

# **ASL Recognition System: Bridging Gaps in Communication Accessibility**

A Thesis Submitted in partial fulfillment of the Requirements of the  
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## **Honors Thesis in Computer Science**

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# Abstract

A concise summary of your research, covering the problem (gaps in existing ASL recognition systems), your proposed solution (ASL recognition tool), methodology, key findings, and conclusions.

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# Preface

Why I chose this topic, personal insights, and what I learned, reference: CS example thesis.pdf (Kyle Maiorana)

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# Chapter 1

## Introduction

Communication is a fundamental human need, and for Deaf and hard-of-hearing individuals, American Sign Language (ASL) serves as a primary mode of expression. ASL is a rich and complex visual language based on hand shape, movement, and nonmanual markers such as facial expressions. Studies emphasizing Deaf-centric design have shown that effective ASL tools must respect the cultural and linguistic practices of the Deaf community (Hibbard et al., 2020 [1]).

Technology has evolved from the past to make communication more accessible, including captioning services, text-based messaging, and video relay services. However, these solutions often rely on real-time interpreters or a shared written language, which can be limiting in spontaneous, in-person conversations.

In recent years, advances in computer vision and machine learning have opened new avenues for automated sign language recognition. Leveraging the power of advanced algorithms and increasingly pervasive hardware (e.g., mobile phone cameras, webcams), engineers and researchers hope to create machines that can recognize ASL hand gestures in real time. While some progress has been made in recognizing static signs or alphabets, challenges remain, especially regarding vocabulary expansion, nonmanual features, and real-world performance. The present work focuses on addressing these challenges by developing a user-centered ASL recognition tool that emphasizes accuracy, speed, and accessibility.

### 1.1 Research Problem

Current ASL recognition systems have several limitations that make them impractical. Some systems recognize only a limited set of signs, which restricts real-world applicability. Others do not account for nonmanual signs, such as facial expressions or head tilts, which are essential in ASL for the expression of tone, grammatical markers, and emotional context.

Additionally, some tools demand specialized sensors that are expensive or inconvenient, thus deterring widespread use.

There is also a broad gap in designing user interfaces that are attentive to the needs and desires of Deaf individuals. Inaccurate calibration procedures, variability of performance under changing lighting conditions, or excessive latency can lower the reliability of a system. These barriers compound to inhibit the real-world deployment potential of ASL recognition technology in everyday communication (Falvo et al., 2020 [2]).

## **1.2 Research Objectives**

The overall goal of this thesis is to design a real-time ASL recognition system using computer vision and machine learning techniques. Specifically, the system must offer high recognition accuracy. The second aim is to enhance user experience by developing an accessible interface that is easy to install and requires minimal calibration or dedicated hardware. Additionally, the system needs to overcome environmental constraints by performing optimally in various lighting and backgrounds so that real environments can be utilized. Finally, the framework needs to be extensible for future additions of other signs, dynamic gestures, and nonmanual signals. By focusing on these core objectives, the system aims to be a foundation for broader applications in education, assistive technology, and inclusive communication devices.

## **1.3 Significance of the Study**

This project holds the potential for shattering communication barriers among the Deaf and hard-of-hearing and for providing meaningful resources for hearing individuals who wish to learn ASL. An effective real-time ASL recognition system can facilitate communication more effectively in public places, schools, and workplaces, particularly where access to interpreters may not be readily available. It can also serve as an interactive learning tool for ASL

learners, offering instant feedback on handshapes to facilitate language learning. The proposed framework can further be extended to encompass the full richness of sign languages, thereby enabling future research studies. By prioritizing usability and involving Deaf/ASL communities in the design, this research underscores the importance of user-centered solutions.

**1.4 Thesis Structure** This thesis is organized into five main chapters:

**1. Chapter 1: Introduction**

Provides the background and context of ASL recognition, defines the research problem, outlines objectives, and explains the study’s significance.

**2. Chapter 2: Literature Review**

Examines existing ASL recognition systems, machine learning techniques, and user-centered design principles. Identifies gaps in the current research and sets the stage for the proposed approach.

**3. Chapter 3: Software and Application**

Details the methodology, including data collection, model architecture, and real-time inference pipeline. Discusses the design choices and rationale behind the system’s implementation.

**4. Chapter 4: Results**

Presents empirical findings, including model performance metrics, real-time testing results, and user feedback. Analyzes both quantitative and qualitative data.

**5. Chapter 5: Conclusion**

Summarizes key insights, highlights contributions, and suggests avenues for future work. Reflects on the system’s potential impact on accessibility and communication technologies.

# Chapter 2

## Literature Review

### 2.1 Introduction

This literature review surveys various methods and technologies employed in American Sign Language (ASL) recognition systems. The goal is to establish how our approach, aimed at real-time recognition and user-friendly interaction fits into the existing body of work. By examining both hardware-based and vision-based solutions, we highlight the fundamental challenges and opportunities in creating accessible tools for Deaf and hard-of-hearing communities.

### 2.2 Overview of Existing ASL Recognition Systems

Recent developments in sign language recognition often revolve around three main technological streams:

- Computer Vision Approaches
- Depth Sensor Approaches
- Wearable Technology Approaches

Each of these streams has strengths and limitations related to cost, accuracy, ease of deployment, and user comfort. This section reviews notable research in these areas and provides the groundwork for our own system’s design choices.

#### 2.2.1 Computer Vision Approaches

A substantial portion of ASL recognition research leverages standard RGB cameras and a variety of computer vision techniques. Traditional pipelines often involve skin detection,

feature extraction, and hand segmentation before proceeding to classification. More recently, robust libraries like *OpenCV* and frameworks such as *MediaPipe* have significantly simplified and improved hand detection and tracking.

One notable example is the *MediaPipe Hands* solution, an open-source tool by Google<sup>1</sup>. MediaPipe Hands tracks 21 key landmarks on each hand, as illustrated in Figure 1. This framework provides real-time tracking even under challenging conditions such as varied lighting or partial occlusions, which is crucial for the fluid and rapid gestures of sign language.

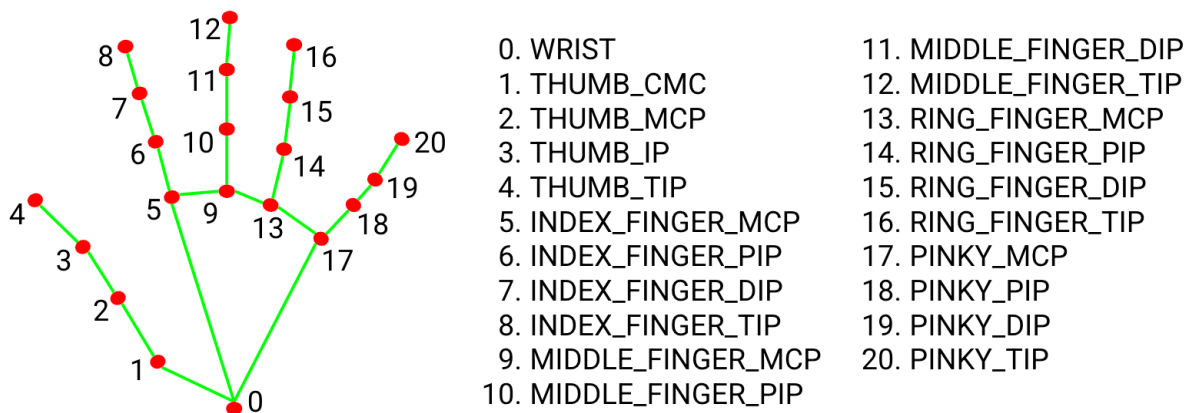


Figure 1: MediaPipe Hands landmarks. Each point corresponds to a specific joint or finger-tip.

Researchers have successfully integrated MediaPipe’s tracking features into sign language systems to reduce the complexity of manual feature engineering. For instance, Debnath and Joe [3] demonstrate a real-time ASL detection setup where MediaPipe is employed to extract hand pose information, thereby reliably differentiating between common ASL hand shapes and movements.

## 2.2.2 Depth Sensor Approaches

Beyond standard RGB cameras, *depth sensors* capture three-dimensional information about hand positions. Notably, Avola et al. [4] illustrate how the Leap Motion Controller can track the skeletal structure of the hand with fine-grained accuracy, enabling precise

<sup>1</sup><https://github.com/google-ai-edge/mediapipe/blob/master/docs/solutions/hands.md>

measurement of joint angles. This capability is beneficial for distinguishing similar signs that differ only slightly in finger placement or orientation.

### **2.2.3 Wearable Technology Approaches**

Finally, some research efforts rely on *wearable devices*, such as glove-based sensors, to record hand movements. These systems, often equipped with inertial measurement units (IMUs) or bend sensors, can capture motion data in three dimensions. For example, Stefanidis et al. [5] discuss the use of 3D technologies in sign language applications through wearable platforms. While potentially more accurate, such devices can be costly or cumbersome, limiting their broad adoption for everyday use.

## **2.3 Summary**

In summary, contemporary ASL recognition solutions range from purely vision-based approaches (e.g., MediaPipe Hands combined with OpenCV for live detection) to more specialized hardware solutions (e.g., depth sensors and wearable gloves). Among these, live vision-based detection using MediaPipe and OpenCV offers the optimal balance of high accuracy, cost-effectiveness, and ease of integration, making it the best choice for designing robust, real-time ASL recognition systems that can be easily adopted in real-world contexts.

## **2.4 Machine Learning Approaches for Gesture Recognition**

Advances in deep learning have been essential in enhancing sign language recognition by addressing both spatial and temporal complexities. In our work and as demonstrated in previous studies, a combination of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks has been used to capture static hand features as well as the dynamic information inherent in continuous gestures.

### 2.4.1 Convolutional Neural Networks (CNNs) for Static Sign Recognition

CNNs excel at extracting spatial features from images or individual video frames. Their layered architecture enables the learning of hierarchical representations that can effectively distinguish subtle differences in hand shape and orientation. In the context of ASL recognition, CNNs have been successfully used to classify isolated, static signs before further processing is applied (Debnath and Joe, 2024 [3]).

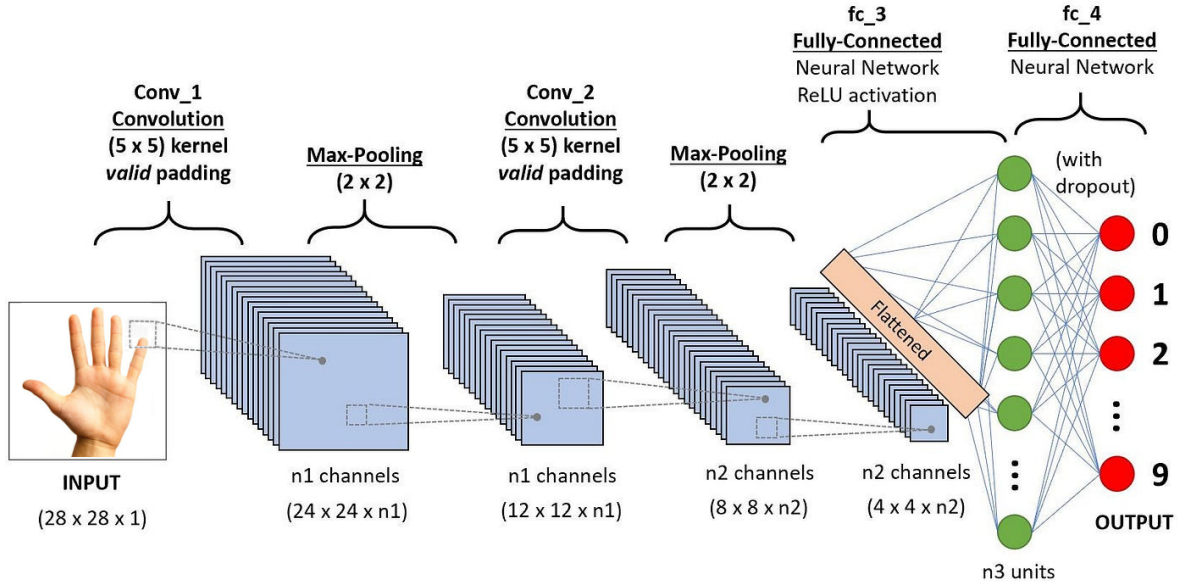


Figure 2: An illustration of a CNN architecture depicting convolutional layers, pooling layers, and fully connected layers, highlighting the extraction of features from a hand image.

### 2.4.2 Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTMs) for Dynamic Sign Recognition

Dynamic signs which involve motion and transitions require models that can capture temporal dependencies. Traditional RNNs are naturally suited for sequential data, but they often encounter difficulties such as vanishing gradients when processing long sequences (Avola et al., 2019 [4]; Liu et al., 2016 [6]). LSTM networks, introduced to overcome these limitations, incorporate memory cells and gating mechanisms that enable them to retain

and update information over extended periods (Hochreiter and Schmidhuber, 1997 [7]; Co-lah’s Blog, 2015 [8]). These capabilities make LSTMs particularly effective for recognizing continuous ASL gestures.

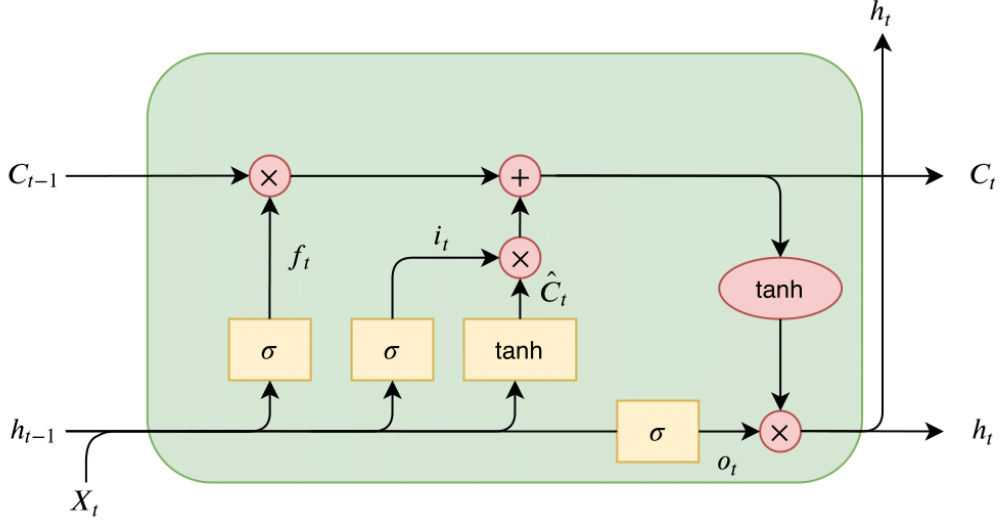


Figure 3: A diagram showing the internal structure of an LSTM cell—including input, forget, and output gates—and an unrolled LSTM network across a sequence of video frames.

Hybrid architectures that combine CNNs and LSTMs have also proven effective. In such systems, CNNs first extract deep features from each frame, and these features are then processed by LSTMs to capture the sequential dynamics of the gesture (Papastratis et al., 2021 [9]; Ru and Sebastian, 2023 [10]). This two-stage approach enhances accuracy, particularly in real-world scenarios where both spatial and temporal information are crucial.

### 2.4.3 Handling Static vs. Dynamic Signs

The choice of model architecture is dictated by the nature of the sign:

- **Static Signs:** When the sign consists of a fixed hand posture, CNNs can be employed alone to capture the necessary spatial features.
- **Dynamic Signs:** For gestures that involve motion, models such as RNNs and, more effectively, LSTMs are essential. Their ability to model long-term dependencies allows



them to interpret the temporal evolution of a gesture accurately. Many systems adopt a two-stage approach, first applying CNNs for frame-wise feature extraction, followed by LSTMs to model the sequential aspects of the gesture (Lee et al., 2021 [11]).

#### 2.4.4 Integration of Recursive Neural Network Approaches

Recent work has also explored recursive neural network architectures for capturing hierarchical structures in sign language gestures (Borges-Galindo et al., 2024 [12]). Although our primary focus is on CNN-LSTM hybrids, recursive models offer a promising alternative for handling complex information in gestures and may be considered for future extensions of our system.

### 2.5 Base Repository for Implementation

Our ASL recognition system builds upon the open-source repository by K. Takahashi, “hand-gesture-recognition-mediapipe” [13]. This repository provides a robust baseline that leverages the MediaPipe library for real-time hand and body landmark detection. By integrating MediaPipe’s efficient tracking algorithms with our CNN-LSTM architecture, our system extracts key spatial features and processes them in real time for accurate gesture recognition.

This base repository has been instrumental in our progress, enabling rapid prototyping and rigorous testing under real-world conditions.

### 2.6 Challenges and Gaps in Current Systems

Despite significant advances in ASL recognition technologies, several critical challenges and gaps remain that hinder widespread adoption in real-world settings:

- **Limited Vocabulary and Generalization:** Many existing systems are designed to recognize only a restricted set of signs, making it difficult to scale to larger vocabularies.

This limitation often stems from insufficient training data and models that are tuned for a narrow set of gestures (Debnath and Joe, 2024 [3]). Consequently, these systems struggle to generalize across different signers or adapt to variations in signing styles.

- **Difficulty Capturing Nonmanual Signals:** Effective sign language communication relies not only on hand gestures but also on nonmanual signals such as facial expressions and head tilts. Current approaches often neglect these critical features due to the complexities involved in accurately capturing and processing them. As a result, essential grammatical and emotional nuances are frequently lost, limiting the overall accuracy and naturalness of the interpretation (Avola et al., 2019 [4]).
- **Poor Performance in Real-World Environments:** Many systems demonstrate high accuracy under controlled conditions; however, performance typically degrades in real-world scenarios. Factors such as variable lighting conditions, dynamic backgrounds, and ambient noise can adversely affect both the feature extraction process and the robustness of the model (Liu et al., 2016 [6]). These challenges underscore the need for systems that maintain high performance in diverse and unpredictable environments.
- **User Interface and Accessibility Shortcomings:** Beyond the technical aspects of recognition, user experience plays a pivotal role in the adoption of ASL systems. Current implementations often suffer from complex calibration procedures, unintuitive interfaces, or hardware requirements that are not easily accessible to the Deaf community. Such issues can discourage user engagement and limit the practical utility of the technology (Hibbard et al., 2020 [1]).

## 2.7 Conclusion

In summary, while state-of-the-art ASL recognition systems have made commendable progress, significant gaps remain, particularly in vocabulary generalization, the integration of

nonmanual signals, robustness in real-world conditions, and user accessibility. Our proposed system addresses these issues by leveraging a hybrid CNN-LSTM architecture integrated with MediaPipe for real-time, robust hand and body landmark detection. By focusing on a user-centered design and optimizing performance under varying environmental conditions, the system aims to offer:

- **Real-Time Performance:** Ensuring quick and accurate recognition through efficient deep learning models and streamlined data processing pipelines.
- **Robust Detection:** Enhancing accuracy across a wide range of signs, including both manual and nonmanual signals, by employing advanced feature extraction and temporal modeling techniques.
- **User-Friendly Interface:** Prioritizing accessibility and ease of use, with minimal calibration requirements and an intuitive design that caters to the needs of Deaf and hard-of-hearing individuals.

This conclusion sets the stage for the subsequent methodology chapter, where we will detail the system architecture, data acquisition procedures, and the experimental protocols implemented to validate our approach.

# Chapter 3

## Software and Application

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### 3.1

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# Chapter 4

## Results

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### 4.1

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## Chapter 5

### Conclusion

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#### 5.1

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