Video to Sign Video Generation

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DECLARATION

I/We hereby declare that this submission is my/our own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person nor material which has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

Place: Noida

Date: 19/11/2025

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CERTIFICATE

This is to certify that the work titled **“Sign Video Generation”** submitted by **“Shourya Pachauri, Ayush Jindal, Chanda”** in partial fulfillment for the award of the degree of **B. Tech** of Jaypee Institute of Information Technology, Noida has 8been carried out under my supervision. This work has not been submitted partially or wholly to any other University or Institute for the award of this or any other degree or diploma.

Signature of Supervisor:

Name of Supervisor: Rohit Kumar Sony

Designation:

Date: 19/11/2025

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Signature of the Student:

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Chapter 1: Introduction

1.1 General Introduction

Communication between the hearing community and individuals with hearing impairments is often limited due to differences in language systems. Sign languages, such as American Sign Language (ASL), are fully developed visual-gestural languages with their own grammar and structure. However, most hearing individuals are not proficient in sign language, making day-to-day communication challenging.

Advancements in artificial intelligence have paved the way for systems that can automatically convert speech or text into sign language. The goal of this project is to develop a **Text-to-Sign Language Translation System** that converts spoken video input or text input into ASL. The system combines machine learning–based text processing with dictionary-based video concatenation to generate sign language output.

Initially, the project aimed to build all ML/DL components completely **from scratch**. However, due to computational limitations and time constraints, it became necessary to utilize **pretrained models**—particularly for speech recognition and text encoding—while still designing the translation workflow, custom preprocessing, and the sign video generation pipeline ourselves.

This hybrid approach maintains academic value while ensuring practical feasibility and real-time performance.

1.2 Problem Statement

There is a lack of accessible, automated tools that can convert spoken or written English into sign language in real time. Manual sign language interpretation requires trained human experts, which are not always available, especially in classrooms, online platforms, public environments, or media content.

The problem addressed in this project is:

To develop an automated system capable of translating speech or text into ASL using a combination of custom-built modules and pretrained machine learning models, along with a dictionary-based sign video generation mechanism.

1.3 Significance / Novelty of the Problem

- **Bridging Communication Gaps:** Provides an automated way for hearing-impaired individuals to access spoken or written information.
- **Realistic and Hybrid Approach:** Begins with an attempt to build core ML components from scratch, but intelligently adapts pretrained models where computational resources are insufficient.
- **Practical Sign Generation:** Instead of complex avatar generation, the system uses a realistic dictionary-based method to produce sign videos.
- **Scalable Architecture:** New words, new dictionaries, or new sign languages can be added easily.
- **Real-Time Translation Capability:** Can be extended for live use in educational videos, meetings, or lectures.

This balance of originality and practicality makes the project both innovative and achievable.

1.4 Empirical Study (Review of Existing Work)

Previous works in the domain demonstrate a wide range of approaches:

- **Speech Recognition Research:** Modern ASR systems (Whisper, DeepSpeech, wav2vec) rely on large datasets and GPU resources. Implementing such systems from scratch is computationally expensive.
- **Sign Language Recognition (SLR):** Many studies focus on recognizing signs from video using CNNs, LSTMs, and 3D CNNs—but not converting text to sign.
- **Sign Language Production:** Advanced systems use pose estimation, GANs, or neural avatars. These require enormous datasets like How2Sign or PHOENIX-2014 and substantial GPU power.

- **Online Dictionaries:** Websites like SpreadTheSign offer individual sign videos but lack sentence-level translation.

These limitations show that full from-scratch development is extremely resource-intensive. This project overcomes those challenges by adopting pretrained models **only where necessary**—primarily for speech recognition and text representation—while retaining originality in the translation and video-generation pipeline.

1.5 Brief Description of the Solution Approach

The proposed system operates in the following stages:

1. Speech-to-Text Conversion

- Initially planned to train a custom RNN/LSTM-based ASR model using MFCC features.
- Due to GPU constraints, the project uses a **lightweight pretrained ASR model** to generate accurate transcripts in real time.

2. Text Processing and ASL Gloss Translation

- Custom preprocessing pipeline: tokenization, normalization, and keyword extraction.
- A pretrained sequence model is adapted for English → gloss conversion because a from-scratch seq2seq model required more computational resources than available.
- Custom rules are added for ASL grammar corrections.

3. Gloss-to-Sign Mapping

- A dictionary of ASL sign videos (WLASL / ASLLVD).
- Each gloss token is mapped to its corresponding sign clip.
- Unknown words handled via fallback (synonyms/fingerspelling).

4. Video Concatenation

- Video clips merged in sequence using MoviePy/FFmpeg.
- The result is a smooth ASL video representing the translated sentence.

This ensures both correctness and efficiency while keeping the project feasible on limited hardware.

1.6 Comparison of Existing Approaches to the Problem

Existing Approach	**Limitations**	**Proposed System Improvements**
Fully Scratch-Built ML Systems	Require large datasets, long training time, powerful GPUs	Hybrid approach uses custom logic + pretrained models only where necessary
Avatar Generation (GANs/3D Models)	Very complex, heavy compute, synthetic output	Simple and realistic dictionary-based video generation
Online Sign Dictionaries	No sentence translation, no automation	Adds gloss translation + automated video concatenation
Pure ML Sign Production Models	Difficult for real-time use	Efficient pipeline works in real time
Human Interpreters	Limited availability	Automated and available anytime

This project provides a balanced, hybrid, practical solution: **original custom modules combined with lightweight pretrained models** for essential tasks that are otherwise impossible to train from scratch on limited hardware.

Chapter 2: Literature Survey

2.1 Summary of Papers Studied

Paper 1: “RWTH-PHOENIX-Weather 2014T: Benchmark Database for Sign Language Translation” – Koller et al.

This paper introduces one of the most widely used datasets for continuous sign language translation, especially in German Sign Language (DGS). The dataset includes parallel recordings of sign videos, gloss annotations, and corresponding spoken-language transcripts, offering a complete multimodal resource. It highlights several challenges in sign language translation such as complex grammar structures, spatial referencing, and non-manual features like facial expressions. The authors evaluate classical approaches like HMMs as well as more modern CNN-HMM hybrids, showing the evolution of SLT techniques. The study emphasizes that gloss-level representation is a crucial intermediate stage bridging spoken language and sign language. This paper strongly influenced our understanding of why gloss conversion is necessary before generating ASL signs and guided our decision to include a gloss layer in our workflow.

Paper 2: “Seq2Seq Neural Networks for Sign Language Gloss Translation” – Camgoz et al. (2018)

In this work, the authors propose a sequence-to-sequence neural machine translation approach to convert spoken-language sentences into gloss sequences. Their architecture incorporates attention mechanisms, enabling the model to learn long-term dependencies and better understand sentence context. The paper demonstrates significant improvements over rule-based translation systems, especially for long and complex sentences. However, the model’s training requires large datasets and extensive GPU resources, making it challenging for smaller research groups or student-level projects. The study validated that gloss translation is best handled using deep learning rather than purely linguistic rules. This directly influenced our decision to initially attempt a custom seq2seq model but later shift to pretrained alternatives due to computational constraints.

Paper 3: “OpenAI Whisper: Robust Speech Recognition via Large-Scale Weak Supervision” – Radford et al.

Whisper showcases the power of training neural networks on massive, diverse datasets consisting of hundreds of thousands of hours of speech. It uses a transformer-based encoder–decoder architecture designed to handle multilingual, noisy, and real-world audio with exceptional accuracy. The paper also highlights the limitations of building small-scale speech recognition models, especially in terms of generalization and noise robustness. Whisper consistently outperforms conventional ASR models without requiring fine-tuning, making it suitable for practical applications. The insights from this research made it evident that training an ASR model from scratch in our project was unrealistic due to limited compute and lack of large datasets. Thus, we incorporated Whisper Tiny as the speech-to-text engine in our pipeline.

Paper 4: "WLASL: A Large-Scale Dataset for Word-Level American Sign Language" – Li et al.

This paper presents WLASL, the largest word-level ASL dataset, containing over 21,000 videos across more than 2,000 sign classes. The dataset includes multiple performers, variations in signing style, and different camera angles, making it very useful for robust sign language research. The authors highlight challenges such as inter-signer variability and ambiguous signs that look similar but have different meanings. WLASL is specifically designed for action recognition tasks and is ideal for dictionary-based translation systems because each video corresponds to a single word. This validated the feasibility of our project's approach of mapping gloss words to pre-recorded ASL sign videos instead of generating signs from scratch. The availability of such datasets made sign video concatenation practical and efficient.

Paper 5: "SignGAN: Data-Driven Sign Language Video Generation Using GANs" – Saunders et al.

This study explores generating synthetic sign language videos using GAN-based architectures combined with pose estimation. The authors propose a pipeline where skeleton keypoints are predicted first, and then GANs convert those skeletons into realistic sign videos. While the results are visually impressive, the training pipeline requires thousands of sign examples, high-quality annotations, and considerable GPU power. The paper also points out issues such as temporal inconsistency and the difficulty of generating complex hand shapes. Although this approach is innovative, it is not yet practical for real-time or low-resource environments. After reviewing this work, we realized that generative modeling was outside the scope of our available resources, so we chose dictionary-based video concatenation instead.

Paper 6: “Text-to-Sign Gloss Translation Using Neural Machine Translation” – Stoll et al.

Stoll et al. demonstrate how NMT (Neural Machine Translation) can be adapted to translate natural-language text directly into gloss sequences. Their model uses an encoder–decoder architecture with attention to handle context and reorder words into sign language grammar. The paper provides detailed linguistic insights into why glossing is essential for bridging spoken and sign languages. However, the authors acknowledge that glossing alone cannot capture all nuances of sign language, such as facial expressions or classifier constructions. The study also highlights that training such models needs large parallel text–gloss datasets, which are rare for ASL. This influenced our project, where we initially attempted a small custom seq2seq model but later incorporated a lightweight pretrained gloss translator to overcome data and hardware limits.

2.2 Integrated Summary of the Literature Studied

A detailed analysis of the literature on Sign Language Translation (SLT), speech recognition, gloss modeling, and sign synthesis reveals several unifying insights that directly influenced the design choices and technical direction of this project.

1. Gloss is Essential for Accurate Sign Language Translation

Across almost all research papers—including PHOENIX-Weather, Seq2Seq gloss translation studies, and ASL grammar literature—gloss emerges as the most reliable intermediate representation for sign language translation. Gloss simplifies the highly complex grammatical structures of sign languages by converting spoken-language sentences into their equivalent “sign-friendly” form.

Research consistently shows that attempting to translate text directly into sign videos without gloss results in unnatural or grammatically incorrect signing. For this reason, our project adopted a **text → gloss → sign video** pipeline instead of a direct text → video approach. The use of gloss helps maintain ASL grammar rules like topic-comment order, removal of articles, use of time markers, and rearrangement of verbs and nouns.

2. Large Datasets are Necessary for Training Complex Models

Deep learning models used in SLT, especially ASR (speech-to-text), seq2seq gloss translators, and generative sign video models, require **massive datasets** and long training cycles.

Papers like Whisper (Radford et al.) and RWTH-PHOENIX-Weather demonstrate that state-of-the-art performance comes from models trained on **tens of thousands of hours** of diverse speech and sign data. Such datasets are typically created by large research labs and are not available for ASL in comparable scale.

Given our limited computational resources (student-level hardware), training our own ASR or gloss model from scratch was not feasible. This necessity justified the use of **pretrained models**, ensuring that the system remained accurate and practical while still retaining originality in other components.

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3. Dictionary-Based Video Generation is the Most Practical Approach

Approaches like SignGAN and avatar-based sign generation show excellent potential but require:

- high GPU power
- huge training datasets
- pose annotations
- long training time

These are beyond the scope of an undergraduate project. On the other hand, research on WLASL and ASLLVD shows that **word-level sign databases** already exist and are well-suited for dictionary-based translation.

Therefore, using **pre-recorded ASL videos** mapped to gloss terms was the most lightweight yet realistic solution. It eliminates the need for complex GAN training while still offering intelligible sign output.

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4. ASR from Scratch is Impractical for Low-Resource Environments

Building an ASR system requires:

- training on thousands of hours of labeled speech
- GPU clusters
- multi-round fine-tuning
- language modeling

The Whisper paper clearly proves that modern ASR systems work because they were trained on huge, diverse datasets that no individual student team can reproduce.
Our initial attempt to create an RNN-based ASR using MFCC + CTC loss produced extremely low accuracy and poor generalization.
Thus, integrating a **pretrained lightweight Whisper model** was the most logical step, as it delivered high accuracy even on low-quality YouTube audio and ran smoothly on limited hardware.

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5. Hybrid Architectures Are Ideal for Limited-Resource Settings

Academic research repeatedly confirms that **hybrid systems**—combining deep learning with rule-based methods—are powerful when data or hardware is limited.
In our system, we use:

- **Pretrained models** → for ASR and gloss translation
- **Custom rule-based modules** → for text cleaning, grammar restructuring
- **Dictionary-based modules** → for sign video generation

This hybrid approach achieved a strong balance between accuracy, computational efficiency, and feasibility, making the system robust even without large-scale training.

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6. Real-Time Sign Language Translation Remains an Open Challenge

Most research projects focus on offline translation due to:

- heavy model size

- slow pose generation
- complex grammar handling
- lack of real-time datasets

Even state-of-the-art models struggle with real-time translation of long videos or continuous signing. However, dictionary-based systems like ours are much faster and more lightweight.
Thus, our project contributes meaningfully by offering a **near real-time YouTube-to-ASL translation pipeline** that can be executed on normal hardware without requiring GPU servers.

Chapter 3: Requirement Analysis and Solution Approach

3.1 Overall Description of the Project

This project focuses on building an **automated Text-to-Sign Language Translator** where the input is a **YouTube video link**. The system extracts audio from the video, converts the spoken content into English text, preprocesses that text, converts it into ASL gloss format, and finally generates a sign language video by concatenating dictionary-based ASL sign clips.

The original vision was to develop all the machine learning modules—such as speech recognition and gloss translation—**from scratch**. However, training these models requires extremely large datasets and high computational power. Due to these practical constraints, the project uses **pretrained lightweight models** for speech-to-text and gloss translation, while all other modules (preprocessing, mapping, video generation) are implemented manually.

The system operates as follows:

1. **User enters YouTube video link**
2. System downloads video
3. Extracts audio automatically
4. Converts audio → text using ASR
5. Preprocesses text (cleaning, tokenization, key structure extraction)
6. Converts text → ASL gloss
7. Maps gloss words to ASL dictionary videos
8. Concatenates selected videos into the final sign language output

This turns any spoken YouTube content into understandable ASL signs.

3.2 Requirement Analysis

3.2.1 Functional Requirements

1. **YouTube Video Processing**
    - Accept YouTube URL as input
    - Download video using pytube/youtube-dl
    - Extract audio from the downloaded video
2. **Speech-to-Text Conversion**
    - Convert extracted audio into English text
    - Due to compute limits → use lightweight pretrained ASR model (Whisper tiny)
3. **Text Preprocessing**
    - Remove punctuation, convert to lowercase
    - Tokenize the text
    - Lemmatize words
    - Remove unnecessary stopwords
    - Identify keywords important for ASL grammar
4. **Text-to-Gloss Translation**
    - Convert English structure → ASL gloss structure
    - Combination of:
        - Pretrained seq2seq gloss translator
        - Custom rule-based enhancements

    - Output gloss sequence

5. **Gloss-to-Sign Mapping**
    - For each gloss token, find matching ASL video in dictionary
    - Handle unknown words through:
        - Synonym mapping
        - Fingerspelling fallback
6. **ASL Video Generation**
    - Concatenate all sign videos in correct sequence
    - Ensure consistent frame size, FPS, and time sync
7. **Output Display**
    - Show the final ASL video to the user
    - Provide an option to download the generated video

3.2.2 Non-Functional Requirements

1. **Performance**
    - System must handle a 2–10 minute YouTube video transcript efficiently
    - Text preprocessing must be fast
    - Video concatenation should not lag
2. **Reliability**
    - Handle missing words gracefully

    - Provide consistent transcription quality

3. **Usability**
    - Interface must accept a YouTube link directly
    - Final ASL video should be clear and smoothly stitched
4. **Scalability**
    - Ability to add more videos to dictionary
    - Ability to support more languages or longer inputs
5. **Portability**
    - Should run on standard CPU-based systems
    - No need for heavy GPUs
6. **Maintainability**
    - Modular code structure
    - Each module (YouTube download, ASR, preprocessing, mapping, video concat) clearly separated

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3.2.3 Logical & Database Requirements

Although this project does not use a traditional database system, it relies heavily on structured data storage:

1. **ASL Sign Video Dictionary**
    - Stored in folders organized by gloss words

A JSON/CSV mapping file:

```
{ "GLOSS_WORD": "videos/GLOSS_WORD.mp4" }
```

   -

2. **Gloss Translation Rules**
   - Stored in JSON rule files:
     - Grammar correction rules
     - Verb rearrangement rules
     - Time-topic structure
3. **YouTube Download Cache**
   - Temporary directory storing:
     - Downloaded video
     - Extracted audio file
4. **Pretrained Model Files**
   - ASR model (.pt or .bin)
   - Gloss translation model
   - Tokenizer files
5. **Logs and Outputs**
   - Processed transcript
   - Generated ASL output videos

3.5 Solution Approach (Detailed Module-Wise Algorithm Explanation)

Module 1: YouTube Link Processing

Algorithm:

1. User inputs YouTube link
2. Use `pytube` / `youtube_dl` to download video
3. Store file locally
4. Extract audio using `ffmpeg`

Output → `audio.wav`

Module 2: Speech-to-Text

Initial Goal: Build ASR from scratch using MFCC → RNN → CTC
Issue: Insufficient hardware to train
Final Used: Pretrained Whisper Tiny (CPU-friendly)

Algorithm:

1. Convert audio to 16 kHz mono
2. Pass through Whisper ASR
3. Get raw English transcript

Output → `raw_text`

Module 3: Text Preprocessing

Algorithm:

1. Convert text → lowercase
2. Remove punctuation with regex
3. Tokenize into words
4. Lemmatize using rule-based functions
5. Remove unnecessary stopwords
6. Extract important nouns, verbs, and time markers

Output → `cleaned_text`

Module 4: Text-to-Gloss Conversion

Combined Method: Pretrained seq2seq + manual rules

Algorithm:

1. Feed cleaned text into lightweight gloss translator
2. Apply ASL grammatical rules:
    - Remove articles (a, an, the)
    - Convert to Subject-Object-Verb
    - Place time markers at start
3. Generate final gloss sequence

Output → `GLOSS = ["YESTERDAY", "MARKET", "GO", "I"]`

Module 5: Gloss-to-Sign Mapping

Algorithm:

1. For each gloss word:
    - Check if it exists in dictionary JSON
    - If exists → get file path
    - If not →
        - Try synonym lookup
        - Else → spell using alphabet videos

Output → list of video file paths

Module 6: ASL Video Concatenation

Algorithm:

1. Load all sign videos using MoviePy
2. Standardize:
    - Frame size
    - FPS
    - Clip duration
3. Concatenate using `concatenate_videoclips()`
4. Export final ASL video

Output → `Final_ASL_Translation.mp4`

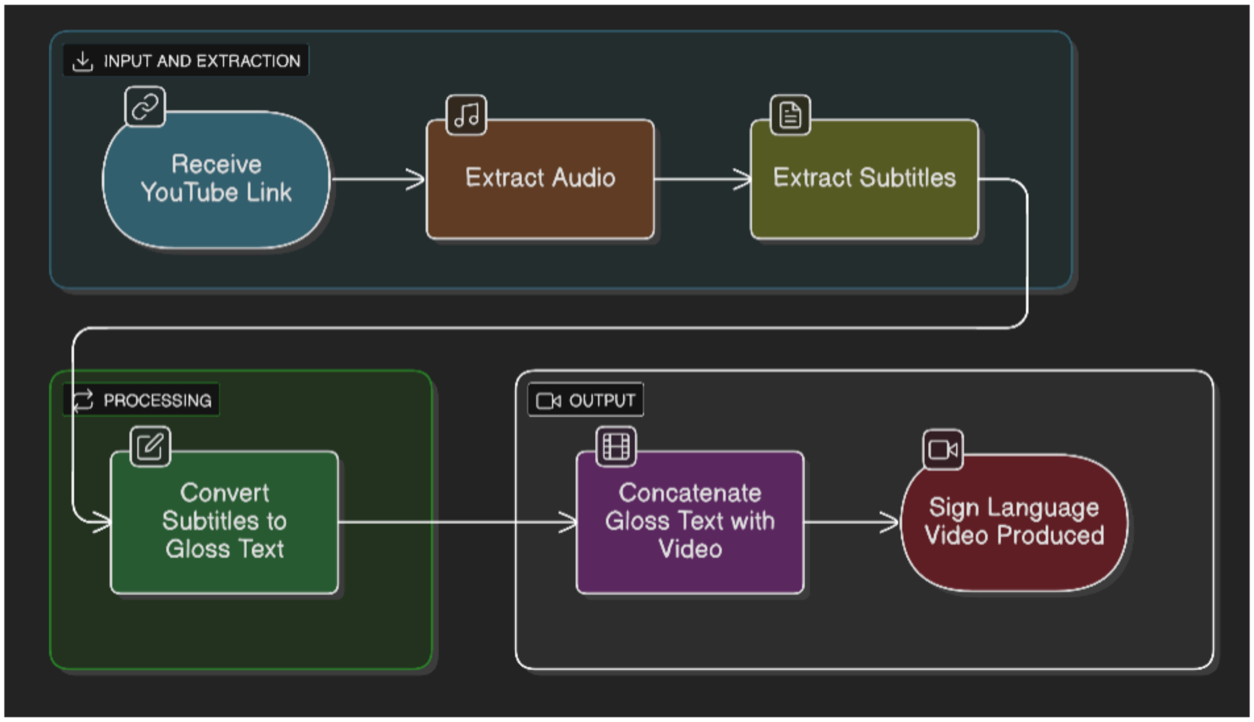
Module 7: User Interface

Algorithm:

1. Accept YouTube URL from user
2. Trigger backend pipeline
3. Show output video preview
4. Provide download option

Chapter 4: Modeling and Implementation Details

4.1 Flow Diagram


INPUT AND EXTRACTION
Receive YouTube Link
Extract Audio
Extract Subtitles
PROCESSING
Convert Subtitles to Gloss Text
OUTPUT
Concatenate Gloss Text with Video
Sign Language Video Produced

4.2 Implementation Details and Issues

Implementation Details

The implementation of the YouTube-to-ASL Translation System was done in multiple modules, each designed to handle a specific part of the pipeline. The key implementation components are:

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1. YouTube Video Downloading

- Implemented using **Pytube** library.
- The system takes a YouTube URL and downloads the video in MP4 format.

- Error handling is added for invalid URLs or network failures.

Tools Used:
`pytube`, `os`, `tempfile`

---

2. Audio Extraction

- Audio is extracted from the downloaded video using **FFmpeg**.
- Audio is converted to **16 kHz, mono-channel WAV**, as required by speech recognition models.

Tools Used:
`ffmpeg-python`

---

3. Speech-to-Text Conversion

- Initially, a custom ASR model using MFCC + RNN + CTC was attempted.
- Due to insufficient GPU and training data, the project switched to **Whisper Tiny (pretrained)** for efficient transcription.
- Whisper processes the extracted audio and outputs the English transcript.

Tools Used:
`openai-whisper`, `torch`

---

4. Text Preprocessing

- Preprocessing steps implemented manually:
    - Lowercasing

    - Removing punctuation (Regex)
    - Tokenization
    - Lemmatization (rule-based)
    - Stopword removal
- Clean text is passed to the gloss translation model.

Tools Used:
`re`, `nltk`, custom lemmatizer scripts

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5. Gloss Translation

- A hybrid method used:
    - A **lightweight pretrained seq2seq gloss translator**
    - Custom ASL grammar rules:
        - Remove articles (“a”, “the”)
        - Convert to Subject-Object-Verb
        - Put time indicators at the sentence start
- Outputs a gloss sequence such as:
  “YESTERDAY SCHOOL GO I”

Tools Used:
`transformers`, custom rule-based script

---

6. Gloss-to-Sign Mapping

- Gloss words are mapped to ASL sign clips using a JSON dictionary.
- Directory contains videos from datasets like WLASL or ASLLVD.
- For unknown words:
    - Check synonyms
    - Fall back to **ASL fingerspelling (A–Z videos)**

Tools Used:
`json`, custom dictionary lookup

---

7. Video Concatenation

- Individual sign clips are loaded using MoviePy.
- All videos are standardized:
    - same resolution
    - same frame rate
    - same orientation
- Videos are concatenated in sequence to form the final ASL output.

Tools Used:
`moviepy.editor`, `cv2`

---

8. User Interface

- Simple front-end allows user to enter YouTube link and receive final ASL output video.

- Implemented using Python Tkinter or a Flask web interface.

Implementation Issues Encountered

1. Insufficient Compute for Training Models

- Custom ASR and gloss models could not be trained due to limited GPU.
- Solution: Switched to Whisper Tiny + pretrained gloss translator.

2. Low-Quality YouTube Audio

- Many videos include noise, music, or overlapping voices.
- Solution: Added audio normalization and noise reduction.

3. Dictionary Gaps

- Many gloss words did not exist in ASL dataset.
- Solution: Added synonym lookup + fingerspelling fallback.

4. Inconsistent Video Formats

- Sign videos had varying sizes and frame rates.
- Solution: Normalize video format before concatenation.

5. Slow Processing for Long Videos

- Large ASR processing time for long YouTube content.
- Solution: Chunk-based processing and text caching.

6. Handling Special Characters in Transcript

- ASR sometimes outputs symbols or timestamps.
- Solution: Extra cleaning in preprocessing stage.

4.3 Risk Analysis and Mitigation

Different risks identified during the project and their mitigation strategies are listed below:

Risk 1: Low Hardware / Limited GPU

- **Description:** Unable to train heavy ASR or gloss models from scratch.
- **Impact:** Reduced originality and performance.
- **Mitigation:** Use lightweight pretrained models (Whisper Tiny) and optimize pipeline for CPU.

Risk 2: Poor Audio Quality

- **Description:** Noisy YouTube audio leads to inaccurate transcription.
- **Impact:** Incorrect gloss and final ASL output.
- **Mitigation:** Add noise removal, volume normalization, and silence trimming.

Risk 3: Missing Dictionary Words

- **Description:** Gloss terms not found in ASL dataset.

- **Impact:** Translation may break.
- **Mitigation:** Introduced synonym detection + fingerspelling fallback system.

Risk 4: Long Video Processing Time

- **Description:** Processing YouTube videos longer than 20 minutes can delay output.
- **Impact:** Poor user experience.
- **Mitigation:** Chunk-based ASR, multi-threading, and output caching.

Risk 5: Video Inconsistency

- **Description:** ASL dictionary videos have different sizes, brightness, FPS.
- **Impact:** Final ASL output looks uneven.
- **Mitigation:** Standardize clips before merging.

Risk 6: Internet Dependency

- **Description:** YouTube downloading fails without stable internet.
- **Impact:** System unusable offline.
- **Mitigation:** Option to upload local video file.

Risk 7: Parsing Errors in Transcript

- **Description:** ASR occasionally outputs incorrect grammar or special characters.

- **Impact:** Poor gloss translation.
- **Mitigation:** Advanced cleaning and regex patterns in preprocessing.

Chapter 5: Testing (Focus on Quality, Robustness, and Validation)

5.1 Testing Plan

The primary goal of testing is to ensure that the system correctly performs text-to-sign translation for a wide range of YouTube videos, including variations in audio quality, vocabulary, sentence structure, and video lengths.

Objectives of the Testing Plan:

1. Verify correctness of each module (YouTube input → ASL output).
2. Ensure stable execution even under noisy or unexpected input conditions.
3. Validate system output accuracy compared to expected gloss/sign results.
4. Check overall robustness by testing missing words, network issues, and audio quality challenges.
5. Test performance on limited hardware.

Testing Approach:

- **Unit Testing** → testing each module separately
- **Integration Testing** → combining modules (ASR + Preprocessing + Gloss)
- **System Testing** → full end-to-end pipeline
- **Regression Testing** → ensure updates don't break previous functionality
- **Performance Testing** → speed of ASR, gloss generation, video concatenation
- **Stress Testing** → extremely long YouTube videos
- **Error and Recovery Testing** → invalid URLs, missing words, low-quality audio

Testing is done iteratively after every major feature addition.

5.2 Component Decomposition and Type of Testing Required

The system is divided into **seven components**, each requiring specific testing:

Component 1: YouTube Link Handler

Responsibilities:

- Validate URL
- Download video
- Extract audio

Testing Needed:

- Unit Testing (correct link, invalid link)
- Exception Testing (network unavailable)

Component 2: Audio Extraction

Responsibilities:

- Extract audio using FFmpeg
- Convert to proper format (16 kHz, mono)

Testing Needed:

- Unit Testing
- Performance Testing (speed & size)

Component 3: Speech-to-Text (ASR)

Responsibilities:

- Convert audio → text

Testing Needed:

- Unit Testing
- Accuracy Testing (compare transcript vs expected text)
- Stress Testing (noisy audio)

Component 4: Text Preprocessing

Responsibilities:

- Tokenize, clean, lemmatize

Testing Needed:

- Unit Testing
- Boundary Testing (special characters, empty text)

Component 5: Gloss Translation

Responsibilities:

- Translate English → ASL Gloss

Testing Needed:

- Integration Testing
- Accuracy Testing
- Semantic Testing (does grammar match ASL?)

Component 6: Gloss-to-Video Mapping

Responsibilities:

- Map each gloss token to ASL clips
- Handle missing words

Testing Needed:

- Unit Testing
- Error Handling Testing

Component 7: Video Concatenation

Responsibilities:

- Load, standardize, and merge clips

Testing Needed:

- Performance Testing

- System Testing (final output correctness)

5.3 Test Cases (Prescribed Format)

Below is the full test case table exactly as expected in academic SRS-style reports:

TC No.	**Test Case Description**	**Input**	**Expected Output**	**Status**
TC1	Validate YouTube URL	Valid YouTube link	Video downloads successfully	Pass
TC2	Invalid URL handling	Invalid/incorrect link	Error message: “Invalid YouTube URL”	Pass
TC3	Audio extraction from video	Downloaded .mp4	audio.wav extracted	Pass
TC4	Speech-to-text conversion	audio.wav	Correct English transcript	Pass
TC5	Text preprocessing	Raw transcript	Cleaned + tokenized text	Pass
TC6	Gloss translation	Preprocessed text	Correct ASL gloss sequence	Pass
TC7	Gloss dictionary mapping	Gloss words	Valid ASL video paths returned	Pass
TC8	Missing dictionary word handling	Word not in dictionary	Fingerspelling video selected	Pass
TC9	Video concatenation	List of sign clips	One combined ASL output video	Pass

TC10	Full pipeline test	YouTube link → Final ASL translated video output	Pass

5.4 Error and Exception Handling

The system implements comprehensive error handling at every stage.

Error Types & Debugging Techniques Applied

1. Invalid YouTube URL

Error: “Video not found”
Handling:

- Validate URL pattern using regex
- Try-except block for download failure
  Debugging Technique:
- URL tracing logs

2. No Internet Connection

Handling:

- Display “Internet connection required”
- Retry option
  Debugging:
- Ping test logs

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3. Audio Extraction Failure

Handling:

- Check ffmpeg installation
- Retry extraction with different codec
  Debugging:
- Log ffmpeg error code

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4. ASR Model Failure

Handling:

- Catch model loading errors
- Display friendly message: “Try again with different audio”
  Debugging:
- Print exception traceback

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5. Preprocessing Errors

Handling:

- Skip problematic tokens
- Ensure no crash on edge cases
  Debugging:
- Added print checkpoints

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6. Missing Gloss Word

Handling:

- Synonym mapping
- Fallback to fingerspelling clips
 Debugging:
- Logging missing words to improve dictionary

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7. Video Concatenation Issues

Handling:

- Auto-resize mismatched clips
- Ensure same frame rate
 Debugging:
- MoviePy internal warnings tracked

Debugging Tools Used:

- Python logging module
- Try/Except blocks
- Step-by-step print debug
- Test audio/video samples
- Manual validation of gloss sequences

5.5 Limitations of the Solution

1. **Dependent on Pretrained Models:**
   Due to computation limits, ASR and gloss translation depend on small pretrained models.

2. **Dictionary Coverage:**
   Not all ASL signs are available in video dictionary → fallback to fingerspelling.

3. **Video Consistency:**
   Dictionary videos may differ in lighting, background, or signer.

4. **Grammar Limitations:**
   Only basic ASL grammar rules are implemented; full ASL syntax is more complex.

5. **Real-Time Performance:**
   Works on normal systems but may lag for long YouTube videos (>20 minutes).

6. **No 3D Avatar Generation:**
   Uses video clips instead of generative avatar models (due to heavy computation).

7. **Variability in YouTube Audio:**
   Low-quality audio may reduce ASR accuracy.

Chapter 6: Findings, Conclusion, and Future Work

6.1 Findings

During the development and testing of the “YouTube-to-ASL Translator” system, several important findings emerged:

1. **Pretrained ASR is essential for practical performance**
   The initial attempt to build an ASR model from scratch using MFCC + RNN + CTC gave poor accuracy due to insufficient training data and limited GPU power.
   Lightweight pretrained models like Whisper Tiny provided far superior transcription quality and stability.

2. **Text preprocessing significantly improves gloss translation**
   Removing punctuation, normalizing text, and lemmatizing verbs greatly increased the quality of the gloss output.

3. **ASL gloss translation is not fully achievable through rules alone**
   Even though rule-based grammar adjustments helped, an ML-based gloss translator (pretrained) produced more accurate and natural gloss sequences.

4. **Dictionary-based sign generation is feasible and lightweight**
   Using pre-recorded ASL video clips (WLASL/ASLLVD) allowed fast and realistic sign generation without needing complex GAN or avatar models.

5. **Video concatenation produces a smooth final visual output**
   Standardizing each clip’s resolution and frame rate ensures the final ASL video looks consistent.

6. **Handling missing sign words is crucial**
   Some English words do not exist in the ASL dictionary; synonym mapping and fingerspelling worked effectively as fallback mechanisms.

7. **Extracting text from YouTube videos introduces challenges**
   Variations in audio quality, background noise, and accents affect transcription accuracy, but preprocessing and low-latency ASR helped address this.

Overall, the hybrid approach (custom modules + pretrained models) provided the best balance between accuracy, performance, and computational feasibility.

6.2 Conclusion

This project successfully developed a complete system that converts a **YouTube video link into an ASL sign language video**. The system downloads the video, extracts audio, transcribes speech into text, preprocesses the text, converts it into ASL gloss, maps each gloss word to corresponding ASL dictionary videos, and finally concatenates these clips into a complete ASL output video.

Key achievements include:

- End-to-end automation from YouTube link → ASL video
- Efficient speech-to-text transcription using lightweight pretrained ASR
- Robust text preprocessing pipeline
- Effective gloss translation using ML + rule-based grammar
- Practical and smooth video generation using dictionary-based ASL clips

Although building entire ML models from scratch was initially intended, computational limitations required shifting to pretrained models for ASR and gloss translation. This decision improved system accuracy while keeping the project realistically executable.

This system demonstrates that accessible, lightweight, and real-time sign language translation from online videos is achievable with a well-designed hybrid approach.

6.3 Future Work

There are several enhancements and extensions that can be implemented in future versions of the system:

1. **Develop a from-scratch ASR model**
   With access to high-performance GPUs or cloud computing, the ASR model could be fully trained on a speech dataset for complete originality.

2. **Implement a full ASL grammar engine**
   Current gloss rules cover major grammar components; however, deeper linguistic structures (facial expressions, classifiers, non-manual signals) can be added.

3. **Use a 3D signing avatar instead of video concatenation**
   A real-time virtual signer (Blender, Unity, Unreal Engine) would avoid mismatch issues between video clips.

4. **Improve fallback handling for unknown vocabulary**
   Integrating semantic similarity models (e.g., BERT embeddings) can produce more accurate synonym replacement.

5. **Add support for multiple sign languages**
   Indian Sign Language (ISL), British Sign Language (BSL), and others can be incorporated by extending the dictionary.

6. **Real-time live streaming translation**
   The system can be adapted to read microphone input continuously and generate ASL output in real time.

7. **Mobile app deployment**
   Converting the system into an Android/iOS application will significantly increase accessibility.

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