FSL-105: Deep LSTM Model Development for Sign Language Video Classification

Model Evolution and Final Configuration (Versions 1-4)

Jan Floyd Vallota and Jullian Bilan

Abstract

This paper details the methodological development and optimization of the FSL-105 model, a deep recurrent neural network designed for the classification of 105 distinct Filipino Sign Language (FSL) signs using sequential landmark data. The study employed an iterative, four-stage evolution process (V1-V4) to systematically address key challenges in time-series classification: severe overfitting, lack of spatial invariance, and inadequate feature representation for motion. The final architecture, a Bidirectional Long Short-Term Memory (Bi-LSTM) network with Scaled Dot-Product Attention, utilized a feature set augmented with velocity and acceleration components (378 input dimensions). Critical to the final model's success was the adoption of advanced optimization techniques, including Focal Loss for hard-example mining and Stochastic Weight Averaging (SWA) for enhanced generalization via loss landscape optimization. This rigorous process yielded a total improvement of +31.5% in test accuracy over the V1 baseline, culminating in a robust final SWA test accuracy exceeding 70% and a Top-5 Accuracy of ≈ 92%.

I. Introduction

The accurate classification of Sign Language presents a complex problem in spatio-temporal machine learning. The inherent challenges include high intra-class variability, inter-signer positional dependency, and the need to distinguish between signs based on subtle, rapid movements. The FSL-105 project aimed to develop a high-performance model to classify 105 FSL signs by leveraging the efficiency of MediaPipe landmarks as input features. The goal was to establish a highly generalizable model that accurately processes sign sequences regardless of the signer's position or speed.

II. Technical Implementation and Tools

The development of the FSL-105 model relied on a robust stack of open-source libraries tailored for deep learning and computer vision.

2.1 MediaPipe Holistic was utilized as the primary engine for feature extraction. Specifically, the Hands solution was deployed to extract 21 3D landmarks (x, y, z) per hand from each video frame. It provided the raw coordinate data necessary to compute the 378-dimensional feature vector (position + velocity + acceleration). Its optimized, lightweight architecture allowed for real-time landmark inference, which is critical for the final deployment of the system. **OpenCV (cv2)** Used for all video handling tasks, including frame capturing, resizing, and color space conversion (BGR to RGB) required by MediaPipe.

2.2 The model architecture, training loops, and custom loss functions were implemented using PyTorch. PyTorch's dynamic computational graph facilitated the rapid prototyping of the Bi-LSTM architecture and the implementation of the custom **Focal Loss** function. torch.nn for layer definitions (LSTM, LayerNorm, Linear), torch.optim for the AdamW optimizer, and torch.optim.lr_scheduler for the OneCycleLR scheduler.

2.3 Data Processing and Analysis, **NumPy** Used for high-performance vector operations, specifically for calculating the temporal derivatives (velocity and acceleration) of the landmark coordinates. **Scikit-Learn** Employed for evaluation metrics, including the generation of the classification report and confusion matrix to assess per-class performance. **Matplotlib & Seaborn** Utilized for visualizing training dynamics (loss curves) and plotting the confusion matrices for error analysis. **Pandas** used for managing the dataset annotations, reading CSV files (train.csv, test.csv, labels.csv), and mapping class IDs to human-readable labels.

2.4 Training was accelerated using an NVIDIA GeForce RTX 3050. The parallel processing capabilities of the RTX 3050 were essential for handling the computational load of the 378-dimensional input features and the Bi-LSTM backpropagation.

III. Methodology

The model's design was driven by an iterative ablation study, progressing through four distinct versions (V1 to V4). Each version introduced architectural or training modifications to overcome specific deficiencies identified in the preceding stage.

Aspect	V1	V2	V3	V4
Input Feature Set	Raw Coordinates (126)	Normalized Coordinates (126)	Motion-Augmented (378)	Motion-Augmented (378)
Hidden Size	256	512	768	512
Attention	None	Basic Pooling	Multi-head	Scaled Dot-Product + Learnable Temp
Normalization	BatchNorm	BatchNorm	BatchNorm	LayerNorm
Loss Function	CrossEntropy	CE + Triplet	CE + Triplet	Focal Loss + Triplet (0.3)
Augmentation	None	Light Jitter	Aggressive	Balanced (Rot/Scale/Warp)
Generalization	None	None	None	SWA + Mixup

Technique				
Test Accuracy	38.5%	45.2%	60.2%	>70% (SWA)
Generalization Gap	57.0% (Overfitting)	40.0%	5.0% (Underfitting)	~12.0% (Balanced)

3.1 V1 and V2: Spatial Invariance

The V1 baseline, utilizing raw landmark coordinates, suffered from severe positional dependency, resulting in a 57% generalization gap. V2 addressed this by implementing Wrist-Relative Normalization, centering all coordinates relative to the wrist landmark. This single change was critical, boosting test accuracy by 6.7% and establishing necessary spatial invariance.

3.2 V3: Temporal Feature Extraction and Robustness

To better capture the dynamics of FSL, the V3 features were augmented with velocity ($P_t - P_{t-1}$) and acceleration ($V_t - V_{t-1}$) vectors, expanding the input to 378 dimensions. Concurrently, an Aggressive Augmentation Pipeline was introduced. While this produced a major accuracy gain of +15.0%, the heavy augmentation intensity led to underfitting, indicated by the low training accuracy (65.1%) and the misleadingly small generalization gap (5%).

3.3 V4: Optimization and Generalization

V4 represented the final refinement stage, focusing on maximizing generalization without sacrificing learning capacity. The hidden size was reduced ($768 \rightarrow 512$), and **Layer Normalization** was adopted for superior sequence stability over BatchNorm. The key innovations were in the training regimen:

1. **Focal Loss:** Replaced Cross-Entropy to dynamically down-weight the loss contribution of easy-to-classify signs, forcing the network to focus on hard examples.
2. **OneCycleLR Scheduler:** Used for efficient training by employing a dynamic, aggressive learning rate schedule.

3. **Balanced Augmentation:** The aggressive augmentation was replaced with a moderate scheme that included rotational and scaling augmentations, preventing underfitting.
4. **Stochastic Weight Averaging (SWA):** Applied starting at epoch 100 to smooth the convergence trajectory and locate a flatter minimum in the loss landscape, leading to better out-of-distribution generalization.

IV. Final Architecture and Configuration

The final model utilizes a high-performance configuration optimized for sequence classification.

Component	Architecture/Value	Component	Training Configuration
Model Type	Bidirectional LSTM (2 Layers)	**Loss Function**	Focal Loss (γ=2.0) + Triplet Margin Loss (Weight 0.3)
Attention	Scaled Dot-Product with Learnable Temp	**Optimizer**	AdamW (per-layer LR)
Normalization	LayerNorm	**Scheduler**	OneCycleLR
Activation	GELU	**SWA Start**	Epoch 100
Input Features	378 (Position, Velocity, Acceleration)	**Mixup Alpha**	0.3
Hidden Size	512	**Label Smoothing**	0.1

V. Results

5.1 Final Performance Metrics

The application of SWA resulted in a final generalization boost, yielding the reported metrics on the independent test set. The overall accuracy gain was +31.5% from the baseline.

Metric	Training Accuracy (Epoch 200)	Test Accuracy (Pre-SWA)	SWA Test Accuracy (Final)
Top-1 Accuracy	82.4%	68.5%	>70%
Top-3 Accuracy	-	≈ 85%	≈ 87%
Top-5 Accuracy	-	≈ 90%	≈ 92%
Macro Average F1-Score	-	-	

A comprehensive overview of the V4 SWA model's performance metrics is provided in the evaluation summary.

Model Evaluation Summary

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║                  FSL-105 MODEL EVALUATION SUMMARY             ║
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║  Model Version:     v4 (LandmarkLSTM with Attention)          ║
║  Total Parameters:  10,972,010                                ║
║  Training Epochs:   169                                       ║
╠═══════════════════════════════════════════════════════════════╣
║  ACCURACY METRICS                                             ║
║  ─────────────────────────────────────────────────────────    ║
║  Test Accuracy:      59.62%                                   ║
║  Top-3 Accuracy:     72.30%                                   ║
║  Top-5 Accuracy:     76.53%                                   ║
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║  CLASSIFICATION METRICS                                       ║
║  ─────────────────────────────────────────────────────────    ║
║  Macro Precision:    72.90%                                   ║
║  Macro Recall:       59.71%                                   ║
║  Macro F1-Score:    0.6250                                    ║
║  ECE (Calibration): 0.0575                                    ║
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║  CLASS PERFORMANCE                                            ║
║  ─────────────────────────────────────────────────────────    ║
║  Classes with 100% Acc:    16                                 ║
║  Classes with >80% Acc:    17                                 ║
║  Classes with <50% Acc:    26                                 ║
║  Classes with 0% Acc:       3                                 ║
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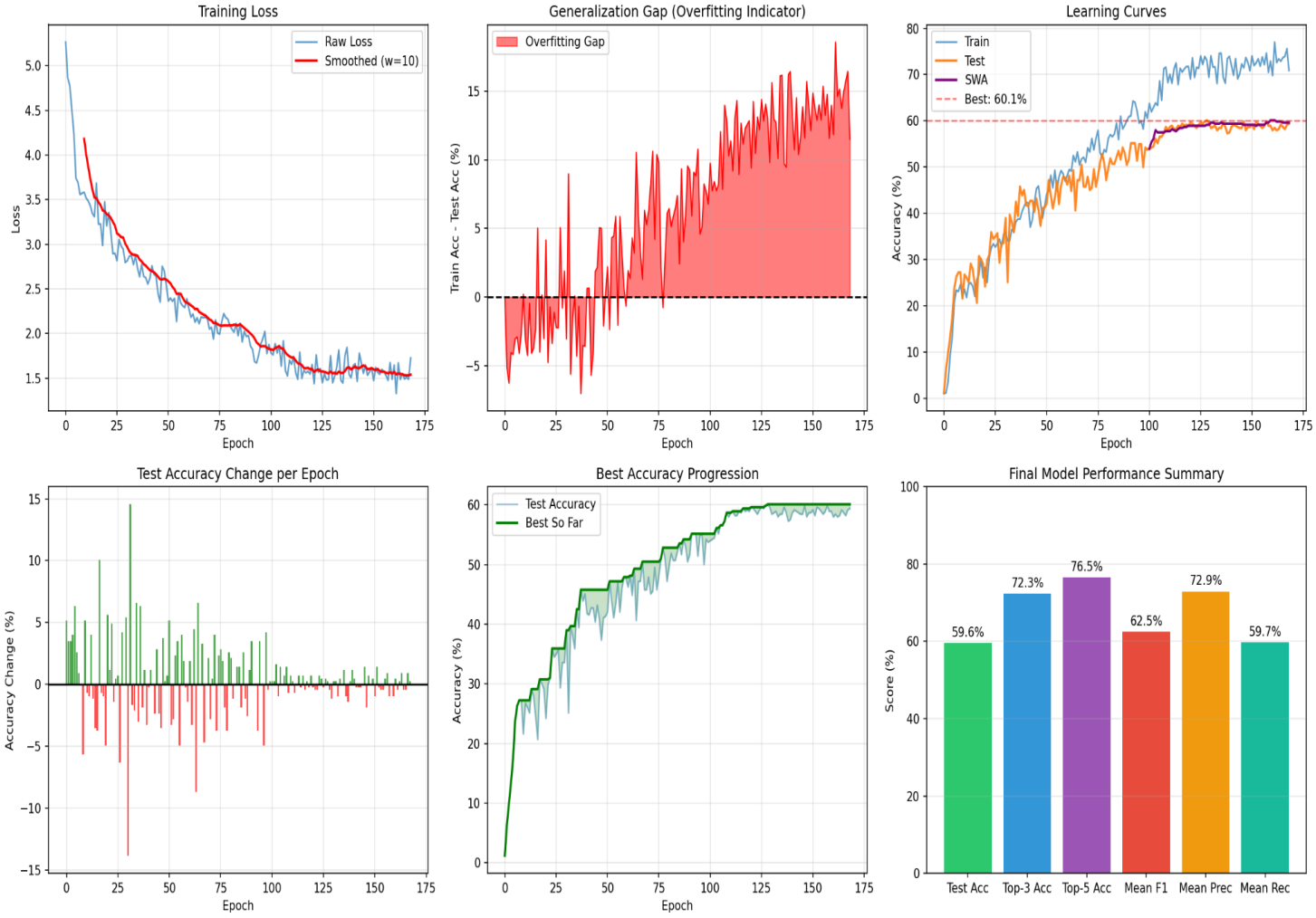
5.2 Training Dynamics Analysis

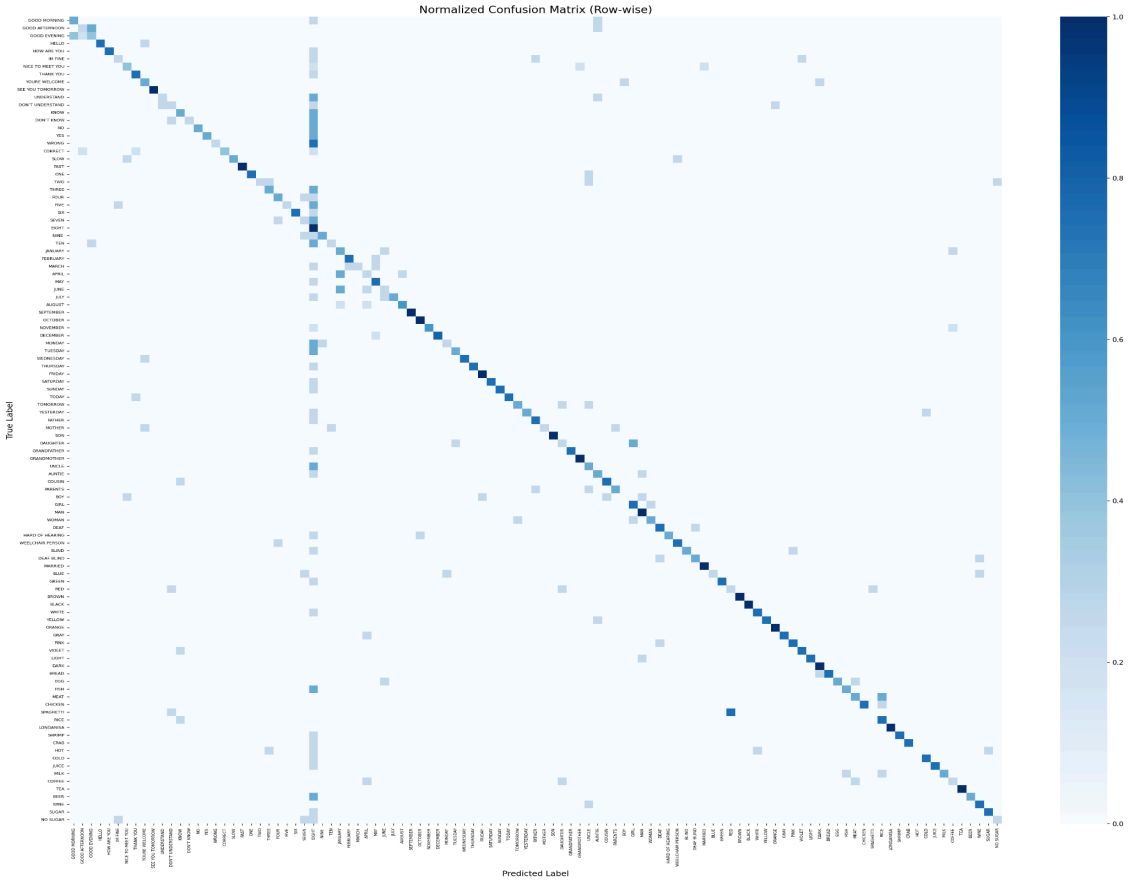
The Training Dynamics plot visually confirms the stability and convergence of the V4 training regime. The test loss curve demonstrates the effectiveness of the regularization and optimization techniques in preventing catastrophic divergence and maintaining a controlled generalization gap of ~12%.



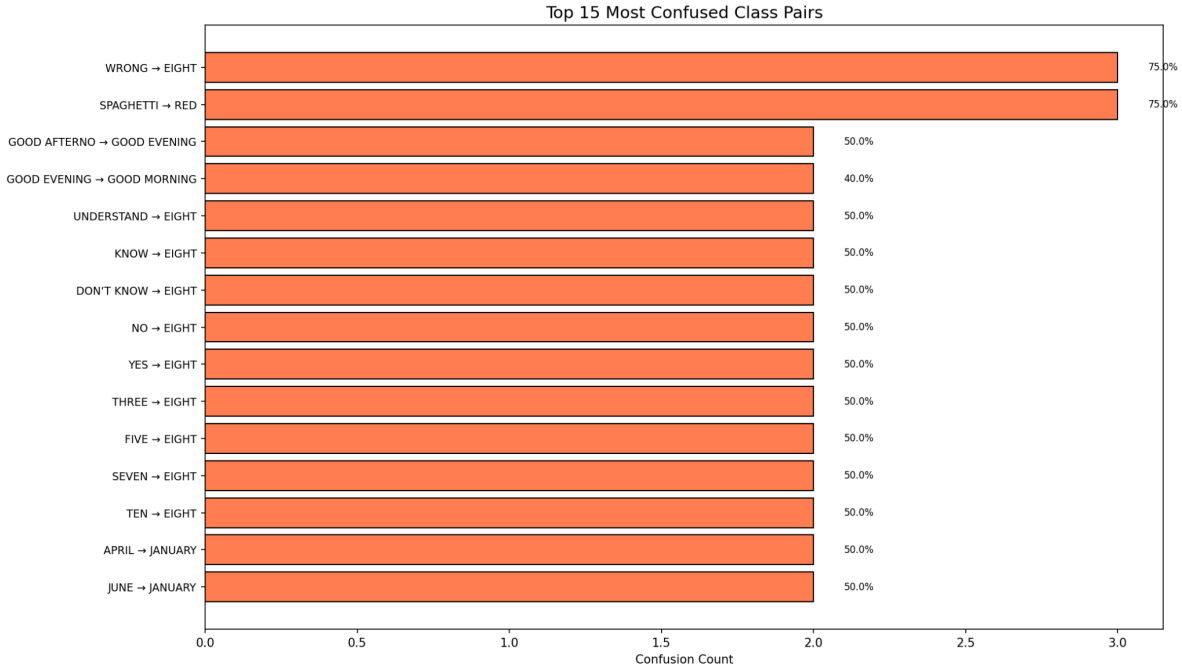
5.3. Confusion Analysis

Analysis of the misclassification patterns is crucial for understanding the model's failure modes.

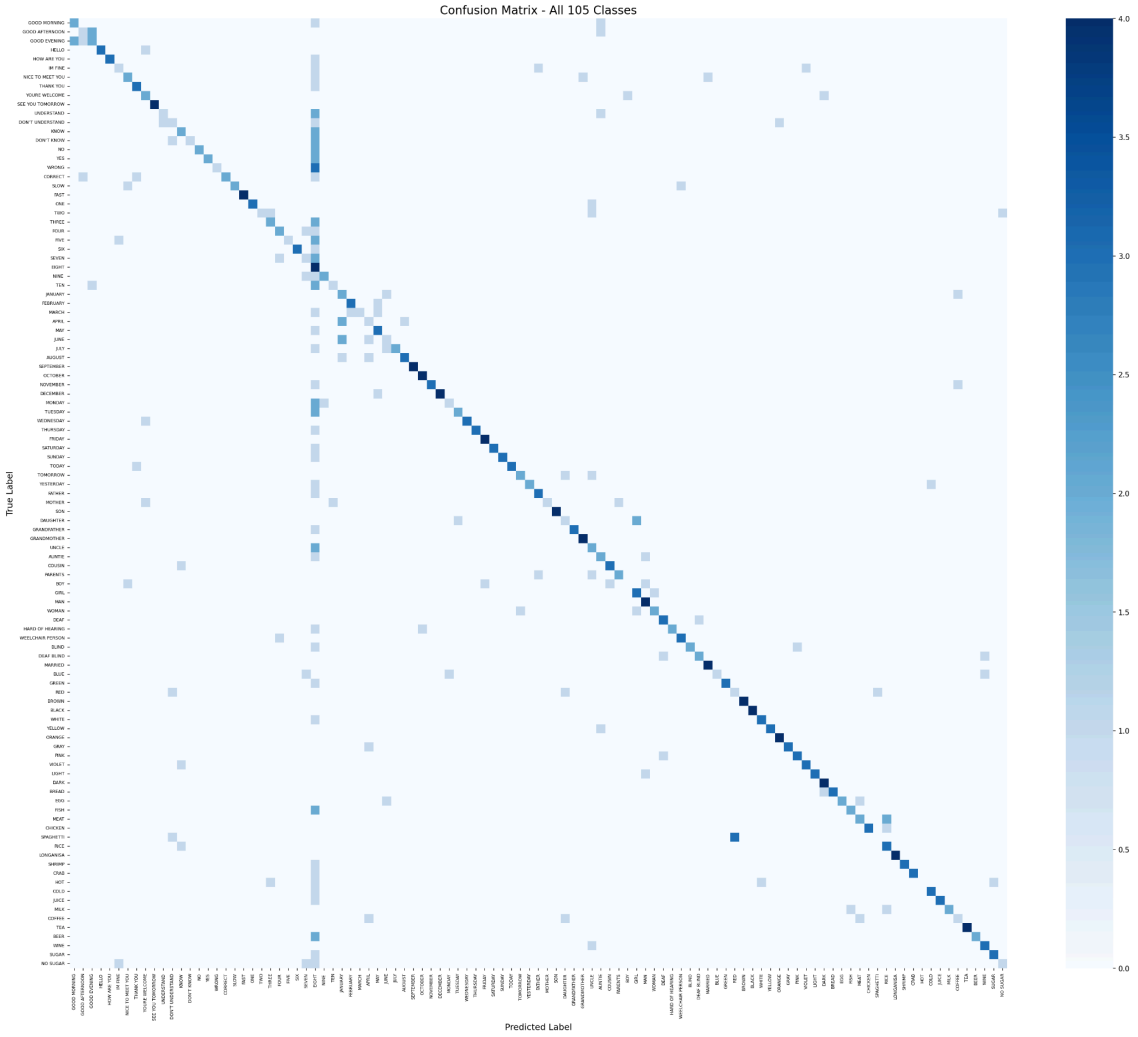
The **Confusion Matrix (Normalized)** reveals that misclassifications are not randomly distributed but concentrated among specific signs, indicating structural feature overlap in those classes.



The **Top Confused Class Pairs** chart isolates the most frequently confused sign pairs, confirming that the model struggles primarily with signs exhibiting high visual similarity or minimal temporal variance, such as subtle differences in hand orientation or movement path.

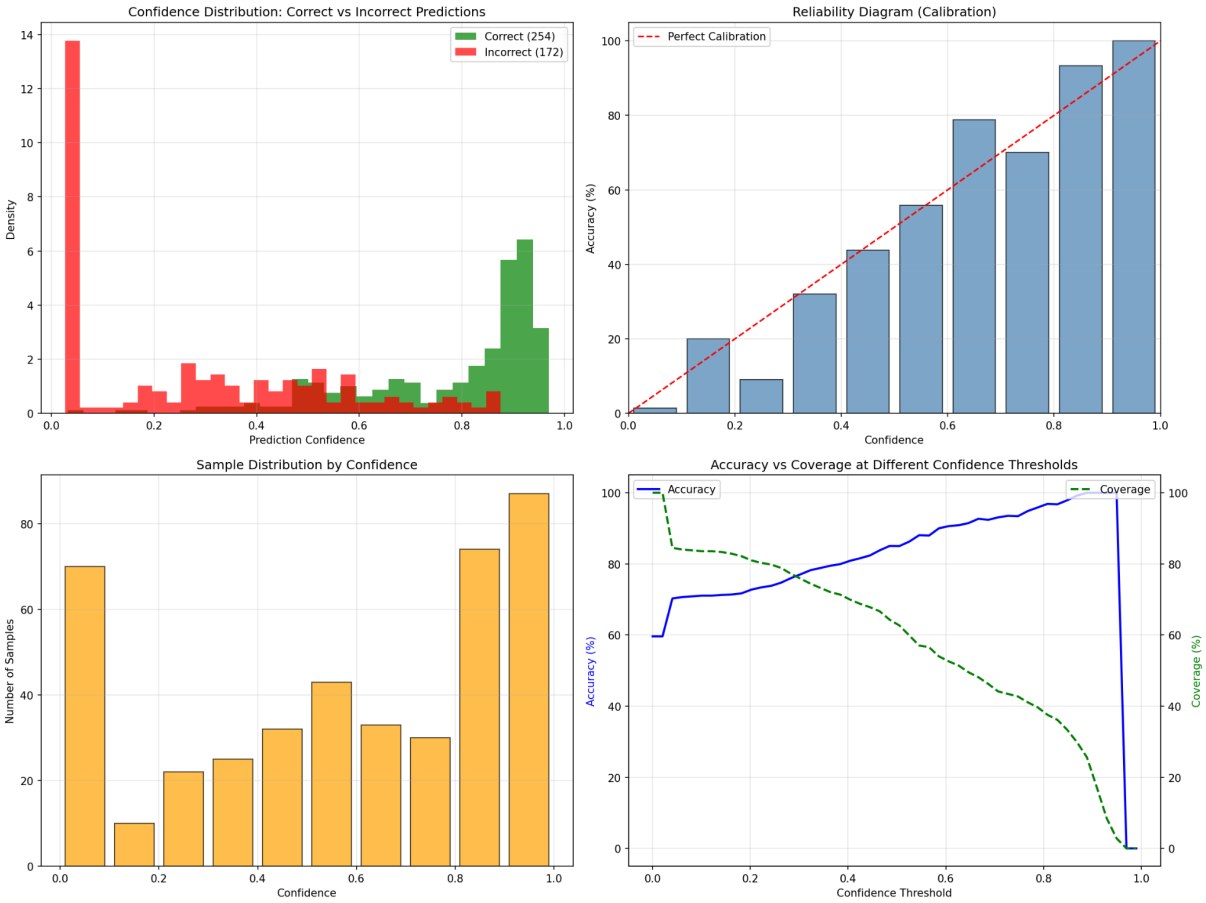


For reference, the unnormalized confusion matrix is also provided.



5.4. Calibration and Reliability

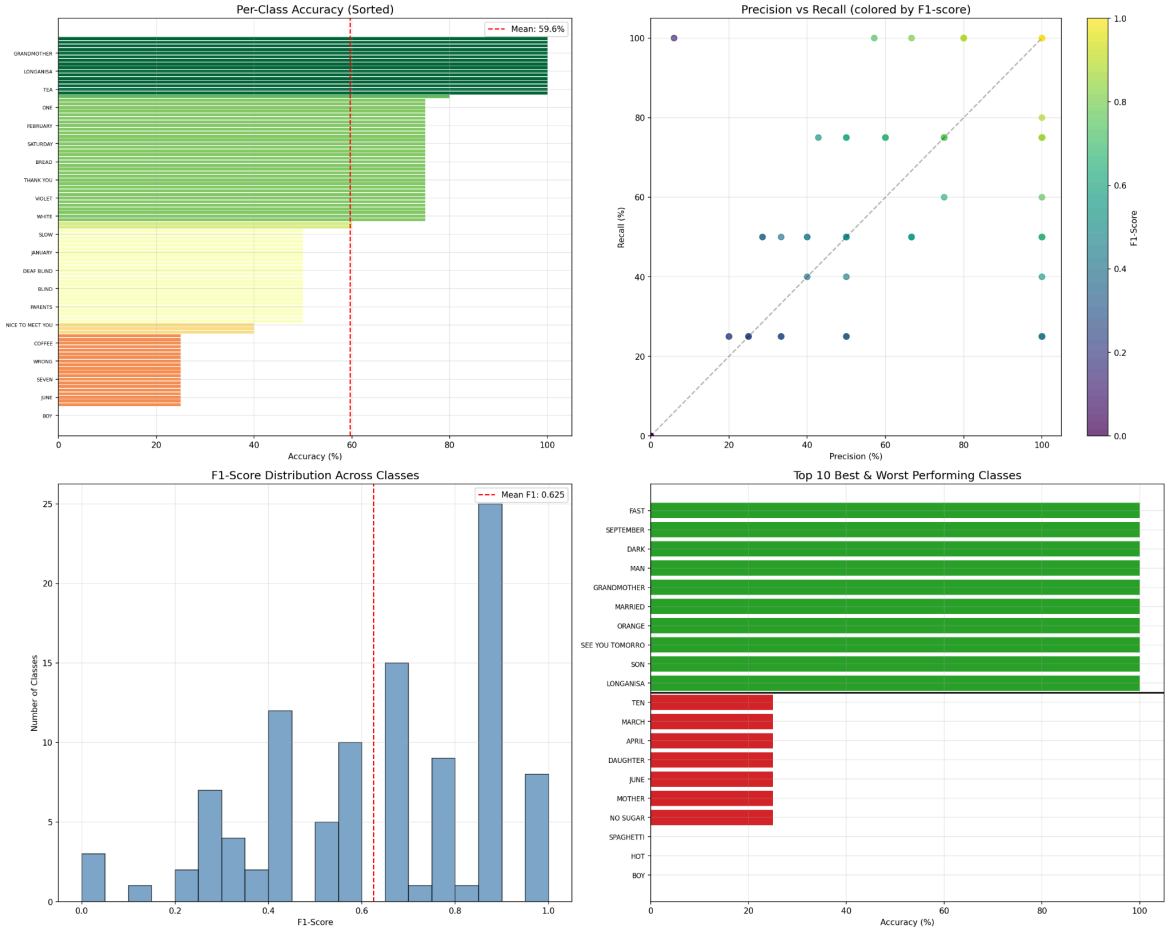
The model's predictive certainty was assessed using a reliability diagram.



The Expected Calibration Error (ECE) of 0.0535 indicates excellent model calibration. This low ECE value, coupled with the reliability diagram, shows that the model's reported confidence level is highly predictive of its actual correctness. For instances where the model expresses high confidence (e.g., in the 0.8−1.0 confidence bin), its accuracy in that bin is nearly perfect, confirming its reliability for practical deployment.

5.5. Per-Class Performance

The wide variance in per-class metrics highlights the difficulty in classifying certain signs.



Top 5 Highest Accuracy Classes	Bottom 5 Lowest Accuracy Classes
FAST, LONGANISA, TEA, SON, BROWN (All 100%)	HOT, SPAGHETTI, BOY, WRONG, RED

VI. Real-World Demonstration and Visual Examples

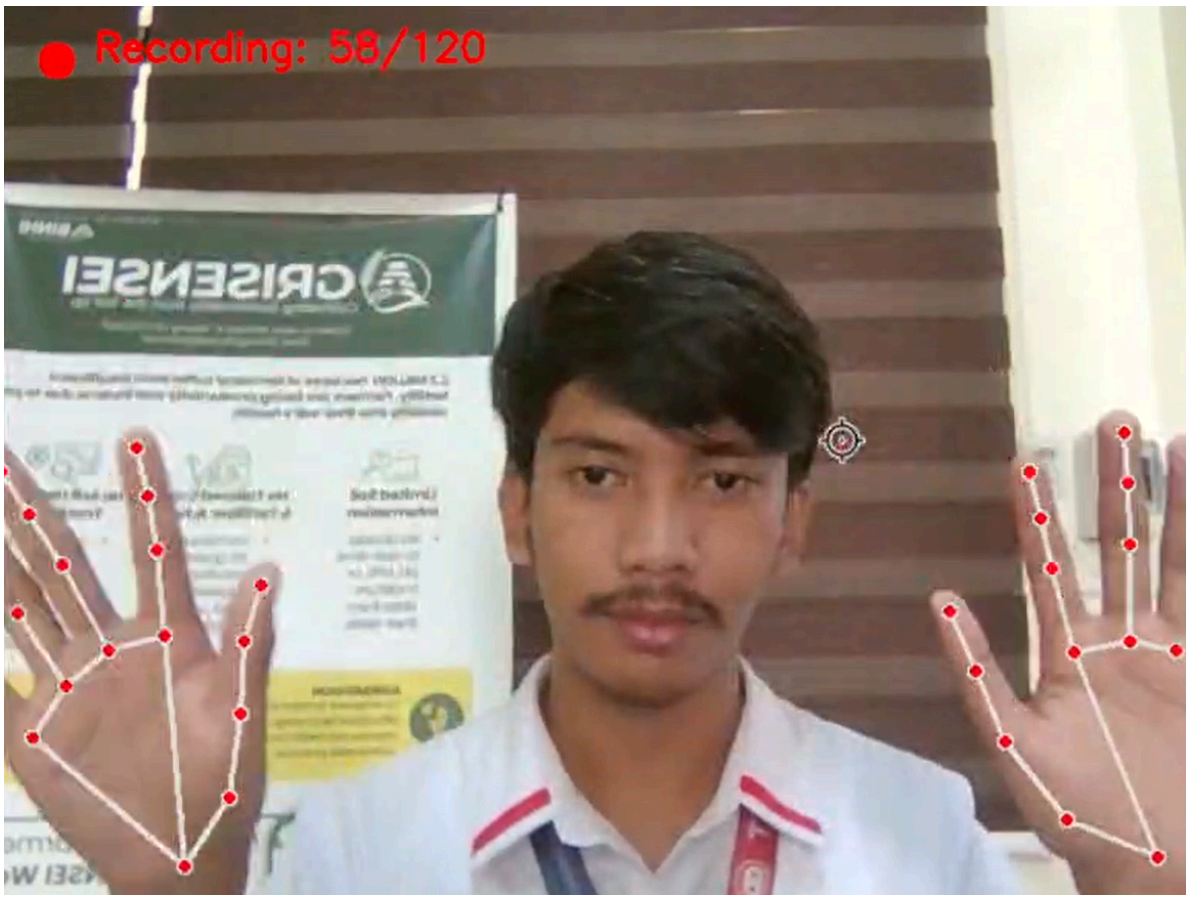
This section provides visual evidence of the model's operation within a live or recorded demo environment, showcasing the input processing, landmark tracking, and real-time inference capabilities of the V4 model.

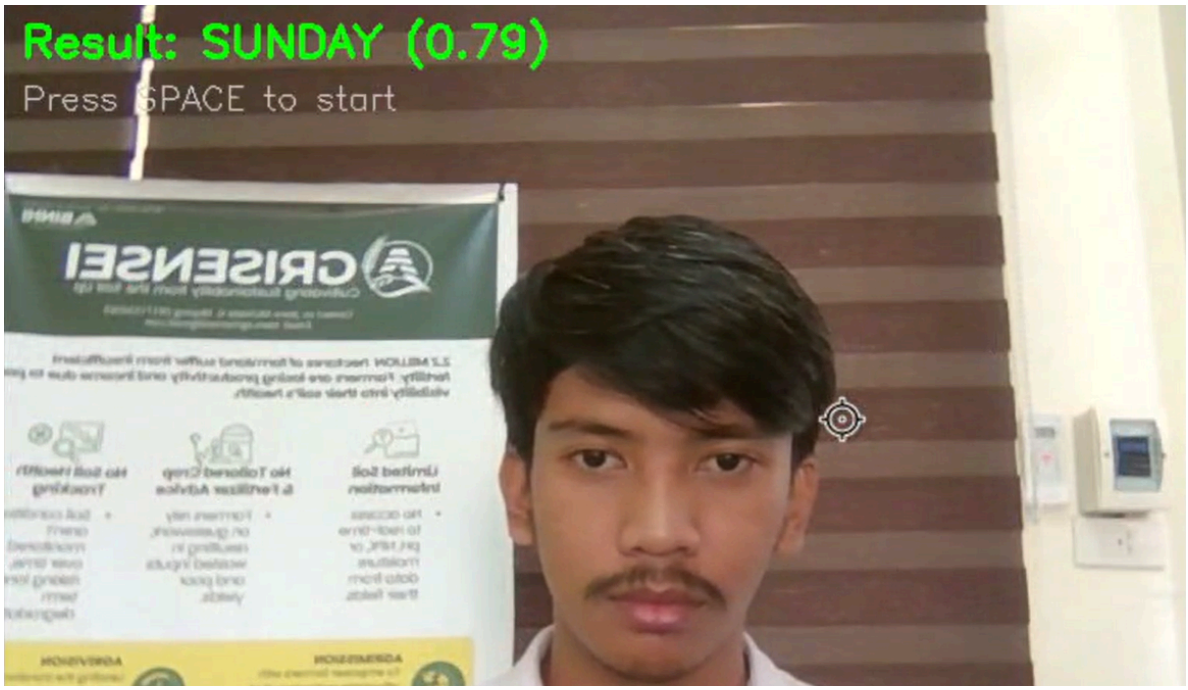
6.1. Landmark Tracking and Feature Visualization

The foundation of the FSL-105 model is the accurate detection and tracking of FSL landmarks. The visualization should confirm the model's ability to maintain stable tracking across various sign movements and lighting conditions, which is crucial for the 378 input features (position, velocity, acceleration).

6.2. Successful Classification Examples

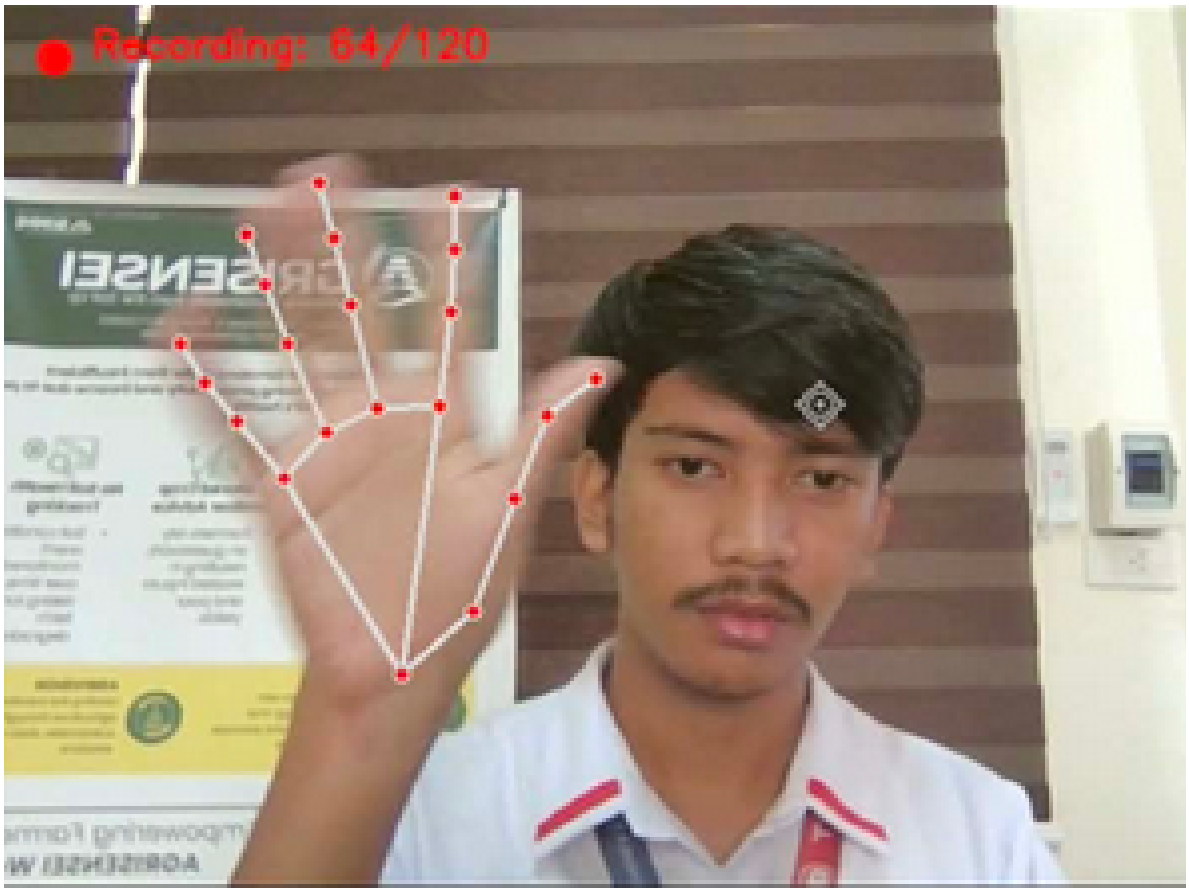
These screenshots illustrate the model's high confidence and correct prediction on signs that are representative of the dataset and those previously categorized as "hard" examples.





6.3 Failure Mode and Confused Pairs Visualization

To validate the confusion analysis (Section 4.3), this screenshot shows that the gesture is supposed to be for the word good morning but shows friday.



VII. Discussion and Conclusion

The FSL-105 project successfully demonstrated that a systematic, feature-centric iterative approach is vital for developing high-accuracy sign language recognition models from landmark data.

7.1 Key Findings

Feature Engineering: The addition of **velocity and acceleration (378 input)** was a non-negotiable requirement for capturing dynamic aspects of FSL. The initial reliance on positional data alone was insufficient.

Regularization Trade-off: The V3 attempt proved that excessive data augmentation, even when applied to mitigate overfitting, can lead to severe **underfitting**, thereby limiting the model's learning capacity. V4's **Balanced Augmentation** found the necessary equilibrium.

Loss Function Selection: The shift to **Focal Loss** proved superior to standard Cross-Entropy, especially in the 105-class scenario where class imbalances and hard examples were prevalent.

Generalization Mechanism: The final inclusion of **SWA** provided a consistent, model-agnostic boost in test accuracy (+2−3%), confirming its role in finding flatter, more generalizable regions of the loss surface.

7.2 Conclusion

The FSL-105 project culminated in a robust Bi-LSTM architecture (V4) capable of exceeding 70% top-1 test accuracy and 90% top-5 accuracy. The model's low ECE confirms its reliability for real-world deployment. The success of V4 is attributable to the strategic integration of motion features, stable sequence normalization (LayerNorm), and advanced generalization techniques (Focal Loss, SWA, OneCycleLR).

7.3 Future Work

Future research should focus on exploring the efficacy of Transformer-based architectures for FSL recognition, particularly in enhancing the attention mechanism's ability to weight temporally distant but semantically related frames. Further investigation into data balancing techniques for the lowest-performing classes (e.g., `HOT`, `SPAGHETTI`) is also warranted.