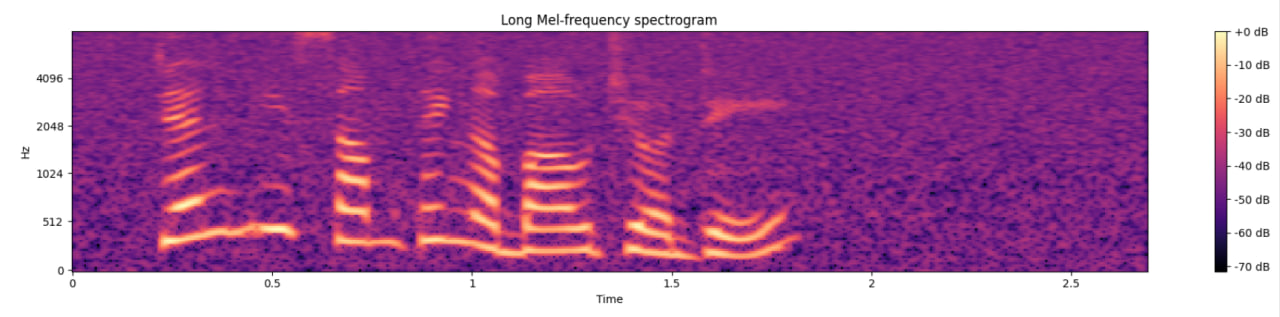


Fig-a Sample-1(English)(Without-Noise) Fig-b Sample-1(English)(With-Noise)



Long-Mel spectrogram of sample-1(without noise)(English)



Long-Mel spectrogram of sample-1(With Noise)(English)

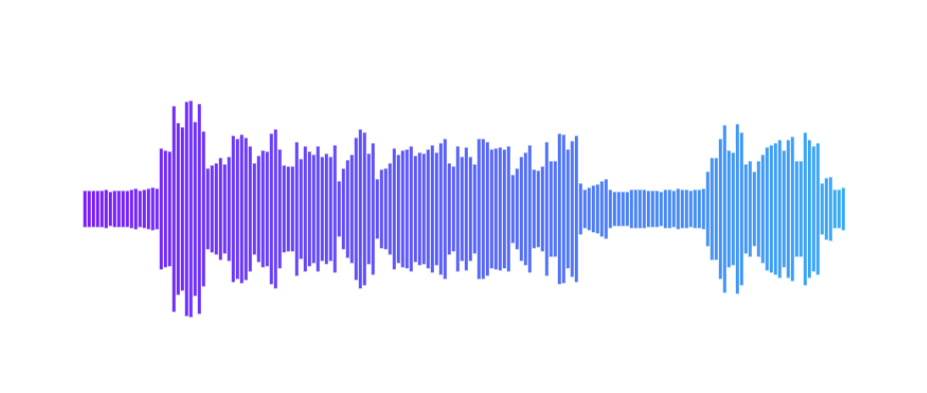
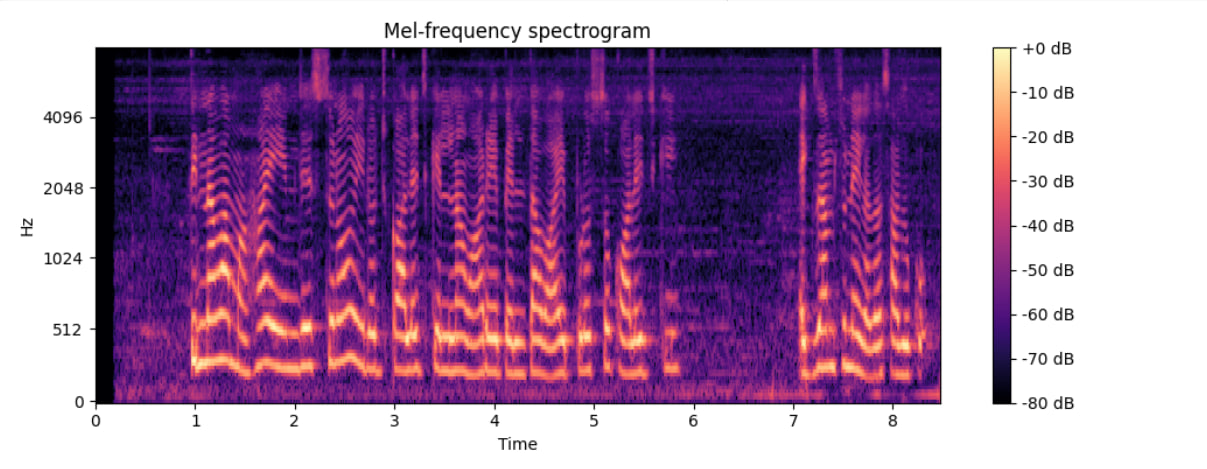
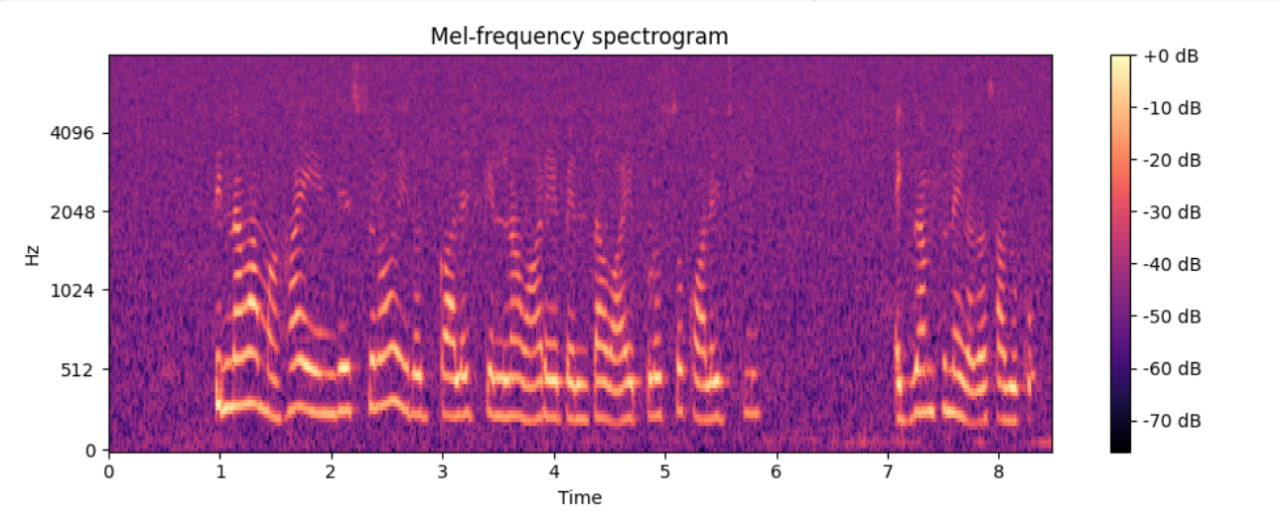
 

Fig-a Sample-2(Telugu)(Without-Noise) Fig-b Sample-2(Telugu)(With-Noise)



Long-Mel spectrogram of sample-1(without noise) (Telugu)



Long-Mel spectrogram of sample-2(With Noise)(Telugu)

# Conclusion and Future Work

The Speech-to-Text with Translation system developed in this research successfully addresses the challenges faced by conventional ASR models by offering an API-free offline solution optimized for Indian languages. The system ensures high transcription accuracy, seamless translation, and enhanced data privacy, making it suitable for deployment in regions with limited internet connectivity. Performance evaluations demonstrate notable improvements in accuracy, speed, and computational efficiency. Moving forward, future enhancements will focus on expanding language support to include more dialects, improving code-switching management, optimizing model efficiency for low-power devices, and integrating AI-driven error correction for greater accuracy. Additional features such as speaker identification, context-aware translation, and stronger security protocols will further enhance the system’s robustness, ensuring a more advanced and user-friendly speech recognition and translation platform.

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