

MixMatch-based Semi-supervised Learning Approach for Cross-domain Locomotion and Transportation Mode Recognition

Team: SITA-BIT

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Problem & Motivation

> Core Challenge:

• Cross-domain Human Activity Recognition is a significant challenge, especially when **no labeled data is available in the target domain**.

> Research Motivation

 We aims to develop a semi-supervised learning framework to effectively leverage unlabeled data and overcome the domain shift problem.

Dataset

> Source Domain (Labeled):

- PAMAP2^[1], UCI HAR^[2], mHealth^[3], RealWorld^[4], and KU-HAR^[5];
- > Target Domain (Unlabeled):
- The Kyutech IMU^[6] dataset provided by the challenge.

We use a Transformer network as the classifier to process the extracted high-

> Feature:

• We use TSFEL library to extract a total of 1872 features from 12 channels (tri-axial + magnitude)

Proposed Method

SHL 2025 Domain

Model Architecture

dimensional features.

Core Mechanics of MixMatch

Data Augmentation

Apply K times augmentations to each unlabeled sample.

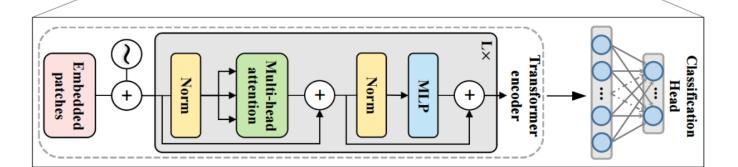
Pseudo-Labeling

• Generate predictions for the augmented unlabeled samples using the current model and average them to create a "pseudo-label".

Soft Label Sharpening

• Reduce the entropy of the pseudo-label by lowering a temperature "T", making the prediction more "confident" to guide model training.

Batch x 1872 Labeled samples Freeze Pseudo label Train Batch x 1872 Unlabeled samples Freeze Pseudo label



MixUp

 Linearly interpolate between labeled samples and pseudo-labeled unlabeled samples to create new, mixed samples for training.

Experimental Result

> Experimental results on Task 2

	Locomotion and transportation mode recognition across dataset domains Advanced domain samples {Train: Cycle(5344); Val: 668; Test: 668; Unlabeled: 1212731;}							
Dataset domains								
	ACC	PRE	REC	F1	MCC	AUC	FLOPs	Params
Basic	0.763	0.766	0.763	0.762	0.746	0.938	0.749K	2.992M
Enhanced	0.732	0.736	0.732	0.729	0.713	<u>0.946</u>	0.749K	2.992M
Advanced	0.768	0.772	0.768	0.765	0.751	0.939	0.749K	2.992M

Basic dataset domains: SHL Challenge 2025; Enhanced dataset domains: SHL Challenge 2025 + Kyutech IMU; Advanced dataset domains: SHL Challenge 2025 + Kyutech IMU + Others (i.e. PAMAP2 Dataset, UCI HAR Dataset, mHealth Dataset, RealWorld Dataset, and HAR Dataset); FLOPs is the computational cost per sample inference;

> Core Performance:

After integrating multiple external domain datasets, the method achieved an Accuracy of 76.8% and an F1-Score of 76.5%

Key Findings

- Importance of Multi-Domain Learning: Experiments showed that using only the SHL dataset or adding just the Kyutech IMU dataset resulted in limited or even decreased performance. However, introducing a greater variety of public datasets (the "Advanced domain") significantly improved the model's generalization and final performance.
- Handling Class Imbalance: A resampling strategy effectively mitigated the issue of having too few samples for certain classes in the training set.

Conclusion

Main Contribution: We proposed a MixMatch-based semi-supervised learning framework that successfully addresses the cross-domain HAR problem in a scenario with a completely unlabeled target domain.

- Leverages large-scale unlabeled data through mechanisms like pseudo-labeling and MixUp to adapt to the target domain's distribution.
- Demonstrates that integrating multiple heterogeneous source domains can effectively enhance the model's generalization and robustness to unknown.

Reference

- [1] Introducing a new benchmarked dataset for nactivity monitoring.
- [2] A public domain dataset for human activity recognition using smartphones.
- [3] mHealthDroid: A novel framework for agile development of mobile health applications.
- [4] On-body localization of wearable devices: An investigation of positionaware activity recognition.
- [5] KU-HAR: An open dataset for heterogeneous human activity recognition.
- [6] Acquisition of Unlabeled Dataset for Human Activity Recognition