American Sign Language Recognition Using Dual-Input CNNs

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Introduction

American Sign Language (ASL) is a vital communication method for the Deaf community. Traditional recognition systems rely on static images and struggle in real-time due to lighting, background, and pose variation. This project presents a robust real-time ASL recognition system using a dual-input CNN architecture combining grayscale images and 3D hand landmarks.

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Motivation and Challenges

Image-only models fail under real-world variability. Webcam input introduces lighting, background clutter, and hand jitter. A dual-input system addresses these with visual and spatial awareness.

- **Visual Similarity Between Signs** Many ASL letters (M,N,S,T) have similar hand shapes , making it hard for the machine to observe
- **Live Video Distortions** Real-time environments introduce lighting variation, motion blur, background clutter, and partial occlusions — conditions that static training data doesn't represent well.
- **Heavy Models Struggle in Real Time** Pretrained models like ResNet50, although accurate in validation, are too slow and inconsistent for real-time feedback under noisy conditions.

My Contributions

Dual-Input CNN Architecture: We designed a novel convolutional neural network that processes two input streams—grayscale hand images and 3D landmark coordinates extracted using MediaPipe. This fusion improves spatial awareness and robustness.

Landmark-Guided Input Stream: I introduced landmark-based representation into the classification pipeline, allowing the model to focus on hand structure rather than just appearance.

High Accuracy Under Real-World Conditions: Our model maintains strong performance across various real-time webcam conditions including lighting changes, background clutter, and occlusion.

Real-Time Interactive Feedback: We implemented gesture stability logic and speech synthesis to provide real-time translation from signs to spoken language.

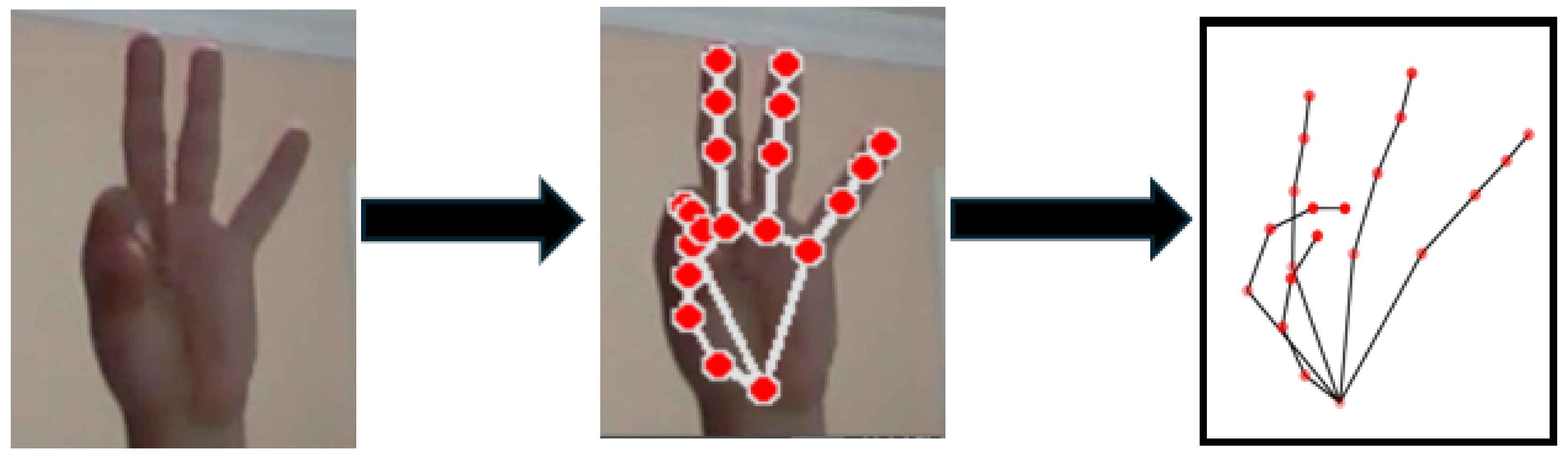


Figure 1. Landmarks extraction

Methodology

I have developed a dual-branch Convolutional Neural Network (CNN) that simultaneously processes grayscale hand images and 3D hand landmark arrays. This multimodal approach enhances robustness in real-world conditions. **Data Pipeline:**

- Webcam captures hand image.
- MediaPipe extracts 21 hand landmarks (x, y, z).
- Grayscale image and landmark array are passed to the CNN model.
- Model outputs a letter prediction if gesture is stable for 1.5 seconds.
- Letters form a sentence, which is spoken aloud with text-to-speech.

Model Architecture:

- **Image Branch:** 3 Conv2D layers + MaxPooling + Dropout.
- **Landmark Branch:** 2 Conv2D layers + Dropout.
- **Fusion:** Flattened outputs are concatenated and passed to dense classification layers.

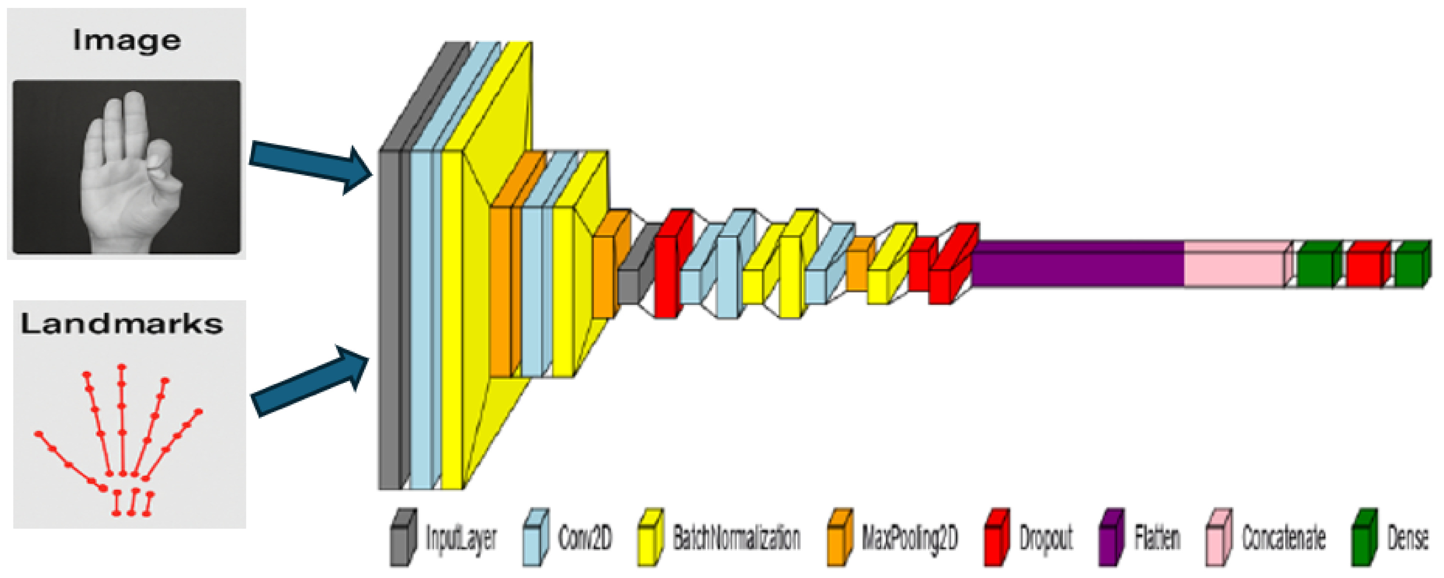


Figure 2. Dual-inputCNN

Experiments and Results

Baseline Comparison:

- **Image-only CNN:** average validation accuracy but poor generalization in real-time.
- **ResNet50:** Accurate but latency-prone and horrible in live usage.

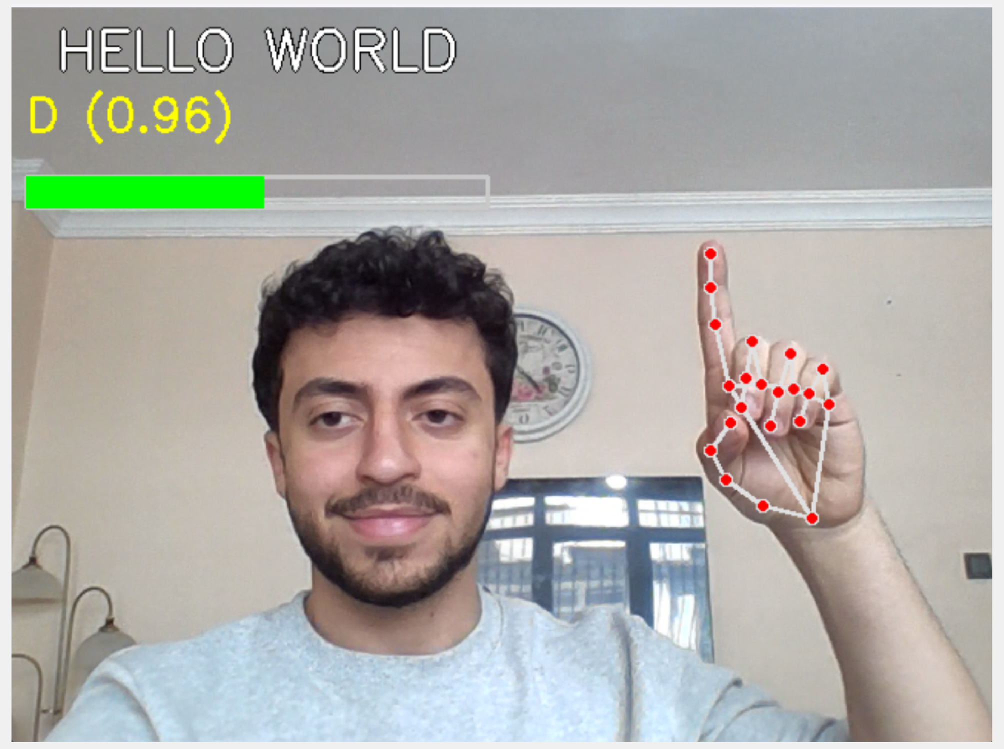
Proposed Dual-Input CNN:

- Combines grayscale image and hand landmark data.
- Achieved stable, accurate predictions in real webcam settings.

Model Performance Summary:

Metric	Score
Accuracy	0.96
Precision	0.96
Recall	0.94
F1-Score	0.94

Model Live Deployment



The system successfully tracks hand gestures in real-time using a laptop webcam.
Once a gesture is held steadily for 1.5 seconds, the corresponding letter is added to the sentence. If the hand is removed, a space is inserted and the word is spoken aloud using a text-to-speech engine.

Conclusion

I developed a real-time ASL recognition system using a dual-input CNN architecture that processes both grayscale hand images and 3D landmarks.

Compared to image-only and transfer learning baselines, our model achieved higher accuracy, better generalization, and stable real-time performance.

The integration of gesture stabilization and text-to-speech feedback makes it practical for real-world accessibility applications

Future Work

- Extend the system to recognize dynamic ASL signs and phrases using video sequences.
- Integrate Recurrent Neural Networks (RNNs) or Transformers to capture temporal patterns.
- Expand the dataset to include more users, lighting conditions, and background diversity.

References

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