Real-Time Sign Language to Speech Conversion on Edge Devices: A Jetson Nano Implementation

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Abstract

Sign Language is essential for deaf and hard of hearing community, yet the lack of effective communication with non-signers often leads to social isolation.

This project emphasizes on the edge computing capabilities of the NVIDIA Jetsan Nano by deploying our American Sign Language (ASL) recognition system with a user-friendly Tkinter interface. The ASL words are recognized through fingerspelling and subsequently forming sentences and converting them to multilingual speech output supporting English, Hindi, and Tamil by integrating Text-to-Speech (TTS) module, leveraging the computational prowess of Jetson Nano.

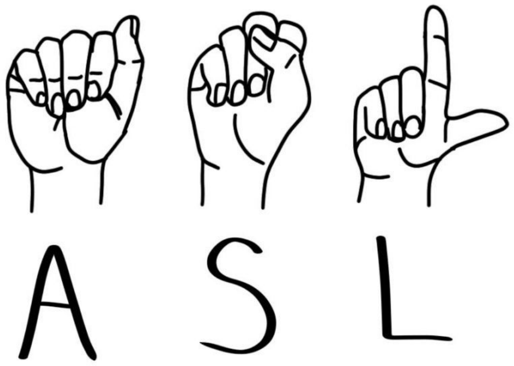


Fig 1. ASL through fingerspelling

Introduction

Sign language is a visual language that uses hand gestures, facial expressions, and body movements to communicate. It enables the Deaf and hard-of-hearing community to express ideas and emotions without relying on speech. Being spatial and expressive, it offers a rich form of communication and plays a vital role in promoting inclusivity.

It consists of 3 major components:

Fingerspelling	Word level sign vocabulary	Non-manual features
Used to spell words letter by letter .	Used for the majority of communication.	Facial expressions and tongue, mouth and body position.

Introduction

American Sign Language (ASL) is a natural language that serves as the predominant sign language of Deaf communities in the United States and most of Anglophone Canada

Fingerspelling is a key aspect of ASL, essential for spelling names and terms without designated signs.

Key Challenges: subtle variability in hand gestures, environmental factors like lighting and camera angles, the need for rapid processing, and diversity in hand features.

Fig 2. ASL Alphabets

Literature Review

We have reviewed various deep learning approaches being used for Sign Language Recognition(SLR), a summary of which is presented in Table 1.

Table 1: Overview of Sign Language Recognition Approaches and Performance

Ref	Type of Sign Language	Algorithm Used	Model Used	Dataset	Testing Accuracy (%)	Limitations/Grey areas
[1]	ASL (Alphabets)	Deep Convolutional Networks	CNN	ASL Alphabet dataset	82.5%	1. Does not emphasize the development of real-time application and primarily focuses on the training and validation phases. 2. The model may be overfitting to specific training conditions and needs to be generalized well to diverse environments.

Literature Review

[2]	ASL (Alphabets)	Video based Human Representations	Transformer	RWTH-PHOENIX-Weather 2014T	87.5%	High computational cost,requires large-scale datasets
[3]	ASl (Alphabets)	Object Detection Network	Transformer	Chicago Fingerspelling in the Wild	92.6%	Struggles with overlapping signs and complex hand movements
[4]	ASL, ISL (Alphabets)	Deep Learning Based	Lightweight CNN; MobileNet V2	Akash Asl alphabet: 87,000 images & ISL-CSLTR	98.77%	1. Doesn’t consider factors such as varying lighting, background noise, or occlusions. 2. Confusion between similar hand signs, such as the letters "P" and "Q,"
[7]	Continuous Sign Language (Words)	Spatial-Temporal Multi-Cue Network	CNN-LSTM	RWTH-PHOENIX-Weather: 75,000 frames	85.4%	1. The complexity of handling multiple cues (hand shape, facial expressions, body posture) presents challenges 2. Relies on video-based inputs for CSLR, which poses limitations in environments with variable lighting, occlusions, or inconsistent background conditions.

Literature Review

[8]	Continuous Sign Language (Words)	Sign Language Transformer	Transformer	RWTH-PHOENIX-Weather: 825,000 frames	85.4%	1.RWTH-PHOENIX-Weather-2014T dataset is specifically focused on weather data, which limits the diversity of signs 2. Employs a transformer-based architecture which is computationally intensive.
[10]	Turkish Sign Language (Words)	CNN-LSTM	3D CNN + LSTM	AUTSL Dataset: 226 sign classes	91.47%	1. Inclusion of Kinect-based recordings limits its generalizability to other real-world settings 2. Highlights a limitation in the model's ability to capture fine-grained distinctions between similar gestures
[11]	Word-level Sign Language (Words)	CNN-based methods	ResNet-50	WLASL dataset: 21,000 signs	93.0%	1. Decrease in performance as the vocabulary size increases. 2. reliance on visual cues(appearance-based approaches) can be problematic in real-world settings, where lighting and background conditions may vary widely

Literature Review

[18]	American Sign Language (Words)	Deep learning-based	MS-ASL Benchmark	MS-ASL dataset: 1,000 classes	94.5%	1. Models perform well in recognizing individual signs, but they still struggle with contextual understanding. 2. The dataset includes videos in unconstrained environments, with significant challenges such as variability in background, lighting, and camera angles
[19]	Indian Sign Language (Gestures/ Continuous Words)	3D CNN	ResNet	ISL Gesture dataset: 10,000 gestures	87%	1. Sensor Limitation reliance on specific 3D hand gesture sensors like Kinect, Leap Motion, and Time of Flight (ToF) 2. System struggles with inter-hand variations and occlusions, leading to non-discriminatory features.
[20]	ASL (Words)	Mediapipe and CNNs	CNN-based	Custom dataset for ASL gestures	95.4%	Limited to predefined gestures, scalability issues

Literature Review

[21]	ASL(Alphabets)	Hybrid	CNN-based	ASL Alphabet dataset	71.4%	1.Struggles to differentiate between certain similar handshapes 2.Doesn't explicitly account for the fluency and transitions between handshapes in fingerspelling
[22]	ASL (Alphabets)	CNN	CNN-based	Custom dataset for ASL gestures	98.84%	Dependency on Predefined Image Resolutions

Literature Review

Device Survey

- **Extensive Evaluation:** Various edge AI devices, including Jetson Nano, Raspberry Pi 4, and Google Coral Dev Board etc were evaluated based on various factors presented in Table 2.

Table 2: Comparison of various computational edge devices

Equipment	NVIDIA Jetson Nano	Raspberry Pi 4	Google Coral Dev Board	Jetson Xavier NX	Jetson AGX Xavier
CPU	ARM A57	ARM Cortex-A72 64-bit	NXP i.MX 8M SOC	8-core ARM	integrated ARM Hexa-Core CPU
No. of cores	4	4	4	8	6
	Freq: 1.43 GHz	Freq: 1.5 GHz	Freq: 1.5 GHz	Freq: 2.26 GHz	Freq: 2.0 GHz
GPU	128-core Maxwell	Broadcom VideoCore VI	Integrated GC7000 Lite graphics	512-Core Volta+NVDLA	512-Core Volta+NVDLA
Power	5W-10W	2.56-7.30W	4TOPS-2W	10/15/30 W	30W
RAM	4 GB	1 GB, 2 GB, 4 GB, 8 GB	1 or 4 GB LPDDR4	8 GB	16 GB LPDDR4

Literature Review

Equipment	NVIDIA Jetson Nano	Raspberry Pi 4	Google Coral Dev Board	Jetson Xavier NX	Jetson AGX Xavier
Camera	2x MIPI CSI-2	MIPI CSI port	MIPI CSI-2	16 lanes MIPI CSI-2	4 line MIPI, USB Camera port
Applications	Smart traffic control	IoT based smart mirror	TensorFlow to detect objects in video streams	Detection of cucumber leaf diseases	Accelerating colorizer of brain cancer for autonomous driving
connectivity	Gigabit Ethernet, Wireless networking adapter	Gigabit Ethernet, RJ45 (WiFi), M.2 Key M (NVMe)	Ethernet, USB Wi-Fi adapter	Gigabit Ethernet, M.2 Key E (WiFi), M.2 Key M (NVMe)	Gigabit Ethernet, GPS, PCIe gen2
Cost	$99	$55	$85.99	$699	$299
OS	Linux4Tegr a	Ubuntu Mate, Snappy Ubuntu Core, etc.	ARM and Linux	Linux r35 codeline	Android and Linux
Ports	4x USB 3.0	2 USB 3.0 ports	USB 2.0/3.0 ports	(4x) USB 3.1 (Host)	USB 3.1 Type-C, Client Port USB 3.0

Literature Review

- **Inference from Device survey:**

Reasons for Jetson Nano being the optimal choice:

- **Cost-Effective:** Affordable at $99 while maintaining strong performance.
- **Compact Design:** Portable and ideal for edge computing.
- **AI Framework Compatibility:** Works seamlessly with TensorFlow, PyTorch, etc.
- **Real-Time Capability:** Handles video streams and gestures efficiently without cloud dependency.

Applications in Literature:

- Proven effective in real-time SLR systems.
- Integrates easily with IoT ecosystems.

Problem Identification

- **Limited Real-Time ASL Recognition Systems on edge devices**

  Existing ASL recognition models often struggle with real-time execution, particularly on edge devices.
- **Integration of Sign Language Recognition with Text-to-Speech**

  Most research stops at text output without transforming recognized signs into natural-sounding speech
- **Sentence-Level Understanding in Sign Language Recognition**

  Most existing works focus on isolated alphabet or word recognition, neglecting sentence formation.
- **Data Scarcity and Lack of Diverse Datasets**

  Creating a self-made dataset for ASL letter recognition, improving over existing datasets

Proposed Solution

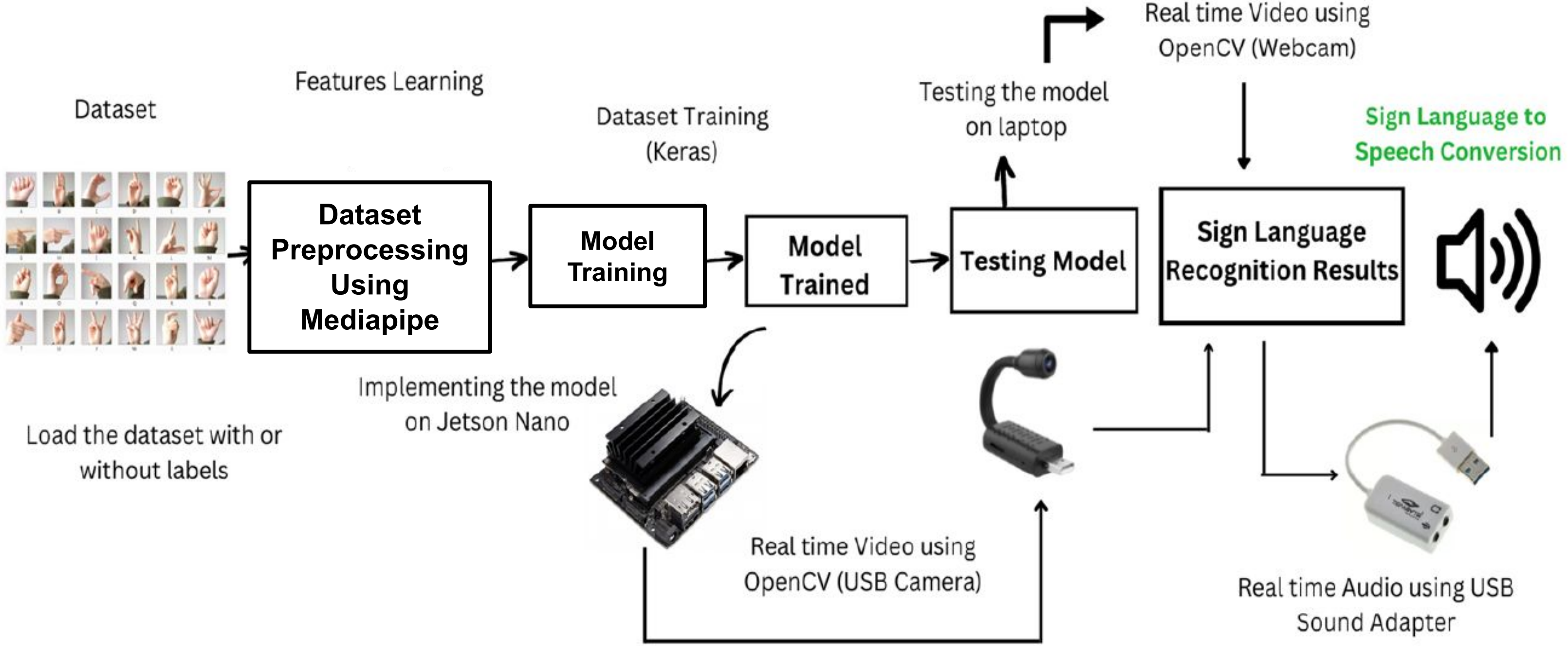


Fig 3: Sign Language Recognition Workflow

System Design

The system architecture of the proposed ASL recognition system is modular, consisting of five main components: **Input, Preprocessing, Recognition, Post-Processing, and User Interface.**

The use case diagram illustrates the workflow, from capturing video frames to converting recognized gestures into real-time text and speech output.

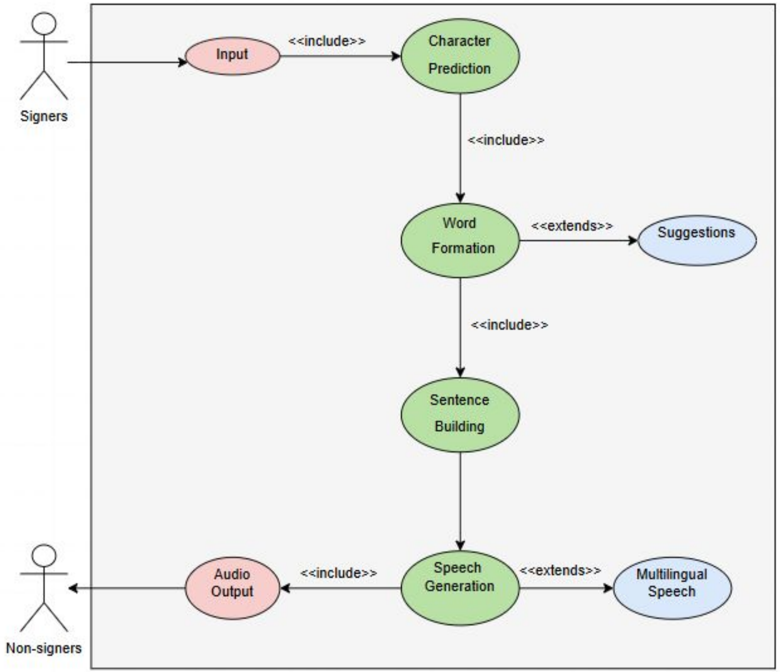


Fig 4. Use Case Diagram

Implementation

Data Collection & Preprocessing

Self made dataset

Training set -> 15,025 images

Testing set -> 6525 image

split up into 25 classes, which includes one blank class and 24 letter classes

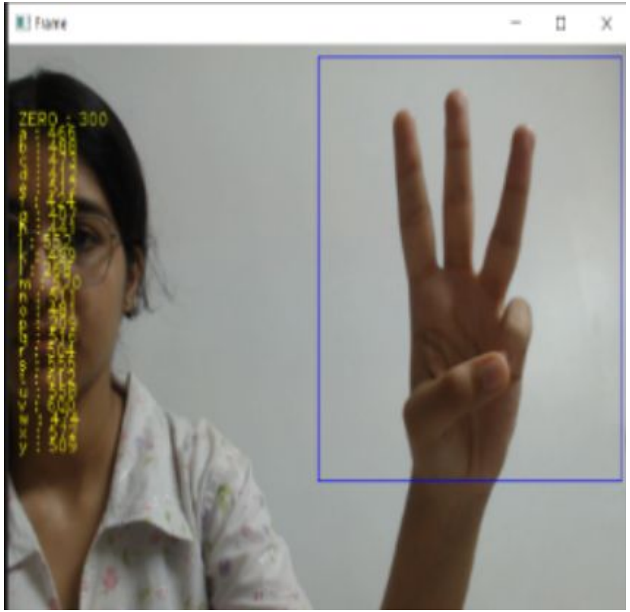


Fig 5. Data collection

Data Preprocessing

- Uses CvZone’s HandDetector to detect and extract hand landmarks.
- Converts the hand into a skeleton representation by drawing key points and connections

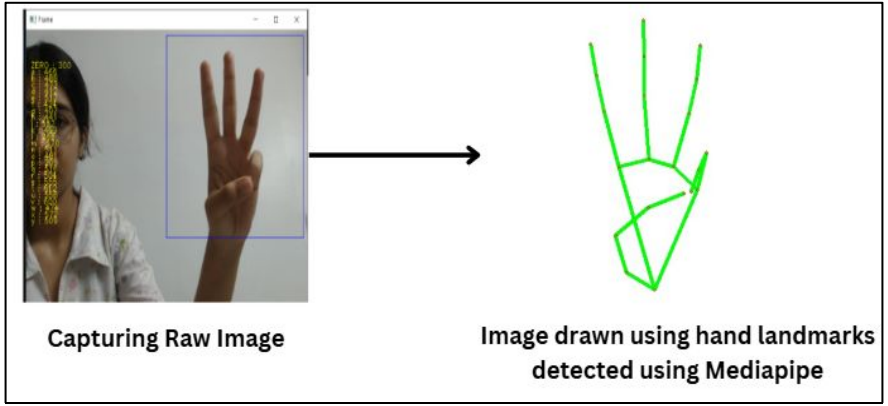


Fig 6: Steps of Data Preprocessing

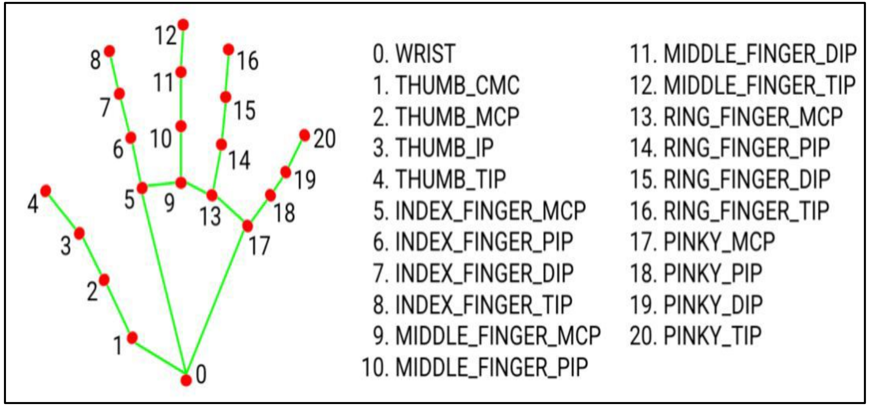


Fig 7 : Hand Landmark Points

Implementation

Model Training

We have used Transfer learning approach - with MobileNetV2 as the base model and custom layers above it to classify the letters into 25 classes

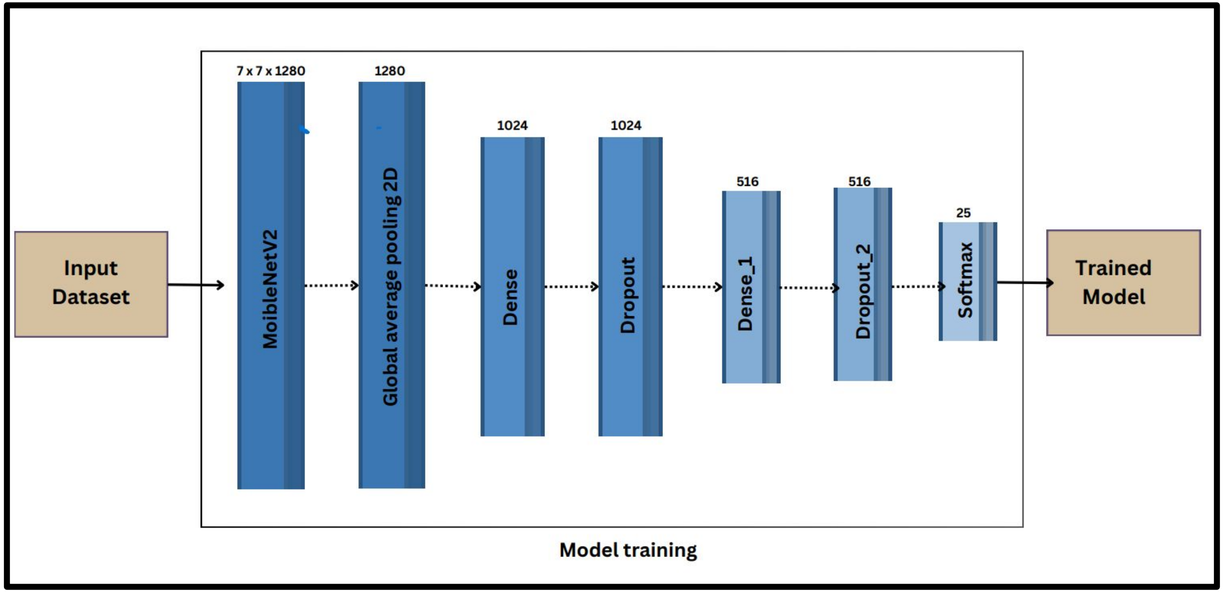


Fig 8. Model Architecture

Implementation

Model Training

Table 3: Comparison of Model Performance

Model	Training Accuracy	Testing Accuracy	Model Size
MobileNetV2	99.8%	93%	16 MB
InceptionV3	99.8%	88.52%	95 MB

Result

The model obtained a training and testing accuracy of 99.84% and 93% respectively.

The figures represent the model accuracy and loss while training for 12 epochs with a batch size of 16.

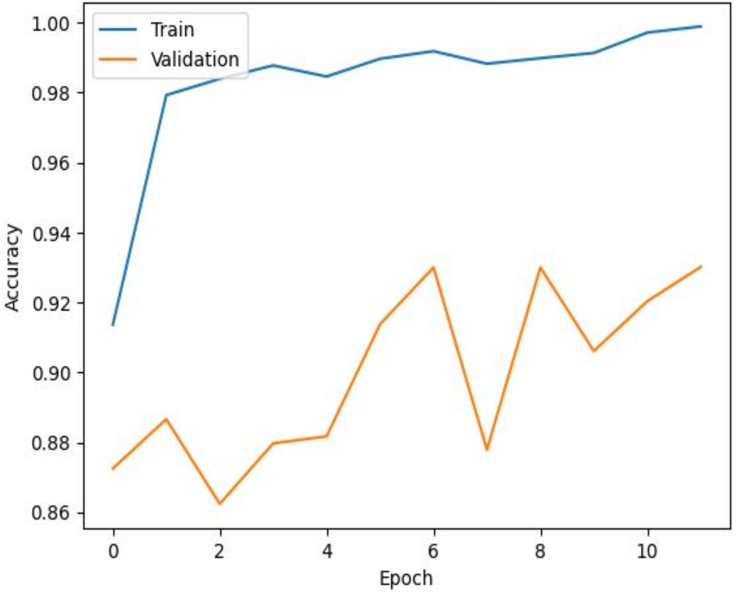


Fig 9. Model Accuracy

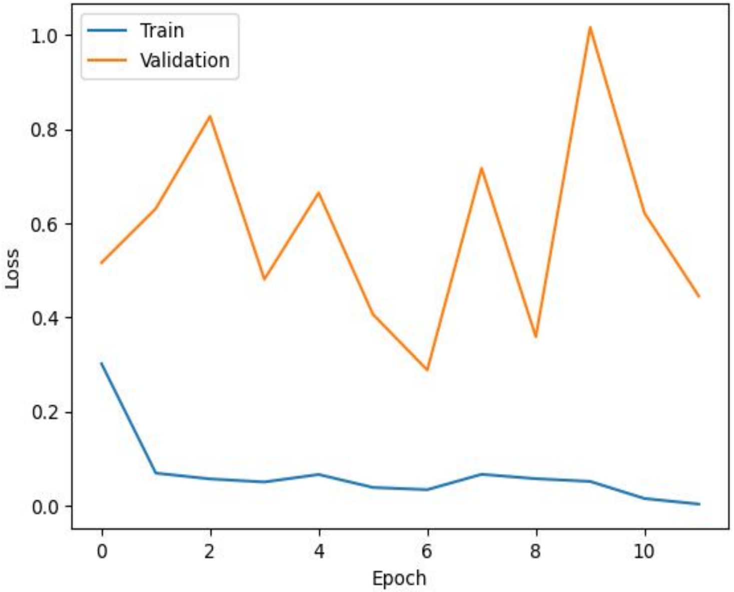


Fig 10. Model Loss

Result

	precision	recall	f1-score	support
0	1.00	1.00	1.00	261
1	0.77	1.00	0.87	261
2	0.99	1.00	1.00	261
3	1.00	1.00	1.00	261
4	0.99	1.00	1.00	261
5	1.00	0.76	0.86	261
6	1.00	1.00	1.00	261
7	1.00	1.00	1.00	261
8	1.00	0.93	0.97	261
9	0.98	0.91	0.95	261
10	0.77	1.00	0.87	261
11	1.00	0.89	0.94	261
12	0.84	0.80	0.82	261
13	0.66	0.99	0.80	261
14	0.91	1.00	0.95	261
15	1.00	0.98	0.99	261
16	1.00	1.00	1.00	261
17	0.91	0.97	0.94	261
18	0.96	0.99	0.98	261
19	0.91	0.68	0.78	261
20	0.99	0.82	0.90	261
21	0.96	1.00	0.98	261
22	1.00	0.96	0.98	261
...				
accuracy			0.93	6525
macro avg	0.94	0.93	0.93	6525
weighted avg	0.94	0.93	0.93	6525

Fig 11. Classification Report

Implementation

GUI Development

- **Tkinter** has been used to create the GUI of the Application.
- The application provides real time detection of letters, which then progressively combined to form **words, and then into meaningful sentences**.
- **Hunspell** library of python has been used to provide word suggestions based on the partially recognized word, enhancing accuracy.

Fig 12.Application GUI

Implementation

Application Deployment on Jetson Nano

- Deployed the SLR system on NVIDIA Jetson Nano for real-time ASL recognition.
- Optimized with TensorRT for fast, low-latency inference.
- Runs locally using JetPack SDK, TensorFlow, and CUDA.
- Compact, efficient, and ideal for edge deployment.
- Utilizes on-device GPU acceleration for smooth performance.
- Eliminates need for cloud connectivity, ensuring data privacy.

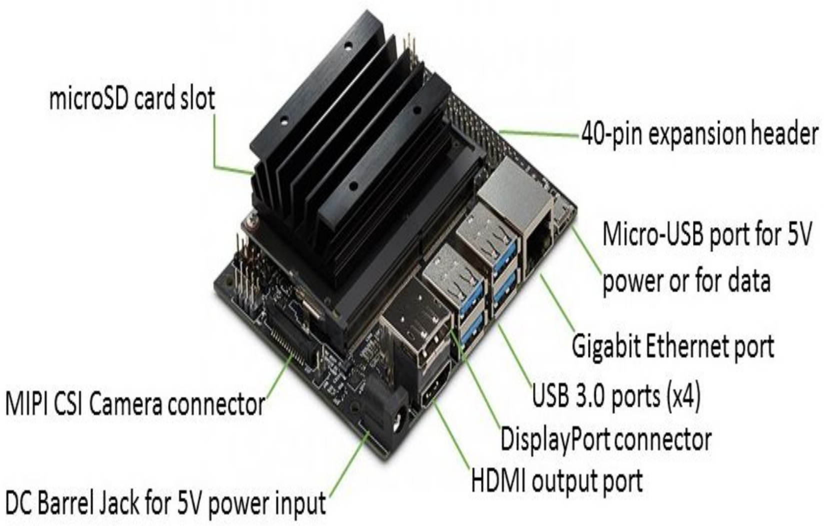


Fig 13. Jetsan Nano

Implementation

Speech Output Integration

- Uses Text-to-Speech (TTS) for audio conversion employing a USB Sound Adapter connected to Jetson Nano
- Provides real-time spoken feedback for communication.
- Supports three languages: Hindi, English, and Tamil.
- Users can select preferred language for speech output via the interface.
- This multilingual approach increases the accessibility by including different regional users

Fig 14. Jetsan Audio Module

Result

Ref	Sign Language	Dataset	Sample Size	Algorithm	Accuracy
[29]	Spanish	Self Captured	28,862	CNN-Resnet	79.96%
[30]	American	Self Captured	2080	RNN	93.4%
[31]	American	NCSLGR	3085	KNN	91.27%
[32]	American	ChicagoFSWild	7304	Hybrid CTC-Attention Model	71.7%
[33]	British	Self Captured	1000	HMM	98.9%
Proposed	**American**	**Self Captured**	**15,025**	**CNN-MobileNet**	**93%**

Table 4. Comparison of previous and proposed work

Conclusion and Future Scope

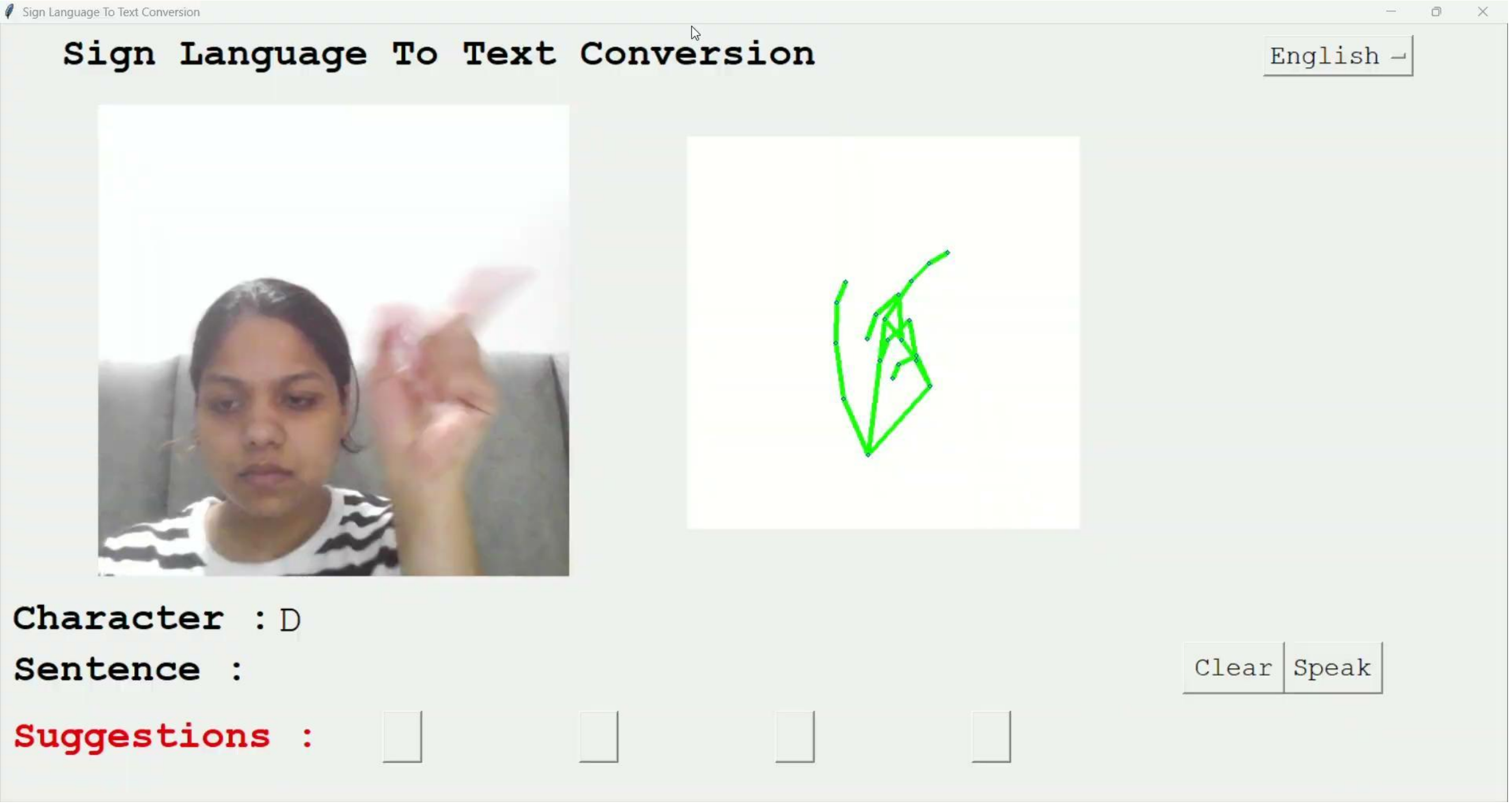
This research developed a real-time ASL fingerspelling recognition system with integrated text-to-speech functionality, achieving high accuracy and promoting accessible and inclusive communication for the Deaf community.

Future Scope:

- **Expanded Gesture Recognition:** Extend recognition to dynamic gestures and full ASL sentences.
- **Performance Optimization:** Enhance real-time speed and resource efficiency for mobile and wearable devices.
- **Multi-Modal Integration:** Incorporate body posture and facial expressions for richer, context-aware translations.

By building on these areas, the system can evolve into a more accurate, comprehensive, and inclusive communication solution.

Demo



Sign Language To Text Conversion
Sign Language To Text Conversion
English
Character : D
Sentence :
Clear
Speak
Suggestions :

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Publications

1. M. Chandna, A. Dasgupta, B. Gupta, R.M., S. R. N. Reddy, and R. Anand, "Bridging the gap: Real-Time ASL Fingerspelling to Sentence Translation," *Proceedings of the 6th International Conference on Intelligence and Speech Technology (AIST-2024)*. (Accepted and presented; publication in proceedings pending).

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19th – 21st March, 2025

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This is to certify that Prof. / Dr. / Mr. / Ms. Bhumika Gupta *has presented/contributed the paper titled* Real-Time Sign Language Recognition Using Deep Learning on Edge Devices: A Jetson Nano Implementation *in International Conference on Emerging Trends and Technologies on Intelligent Systems (ETTIS-2025) in association with the Petroleum-Gas University of Ploiesti, Romania, the University of Haute-Alsace, France and Northeastern University, USA.*

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Publications

3. M. Chandna, A. Dasgupta, B. Gupta, R. M., S. R. N. Reddy, and R. Anand, "Edge AI for real-time sign language to speech conversion: Implementing deep learning on Jetson Nano," *Journal of Psycholinguistic Research*, 2025.- under review(Communicated)

Journal of Psycholinguistic Research - Submission Notification to co-author - [EMID:2937b1663bc45e72] External Inbox x

Journal of Psycholinguistic Research (JOPR) <em@editorialmanager.com> 12:05 PM (4 minutes ago)

to me

Re: "Edge AI for Real-Time Sign Language to Speech Conversion: Implementing Deep Learning on Jetson Nano"

Full author list: Manya Chandna; Abantika Dasgupta; Bhumika Gupta; Ravinder M.; S.R.N. Reddy; Rishika Anand

Dear Ms. Chandna,

We have received the submission entitled: "Edge AI for Real-Time Sign Language to Speech Conversion: Implementing Deep Learning on Jetson Nano" for possible publication in Journal of Psycholinguistic Research, and you are listed as one of the co-authors.

The manuscript has been submitted to the journal by Dr. Ms. Rishika Anand who will be able to track the status of the paper through his/her login.

If you have any objections, please contact the editorial office as soon as possible. If we do not hear back from you, we will assume you agree with your co-authorship.

Thank you very much.

With kind regards,
Springer Journals Editorial Office
Journal of Psycholinguistic Research

THANK YOU