IMPROVING TIME SERIES CLASSIFICATION ACCURACY USING SELF-SUPERVISED LEARNING

Presentation by Saurav Raj

BACKGROUND AND MOTIVATION

Why Self-Supervised Learning

- Traditional supervised learning relies on labeled data, which is limited and costly to acquire.
- Self-supervised learning (SSL) uses unlabeled data, extracting valuable features that can enhance model performance in downstream tasks.
- Gesture recognition in time series data can benefit from SSL by extracting richer feature representations, improving accuracy on the UWaveGestureLibrary dataset.

OBJECTIVE

Goal: To improve the classification accuracy of the UWaveGestureLibrary dataset using self-supervised learning.

Specific Objectives:

1. Implement SSL on an external dataset (HAR dataset) to learn feature representations.

2. Fine-tune a classification model on UWaveGestureLibrary using these learned features.

3. Quantitatively compare the performance with conventional classification methods.

DATA PREPARATION

Datasets Used:

- HAR Dataset (for SSL pre-training): [HAR.zip]
- UWaveGestureLibrary Dataset (for classification): [Gesture.zip]

Preprocessing Steps:

- Missing Values: No missing values detected in both datasets.
- Scaling: StandardScaler used for feature normalization.

Dataset	Shape (Train)	Shape (Validation)	Shape (Test)
HAR	(5881, 618)	(1471, 618)	(2947, 618)
UWaveGestureLibrary	(320, 618)	(120, 618)	(120, 618)

FEATURE EXTRACTION RESULTS

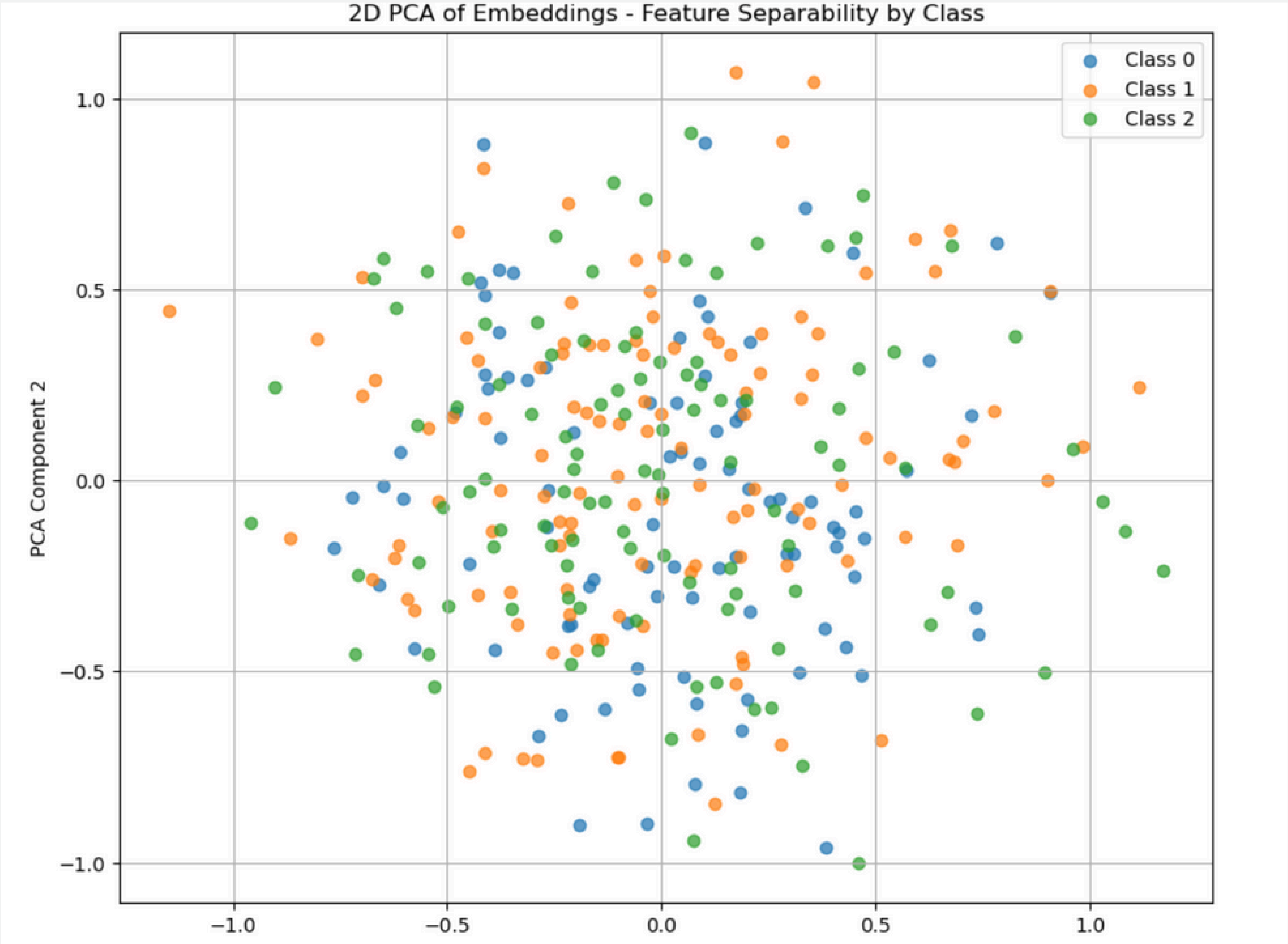
Embeddings: Extracted features from the UWaveGestureLibrary dataset using the trained Siamese Network.

Embeddings Shape:

Train: (320, 64)

Validation: (120, 64)

Test: (120, 64)



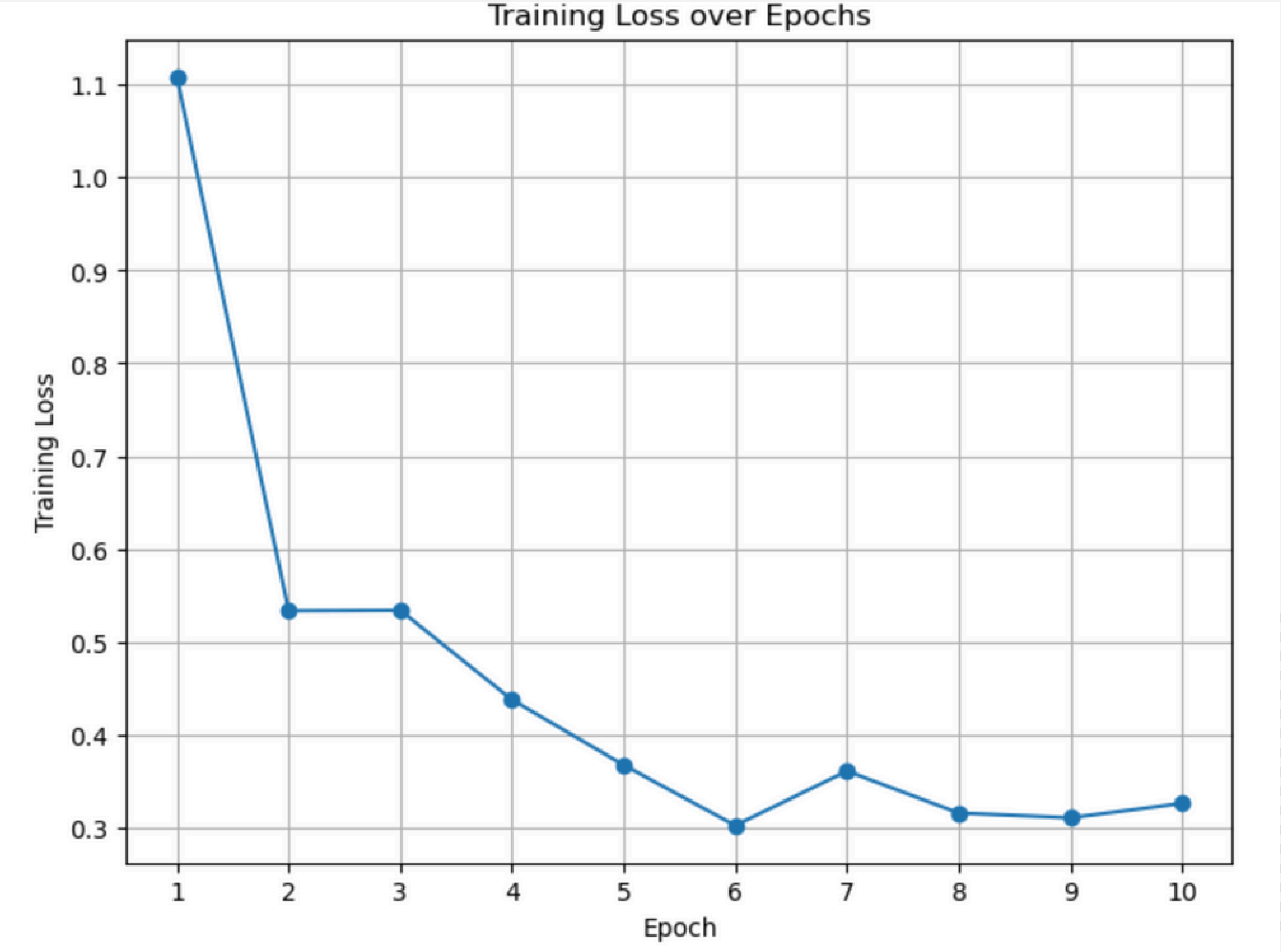
SELF-SUPERVISED LEARNING IMPLEMENTATION

Model: Siamese Network with contrastive loss (NT-Xent Loss).

Hyperparameters:

- Hidden Dim: 128
- Output Dim: 64
- Temperature: 0.5
- Batch Size: 32
- Epochs: 10

Epoch	Loss
1	1.1088
2	0.5333
3	0.5331
....	....
10	0.3257



CLASSIFICATION MODEL SELECTION AND RATIONALE

Models Tested:

- Tuned Classifier (Dense Neural Network with dropout)
- LSTM-based Classifier (with Early Stopping)

Why LSTM?

- LSTM captures sequential dependencies in time series, which improves model interpretability and classification accuracy.

Model	Train Accuracy	Validation Accuracy	Test Accuracy
Tuned Classifier	68.75%	66.67%	66.67%
LSTM Classifier	75.62%	74.17%	74.17%

Table :Accuracy Comparison:

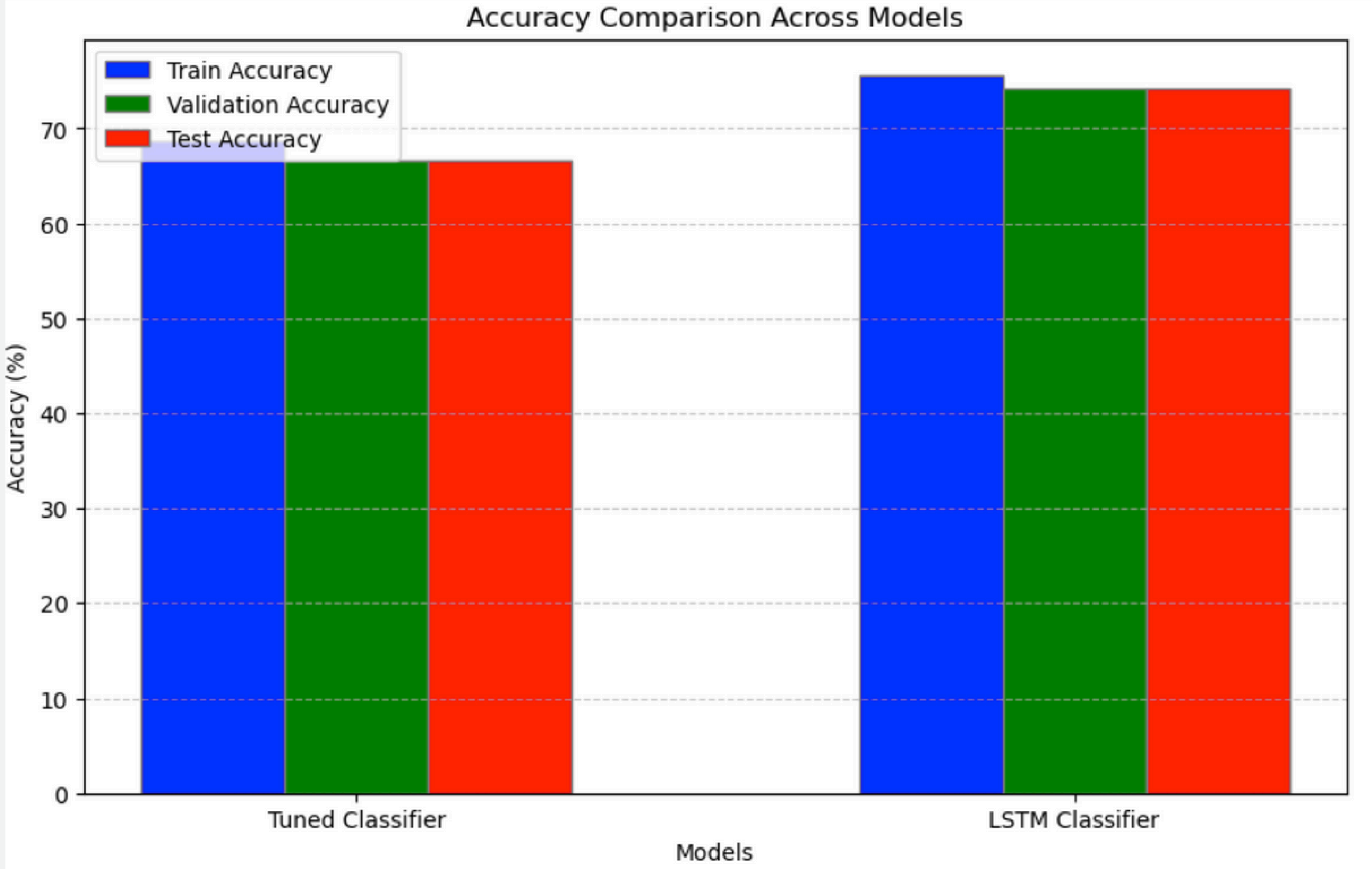
CLASSIFICATION MODEL SELECTION AND RATIONALE

LSTM Performance Improvement:

Test accuracy improved by 7.5% using LSTM over Tuned Classifier.

Early Stopping Triggered

Helps avoid overfitting by halting training early.



EVALUATION METRICS AND RESULTS

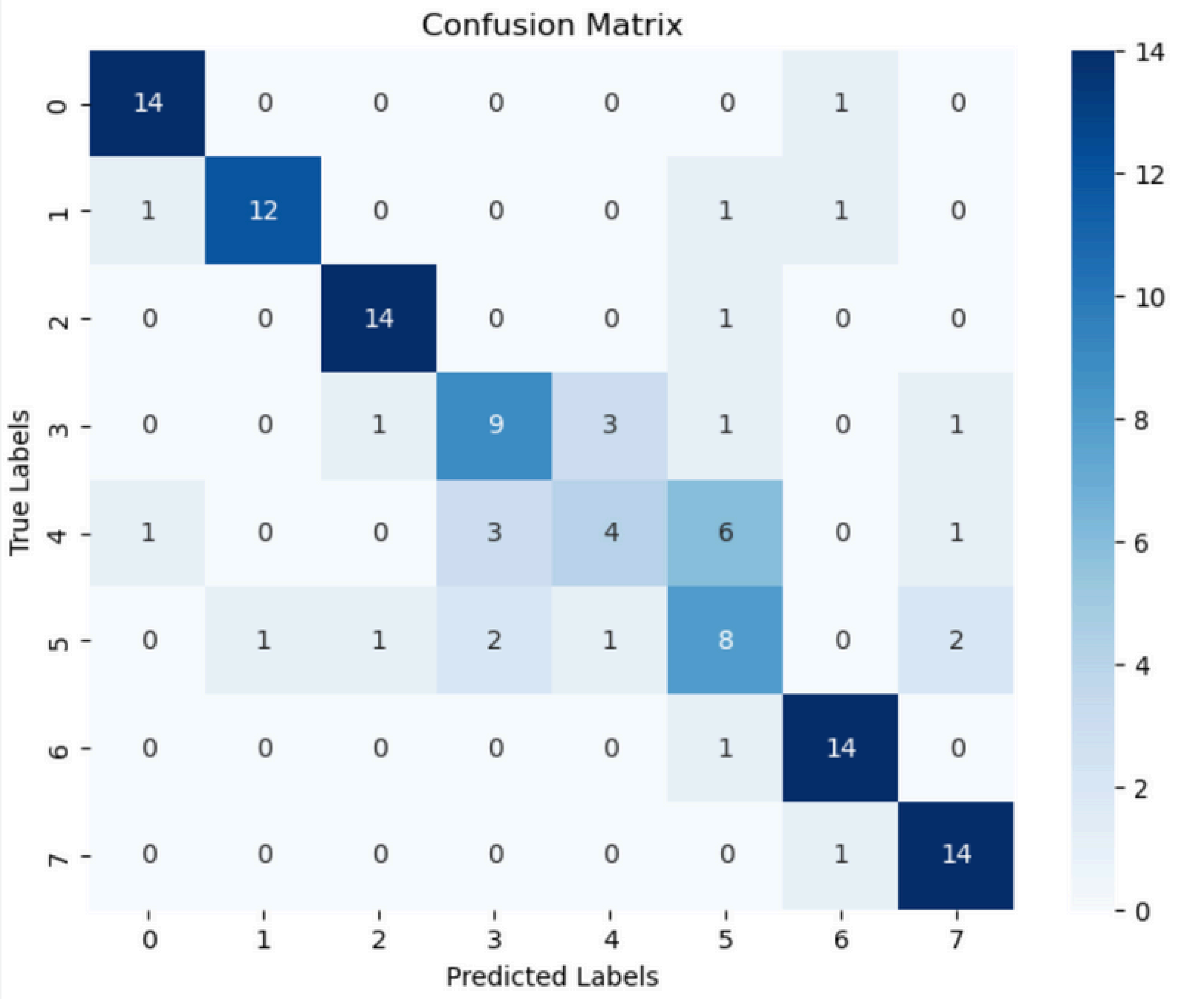
<u>Metrics Used:</u>

- Accuracy
- Confusion Matrix
- Classification Report

(Precision, Recall, F1-score)

Classification Report:

	precision	recall	f1-score	support
Class 0	0.88	0.93	0.90	15
Class 1	0.92	0.80	0.86	15
Class 2	0.88	0.93	0.90	15
Class 3	0.64	0.60	0.62	15
Class 4	0.50	0.27	0.35	15
Class 5	0.44	0.53	0.48	15
Class 6	0.82	0.93	0.88	15
Class 7	0.78	0.93	0.85	15
accuracy			0.74	120
macro avg	0.73	0.74	0.73	120
weighted avg	0.73	0.74	0.73	120



MODEL INTERPRETABILITY AND ERROR ANALYSIS

Error Analysis:

- Class 4 and 5 show lower F1 scores, likely due to overlap in feature space or limited distinctive features.

- Potential Solution: Investigate additional feature extraction methods or different augmentations for better class separability

SUMMARY AND CONCLUSION

Summary:

- Successfully implemented self-supervised learning on HAR data.
- LSTM-based classifier yielded higher accuracy and interpretability on UWaveGestureLibrary.

Key Improvements:

- **7.5% increase in accuracy** using self-supervised learned features.
- **Efficient feature extraction** using contrastive learning and augmentation.

Future Work:

- Experiment with advanced SSL techniques like masked autoencoders or multi-task learning for further improvements.

THANK YOU !

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