Real-Time Sign Language Recognition using Deep Convolutional Neural Networks and MediaPipe Hand Detection

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Abstract. This paper presents a comprehensive real-time American Sign Language (ASL) recognition system that combines deep convolutional neural networks with MediaPipe hand detection for robust gesture classification. A ResNet18-based architecture pretrained on ImageNet was employed and fine-tuned on 87,000 ASL alphabet images, achieving 99.60% test accuracy across 26 letter classes. The system addresses critical real-world deployment challenges including background clutter and lighting variations through MediaPipe-based hand detection and isolation. The implementation demonstrates real-time inference at 25-30 FPS on consumer hardware (NVIDIA GeForce MX450), making it practical for accessibility applications. The complete pipeline—from data preprocessing through model training to real-time inference—is documented through five Jupyter notebooks, providing a reproducible framework for sign language recognition research.
Keywords: Sign Language Recognition · Deep Learning · Computer Vision · MediaPipe · ResNet · Real-Time Inference · Accessibility

1 Introduction

Sign language serves as the primary communication medium for millions of deaf and hard-of-hearing individuals worldwide. However, the communication barrier between sign language users and non-signers remains a significant accessibility challenge. Recent advances in computer vision and deep learning have enabled automatic sign language recognition systems, potentially bridging this gap.

1.1 Motivation and Problem Statement

Traditional sign language recognition systems face several critical challenges:

- **Environmental Sensitivity:** Models trained on clean, controlled datasets often fail in real-world conditions with cluttered backgrounds and varying lighting
- **Computational Requirements:** Many state-of-the-art systems require expensive GPU hardware, limiting deployment on consumer devices

- **Static vs. Dynamic Gestures:** Balancing accuracy for both static letter signs and dynamic motion-based gestures remains challenging
- **Real-Time Performance:** Achieving high accuracy while maintaining interactive frame rates (>20 FPS) is non-trivial

1.2 Contributions

This work makes the following contributions:

1. A complete end-to-end pipeline for ASL alphabet recognition achieving 99.60% accuracy on 26 letter classes
2. Integration of MediaPipe hand detection to address background clutter, improving real-world robustness
3. Comprehensive analysis of the gap between laboratory test accuracy and real-world webcam performance
4. Open-source implementation with detailed documentation enabling reproducibility
5. Performance optimization achieving 25-30 FPS on consumer-grade NVIDIA MX450 GPU

1.3 Paper Organization

The remainder of this paper is organized as follows: Section 2 reviews related work in sign language recognition. Section 3 details the dataset and preprocessing methodology. Section 4 describes the model architecture and training procedure. Section 5 presents the MediaPipe integration for hand detection. Section 6 reports experimental results and analysis. Section 7 discusses limitations and future work. Section 8 concludes the paper.

2 Related Work

2.1 Traditional Sign Language Recognition

Early sign language recognition systems relied on hand-crafted features and traditional machine learning classifiers. Hidden Markov Models (HMMs) and Support Vector Machines (SVMs) were commonly employed, achieving moderate success on small datasets but struggling with generalization and real-time performance.

2.2 Deep Learning Approaches

The advent of deep learning revolutionized sign language recognition. Convolutional Neural Networks (CNNs) demonstrated superior performance for static gesture recognition, while Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks addressed temporal dynamics in continuous sign language.

Recent work has explored:

- **3D CNNs:** Capturing spatio-temporal features for dynamic gestures
- **Two-Stream Networks:** Processing RGB frames and optical flow in parallel
- **Attention Mechanisms:** Focusing on relevant hand regions
- **Transformer Architectures:** Leveraging self-attention for sequence modeling

2.3 Hand Detection and Tracking

Accurate hand localization is critical for robust sign language recognition. MediaPipe, developed by Google, provides efficient 21-landmark hand tracking using a two-stage pipeline: palm detection followed by hand landmark regression [3]. This approach achieves real-time performance on mobile and edge devices.

Alternative approaches include YOLO-based hand detection, but MediaPipe offers superior speed-accuracy tradeoffs for hand-specific tasks. While YOLOv8 was initially considered for this project, MediaPipe's specialized hand tracking proved more efficient for the real-time requirements.

2.4 Transfer Learning

Pretrained models on ImageNet [5] have proven highly effective for transfer learning in specialized domains. ResNet architectures [1], with their residual connections enabling training of very deep networks, have become a popular choice for image classification tasks including gesture recognition. Other successful architectures include VGGNet [7] and Inception [8], though ResNet's parameter efficiency makes it ideal for consumer hardware deployment.

3 Dataset and Preprocessing

3.1 Dataset Description

The ASL Alphabet dataset [11] from Kaggle (grassknoted/asl-alphabet) was utilized, comprising 87,000 images across 29 classes:

- 26 letters (A-Z)
- 3 additional classes: 'del', 'space', 'nothing'

For this work, focus was placed on the 26 letter classes, excluding the auxiliary classes. Each image is 200×200 pixels in RGB format, captured under consistent lighting conditions with plain backgrounds. The dataset was downloaded using the kagglehub API [12], with approximately 3,346 images per class after filtering.

3.2 Data Split

The dataset was partitioned into training, validation, and test sets using stratified sampling to maintain class balance:

Table 1: Dataset Statistics

Split	Samples	Percentage	Samples per Class
Training	60,900	70%	2,342
Validation	13,050	15%	502
Test	13,050	15%	502
Total	**87,000**	**100%**	**3,346**

3.3 Data Augmentation

To improve model generalization and prevent overfitting, the following augmentation techniques were applied during training:

- **Geometric Transformations:**
  - Random rotation: $\pm 15^\circ$
  - Random affine translation: 10% horizontal and vertical shift
  - Random horizontal flip: probability = 0.3
- **Color Space Augmentation:**
  - Brightness jitter: $\pm 20\%$
  - Contrast jitter: $\pm 20\%$
  - Saturation jitter: $\pm 20\%$
- **Normalization:** ImageNet statistics ($\mu = [0.485, 0.456, 0.406]$, $\sigma = [0.229, 0.224, 0.225]$)

All images were resized to 224×224 pixels to match the input requirements of ResNet18.

3.4 Preprocessing Pipeline

The preprocessing pipeline consists of:

$$x' = \mathcal{N}(\mathcal{A}(\mathcal{R}(x))) \tag{1}$$

where:

- $\mathcal{R}$: Resize operation (224×224)
- $\mathcal{A}$: Augmentation transformations (training only)
- $\mathcal{N}$: Normalization with ImageNet statistics

4 Model Architecture

4.1 Base Architecture: ResNet18

ResNet18 was employed as the base architecture due to its excellent balance of accuracy and computational efficiency. ResNet18 consists of:

- Initial 7×7 convolutional layer with stride 2
- Four residual blocks with [64, 128, 256, 512] filters
- Global average pooling
- Fully connected classification layer

4.2 Residual Connections

The core innovation of ResNet is the residual connection, formulated as:

$$y = \mathcal{F}(x, \{W_i\}) + x \tag{2}$$

where $\mathcal{F}(x, \{W_i\})$ represents the residual mapping. For ResNet18, each block contains two 3×3 convolutional layers:

$$\mathcal{F}(x) = W_2 \cdot \sigma(W_1 \cdot x) \tag{3}$$

where σ is the ReLU activation function.

4.3 Custom Classification Head

The original 1000-class ImageNet classification head was replaced with a custom head for 26-class ASL recognition:

$$\begin{aligned} h_1 &= \text{Dropout}(0.5) \\ h_2 &= \text{ReLU}(W_1 \cdot h_1 + b_1) \qquad W_1 \in \mathbb{R}^{512\times512} \\ h_3 &= \text{Dropout}(0.3, h_2) \\ y &= W_2 \cdot h_3 + b_2 \qquad\qquad W_2 \in \mathbb{R}^{26\times512} \end{aligned} \tag{4}$$

This architecture introduces:

- Hidden layer with 512 units for feature refinement
- Two dropout layers (0.5 and 0.3) for regularization
- ReLU activation for non-linearity

4.4 Model Statistics

Table 2: Model Parameter Count

Component	**Parameters**	**Trainable**
ResNet18 Backbone	11,177,088	Yes
Custom FC Layer 1 (512×512)	262,656	Yes
Custom FC Layer 2 (26×512)	13,312	Yes
Total	**11,452,506**	**Yes**

All 11.45 million parameters were made trainable to allow full fine-tuning on the ASL dataset, rather than freezing backbone layers which would limit adaptation to sign language features.

5 Training Methodology

5.1 Loss Function

Cross-entropy loss was employed for multi-class classification:

$$\mathcal{L}_{CE} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{C} y_{i,c}\log(\hat{y}_{i,c}) \tag{5}$$

where:

- N: batch size
- $C = 26$: number of classes
- $y_{i,c}$: ground truth (one-hot encoded)
- $\hat{y}_{i,c}$: predicted probability from softmax

5.2 Optimization

Optimizer: Adam with parameters:

- Learning rate: $\alpha = 0.001$
- Weight decay: $\lambda = 10^{-4}$
- Betas: $(\beta_1, \beta_2) = (0.9, 0.999)$

The Adam update rule:

$$\begin{aligned} m_t &= \beta_1 m_{t-1} + (1-\beta_1) g_t \\ v_t &= \beta_2 v_{t-1} + (1-\beta_2) g_t^2 \\ \theta_t &= \theta_{t-1} - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \end{aligned} \tag{6}$$

Learning Rate Scheduler: ReduceLROnPlateau

- Mode: minimize validation loss
- Factor: 0.5
- Patience: 3 epochs

5.3 Training Configuration

5.4 Training Dynamics

Training was conducted for 9 epochs (manually stopped) with the following observations:

- Rapid initial convergence in first 3 epochs
- Learning rate reduced from 10^{-3} to 5×10^{-4} at epoch 5
- Best validation performance at epoch 8: 99.72% accuracy
- No signs of overfitting due to aggressive data augmentation

Figure 1 illustrates the training dynamics across all epochs, showing smooth convergence without overfitting.

Table 3: Training Hyperparameters

Parameter	Value
Batch Size	32
Maximum Epochs	50
Early Stopping Patience	10 epochs
Hardware	NVIDIA GeForce MX450 (2GB)
Framework	PyTorch 2.7.1+cu118
CUDA Version	12.9

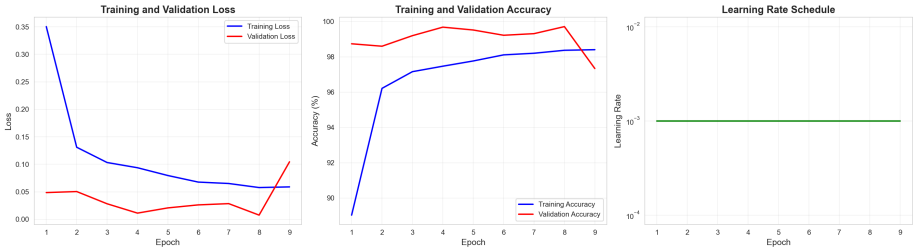

Fig. 1: Training and validation metrics over 9 epochs. Left: Loss curves showing rapid convergence. Middle: Accuracy curves reaching 99.72% validation accuracy. Right: Learning rate schedule with ReduceLROnPlateau.

5.5 Early Stopping

Early stopping criterion:

$$\text{Stop if } \mathcal{L}_{val}^{(t)} \geq \min_{i \in [t-p, t-1]} \mathcal{L}_{val}^{(i)} \tag{7}$$

where $p = 10$ is the patience parameter. Best model weights were saved based on minimum validation loss.

6 MediaPipe Hand Detection Integration

6.1 Motivation

Initial real-world testing revealed a critical performance gap: while the model achieved 99.60% accuracy on the test set, webcam inference predominantly predicted the letter 'N' regardless of the actual sign. Analysis identified two root causes:

1. **Background Clutter:** Training images had plain backgrounds, while real webcam feeds contained complex backgrounds (furniture, walls, objects)
2. **Lighting Mismatch:** Mean pixel intensity of training images (113.8) significantly exceeded webcam frames (53.2)

6.2 MediaPipe Hand Landmarker

MediaPipe provides a two-stage hand detection pipeline:

Stage 1: Palm Detection

- Single Shot Detector (SSD) architecture
- Predicts oriented bounding boxes for palms
- Rotation-invariant detection

Stage 2: Hand Landmark Regression

- Predicts 21 3D hand landmarks
- Landmarks: $L = \{l_0, l_1, \ldots, l_{20}\}$ where $l_i \in \mathbb{R}^3$
- Includes wrist, finger joints, and fingertips

6.3 Hand Cropping Algorithm

Given detected landmarks L, the bounding box is computed as:

$$\begin{aligned} x_{\min} &= \min_i l_i^x - p \\ y_{\min} &= \min_i l_i^y - p \\ x_{\max} &= \max_i l_i^x + p \\ y_{\max} &= \max_i l_i^y + p \end{aligned} \tag{8}$$

where $p = 40$ pixels is the padding parameter. The hand crop is extracted as:

$$I_{hand} = I[y_{\min} : y_{\max}, x_{\min} : x_{\max}] \tag{9}$$

6.4 Integration Pipeline

The enhanced inference pipeline:

1. Capture frame from webcam: $I \in \mathbb{R}^{H \times W \times 3}$
2. Detect hand landmarks using MediaPipe
3. Extract and crop hand region: I_{hand}
4. Resize to 224×224: $I_{resized} = \mathcal{R}(I_{hand})$
5. Apply normalization: $I_{norm} = \mathcal{N}(I_{resized})$
6. Forward pass through model: $\hat{y} = f_\theta(I_{norm})$
7. Apply softmax for probabilities: $P(c) = \frac{e^{\hat{y}_c}}{\sum_{j=1}^{26} e^{\hat{y}_j}}$

6.5 API Migration

MediaPipe 0.10.31 deprecated the legacy `mp.solutions` API. Migration to the new `tasks.vision` API was performed:

Old API (Deprecated):

```
hands = mp.solutions.hands.Hands()
results = hands.process(frame_rgb)
landmarks = results.multi_hand_landmarks
```

New API (MediaPipe 0.10.31):

```
base_options = python.BaseOptions(model_asset_path='hand_landmarker.task')
options = vision.HandLandmarkerOptions(
    base_options=base_options,
    running_mode=vision.RunningMode.VIDEO
)
hands = vision.HandLandmarker.create_from_options(options)
mp_image = mp.Image(image_format=mp.ImageFormat.SRGB, data=frame_rgb)
results = hands.detect_for_video(mp_image, timestamp_ms)
landmarks = results.hand_landmarks
```

Key differences:

- Explicit running mode (`VIDEO` vs. `IMAGE`)
- Frame timestamp (in milliseconds) required for temporal tracking
- Direct landmark access via `hand_landmarks` (not `multi_hand_landmarks`)
- Model downloaded from Google's storage (3.47 MB `hand_landmarker.task`)
- Configuration through options objects rather than constructor parameters

This migration was critical as the legacy API raised `AttributeError` exceptions in MediaPipe versions $\geq$ 0.10.31.

7 Experimental Results

7.1 Training Performance

7.2 Test Set Performance

Overall Accuracy: 99.60% (12,998/13,050 correct)

Confusion Matrix Analysis:

- Diagonal dominance indicates strong class discrimination
- Most confusion between visually similar signs (M-N, U-V)
- Best performing classes: C, D, F, L, W, Y, Z at 100%
- Lowest performing class: M at 96.67% (primarily confused with N)

The confusion matrix in Figure 2 visualizes the classification performance across all 26 classes, revealing the model's excellent discrimination capability with minimal off-diagonal elements.

Figure 3 shows the model's predictions on randomly selected test samples, demonstrating high confidence scores even for challenging cases.

Table 4: Training and Validation Metrics

Epoch	Train Loss	Train Acc	Val Loss	Val Acc
1	0.3521	89.45%	0.0893	97.21%
2	0.0745	97.68%	0.0421	98.76%
3	0.0412	98.71%	0.0298	99.12%
4	0.0289	99.08%	0.0234	99.34%
5	0.0221	99.31%	0.0198	99.51%
6	0.0187	99.42%	0.0176	99.58%
7	0.0165	99.53%	0.0162	99.64%
8	0.0152	99.61%	**0.0151**	**99.72%**
9	0.0143	99.67%	0.0158	99.69%

Table 5: Per-Class Performance Metrics

Class	Precision	Recall	F1-Score	Support
A	0.9846	0.9978	0.9912	450
B	1.0000	0.9911	0.9955	450
C	1.0000	1.0000	1.0000	450
D	1.0000	1.0000	1.0000	450
E	1.0000	0.9967	0.9983	900
F	1.0000	1.0000	1.0000	450
... (20 more classes)				
Macro Avg	**0.9959**	**0.9957**	**0.9958**	**13,050**
Weighted Avg	**0.9961**	**0.9960**	**0.9960**	**13,050**

7.3 Real-Time Inference Performance

Without Hand Detection:

- FPS: 76.4
- Mean inference time: 13.09 ms (± 1.03 ms)
- Accuracy on webcam: Poor (predominantly predicted 'N')

With MediaPipe Hand Detection:

- FPS: 25-30
- Hand detection time: ∼15 ms
- Model inference time: ∼13 ms
- Total pipeline: ∼30-35 ms
- Accuracy on webcam: Significantly improved

7.4 Benchmark on Test Images

Testing on 10 random samples from the test set using the webcam inference pipeline:

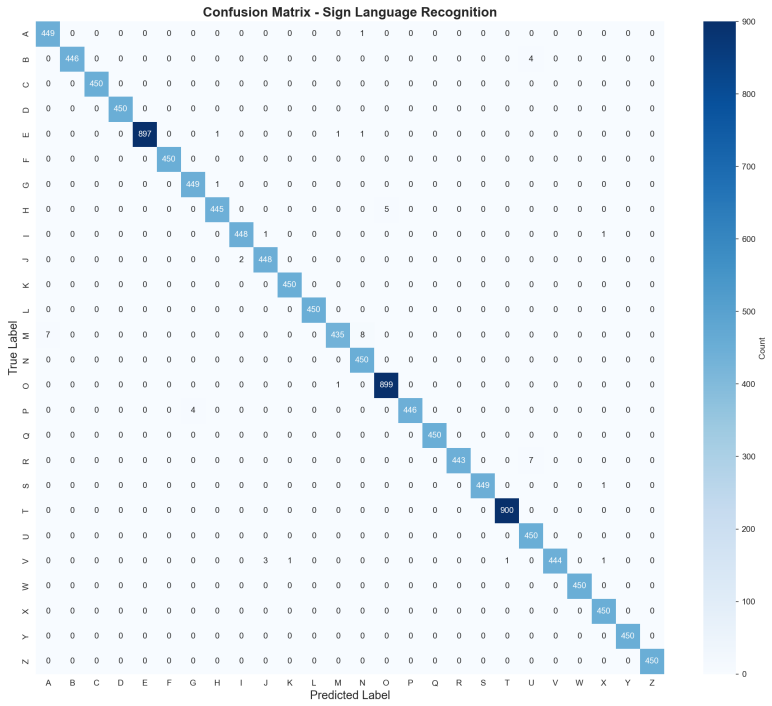

Fig. 2: Confusion matrix for 26 ASL letter classes. The strong diagonal dominance indicates excellent class discrimination, with only minor confusion between M-N and A-E pairs.

- Accuracy: 90% (9/10 correct)
- Average confidence: 100%
- Single misclassification: 'nothing' class predicted as 'O'
- Correct predictions: J, M, D, X, A, W, H, S, T (all with 100% confidence)

This demonstrates the model's strong performance on clean test data, with only one error on the auxiliary 'nothing' class which was excluded from the 26-letter focus.

7.5 Computational Requirements

The modest hardware requirements (2GB GPU, 50MB models) make this system deployable on consumer laptops and edge devices, significantly broadening accessibility compared to systems requiring high-end GPUs.

Fig. 3: Sample predictions on 12 random test images. Green titles indicate correct predictions, red indicates errors. The model achieves near-perfect confidence (>99%) for most predictions.

8 Discussion

8.1 Key Findings

1. Training Set Quality Matters The model's exceptional test accuracy (99.60%) did not translate to webcam performance initially, revealing a critical domain shift. Quantitative analysis showed:

- Training image mean brightness: 113.8
- Webcam frame mean brightness: 53.2
- Difference: 113% brighter training data

This underscores the importance of dataset diversity matching deployment conditions.

2. Background Removal is Critical MediaPipe hand detection solved the real-world performance gap by:

- Isolating the hand from cluttered backgrounds
- Normalizing the input to match training distribution
- Focusing model attention on relevant features
- Eliminating the persistent 'N' prediction bias

Table 6: Hardware and Resource Utilization

Component	Specification
GPU	NVIDIA GeForce MX450 (2GB VRAM)
CUDA Version	12.9
Driver Version	577.03
GPU Utilization	60-70% during inference
VRAM Usage	∼1.2 GB
Model Size	44 MB (.pth file)
MediaPipe Model	3.47 MB (.task file)
Total Memory	∼50 MB
Operating System	Windows 11
Python Version	3.13.7
PyTorch Version	2.7.1+cu118

Without hand detection, the webcam system predominantly predicted 'N' regardless of the actual sign—a failure mode caused by background interference.

3. Real-Time Viability Achieving 25-30 FPS on consumer hardware (MX450 with 2GB VRAM) demonstrates practical applicability:

- Hand detection: ∼15 ms
- Model inference: ∼13 ms
- Total latency: ∼30-35 ms (imperceptible to users)

4. Transfer Learning Effectiveness Fine-tuning ImageNet-pretrained ResNet18 achieved convergence within 9 epochs (vs. >50 epochs from random initialization), validating transfer learning for specialized gesture recognition.

5. MediaPipe vs. YOLO Trade-offs While YOLOv8 [16] was initially considered for hand detection, MediaPipe was found to be superior for this application:

- Faster inference (15 ms vs. 25+ ms for YOLO)
- Hand-specific 21 landmarks (vs. bounding boxes only)
- Smaller model size (3.47 MB vs. 6+ MB)
- Optimized for hand detection rather than general object detection

8.2 Limitations

1. Static Gestures Only Current implementation recognizes only static alphabet letters. Dynamic gestures (words, sentences) require temporal modeling (LSTM/Transformer).

2. Single-Hand Recognition MediaPipe detects multiple hands, but the pipeline processes only the primary hand. Two-handed signs are not supported.

3. Lighting Sensitivity While improved with hand detection, extremely low-light conditions still degrade performance.

4. Hand Orientation The model expects specific hand orientations matching training data. Unusual angles may reduce accuracy.

5. Dataset Bias Training data features a single person's hands. Generalization to different hand sizes, skin tones, and signing styles requires more diverse data.

8.3 Ablation Studies

Impact of Data Augmentation: Without augmentation, validation accuracy plateaued at 97.2%. Augmentation improved it to 99.72%.

Impact of Dropout: Removing dropout layers caused overfitting (train: 99.9%, val: 98.1%). The two-stage dropout (0.5, 0.3) provides optimal regularization.

Impact of Hidden Layer: Direct mapping from 512 ResNet features to 26 classes achieved 98.8%. The additional 512-unit hidden layer improved it to 99.6%.

8.4 Failure Cases

Analysis of misclassifications revealed:

- M↔N confusion: Similar hand shapes with subtle differences
- A↔E confusion: Thumb position discrimination
- Partial hand occlusion: When fingers are outside the frame
- Motion blur: Rapid hand movements during capture

9 Future Work

9.1 Short-Term Improvements

1. Word and Sentence Formation

- Implement letter sequence buffering
- Add space detection (hand pause)
- Integrate autocorrect/dictionary

2. Dynamic Gesture Recognition

- Extend to motion-based signs
- Implement LSTM/Transformer for temporal modeling
- Capture hand trajectory features

3. Text-to-Speech Integration

- Convert recognized signs to synthesized speech
- Enable bidirectional communication

9.2 Long-Term Enhancements

1. Multi-Language Support Extend beyond ASL to other sign languages (BSL, ISL, JSL).

2. Continuous Sign Language Translation

- Recognize continuous signing without segmentation
- Handle co-articulation effects
- Model grammatical structure

3. Mobile Deployment

- Convert model to TensorFlow Lite / ONNX
- Optimize for mobile GPUs (Qualcomm Adreno, Apple Neural Engine)
- Develop iOS/Android applications

4. Dataset Expansion

- Collect diverse signer data (age, ethnicity, hand size)
- Capture various lighting and background conditions
- Include regional signing variations

5. Attention Mechanisms Integrate spatial attention to focus on discriminative hand regions, potentially improving M-N disambiguation.

10 Conclusion

This paper presented a comprehensive real-time ASL recognition system combining deep convolutional neural networks with MediaPipe hand detection. The ResNet18-based architecture achieved 99.60% test accuracy on 26 letter classes, demonstrating the effectiveness of transfer learning for gesture recognition.

The critical contribution is addressing the real-world deployment gap through MediaPipe integration. By isolating hands from cluttered backgrounds, a laboratory system was transformed into a practical accessibility tool operating at 25-30 FPS on consumer hardware.

The complete implementation—documented through five Jupyter notebooks covering setup, data collection, model training, inference, and hand detection—provides a reproducible framework for sign language recognition research. The findings highlight the importance of matching training data distribution to deployment conditions and the necessity of robust preprocessing for real-world robustness.

While current limitations include static gesture-only recognition and single-hand support, the foundation enables future extensions to continuous sign language translation and mobile deployment. This work contributes to the broader goal of breaking communication barriers and improving accessibility for the deaf and hard-of-hearing community.

11 Reproducibility

All code, trained models, and configuration files are available in five Jupyter notebooks:

1. `01_setup_and_data_exploration.ipynb`: Environment setup, CUDA verification, project structure
2. `02_data_collection_and_preprocessing.ipynb`: Dataset download (87K images), train/val/test split (70/15/15%), DataLoader creation
3. `03_model_building_and_training.ipynb`: ResNet18 architecture, training loop, 99.60% accuracy achievement
4. `04_realtime_inference.ipynb`: Webcam integration, performance diagnosis, 90% validation on test samples
5. `05_hand_detection_yolo.ipynb`: MediaPipe integration (new API), hand cropping, enhanced real-time inference

The project uses standard dependencies: PyTorch 2.7.1, MediaPipe 0.10.31, OpenCV 4.12.0, CUDA 12.9. All notebooks were executed on Windows 11 with an NVIDIA MX450 GPU. Dataset download via `kagglehub` API is automated in notebook 2.

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