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A Sensor-site Hybrid Algorithm Pipeline for Locomotion and Transportation Mode Recognition

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Problem & Motivation

➢ Three Challenge:

- Sensor Modality Dropout.
- Varying Device Placement
- Limited Model Generalization

We aim to deliver a framework that can adapt to partial data loss, changes in sensor positions, and maintains high recognition accuracy.

Dataset

➢ SHL Dataset 2025 [1][2]:

- 4 sensor locations (bag, hips, torso, hand)
- 8 modes of locomotion and transportation
- The sensor data are divided into data frames with a 5-second window, each containing 500 samples

➢ Feature:

- We use TSFEL[3] to extract a total of 156 features from each channel.

Proposed Method

➢ Overall Workflow

Data Mixing

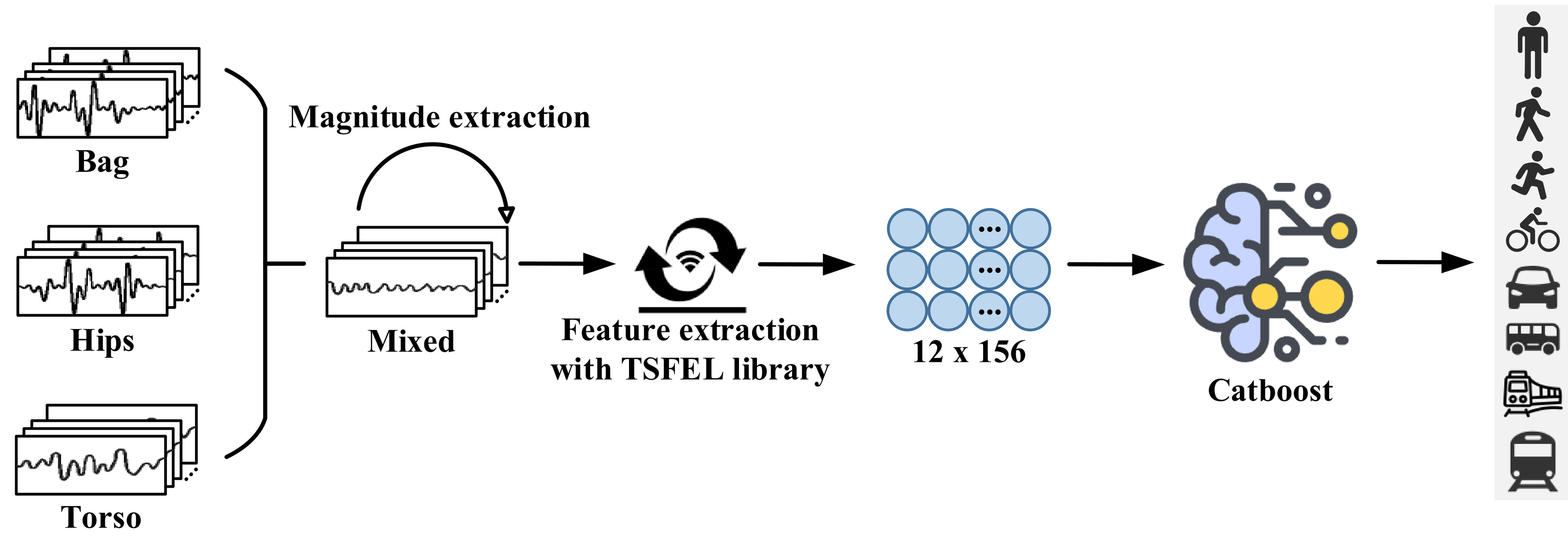
- Sensor data from 3 different placements are mixed and processed through a unified procedure, eliminating the need to identify the device location beforehand.

Feature Extraction

- Magnitude features are computed, followed by the extraction of 156 mixed features from each channel.

Classification Model

- A **CatBoost Classifier** is used. As a gradient boosting decision tree algorithm, CatBoost does not require feature normalization, naturally handles sparse inputs from missing data, and supports GPU acceleration for efficient training.



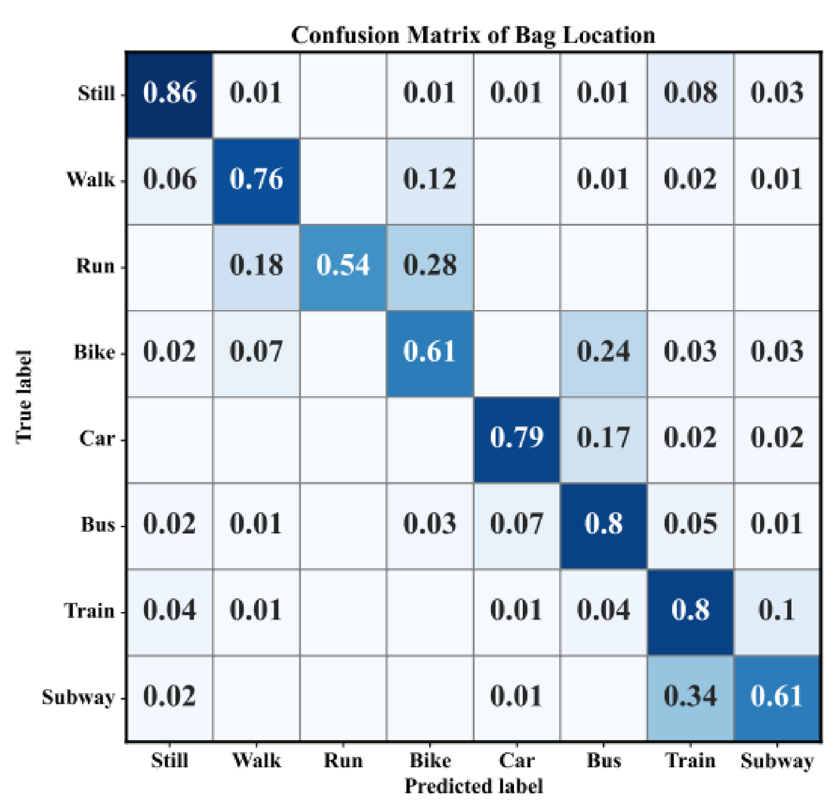
Experimental Result

➢ Results of Experiment.

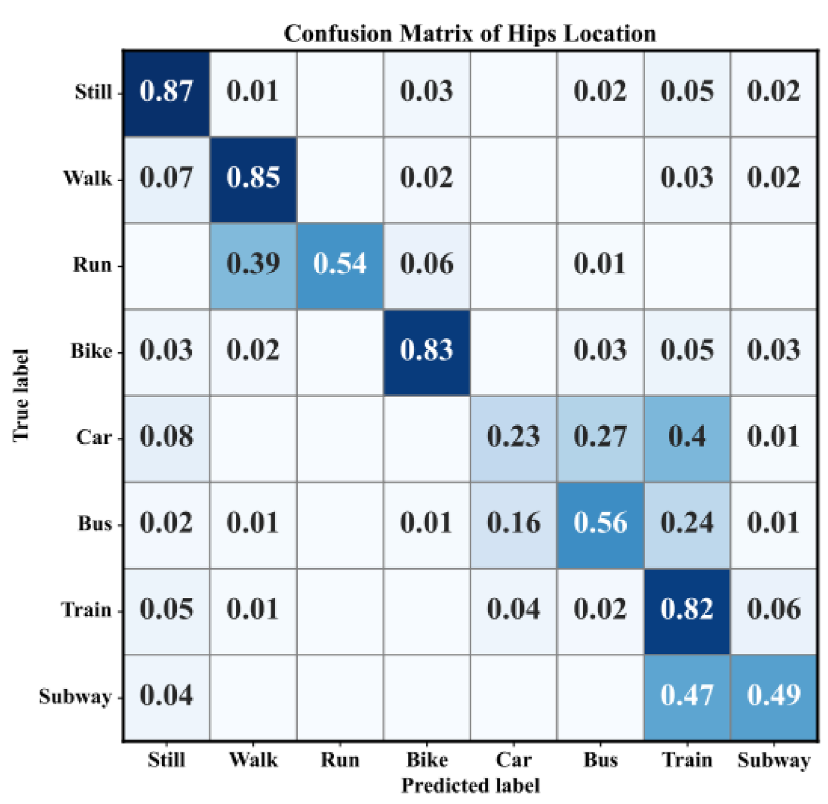
Method	Phone location	Zero-filling Strategy	Locomotion and transportation mode recognition							
			SHL validation dataset: There are 28,789 samples from each location							
			ACC	PRE	REC	F1	MCC	AUC	FLOPs	Params
Ours	Bag	Without zero-filled	<u>**0.761**</u>	<u>**0.789**</u>	<u>**0.761**</u>	<u>**0.766**</u>	<u>**0.721**</u>	<u>**0.971**</u>	0.844K	73.688K
Ours	Bag	Stochastic zero-filled	0.754	0.784	0.755	0.760	0.714	0.969	0.844K	73.688K
Ours	Hips	Without zero-filled	0.688	0.735	0.688	0.680	0.643	0.950	0.844K	73.688K
Ours	Hips	Stochastic zero-filled	0.683	0.729	0.683	0.676	0.637	0.948	0.844K	73.688K
Ours	Torso	Without zero-filled	0.692	0.760	0.692	0.697	0.646	0.950	0.844K	73.688K
Ours	Torso	Stochastic zero-filled	0.685	0.755	0.685	0.691	0.638	0.948	0.844K	73.688K
Ours	Mixed	Without zero-filled	**0.714**	**0.764**	**0.714**	**0.718**	**0.669**	**0.956**	0.844K	73.688K
Ours	Mixed	Stochastic zero-filled	0.708	0.759	0.708	0.713	0.662	0.954	0.844K	73.688K

Tablenotes: FLOPs is the computational cost per sample inference.

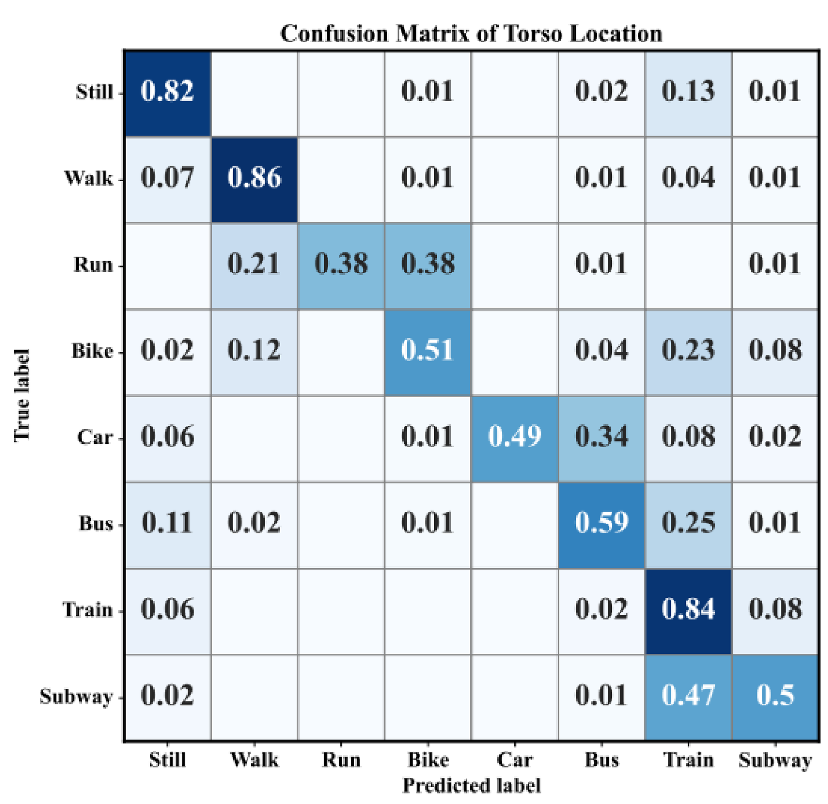
➢ Confusion matrix of the validation dataset



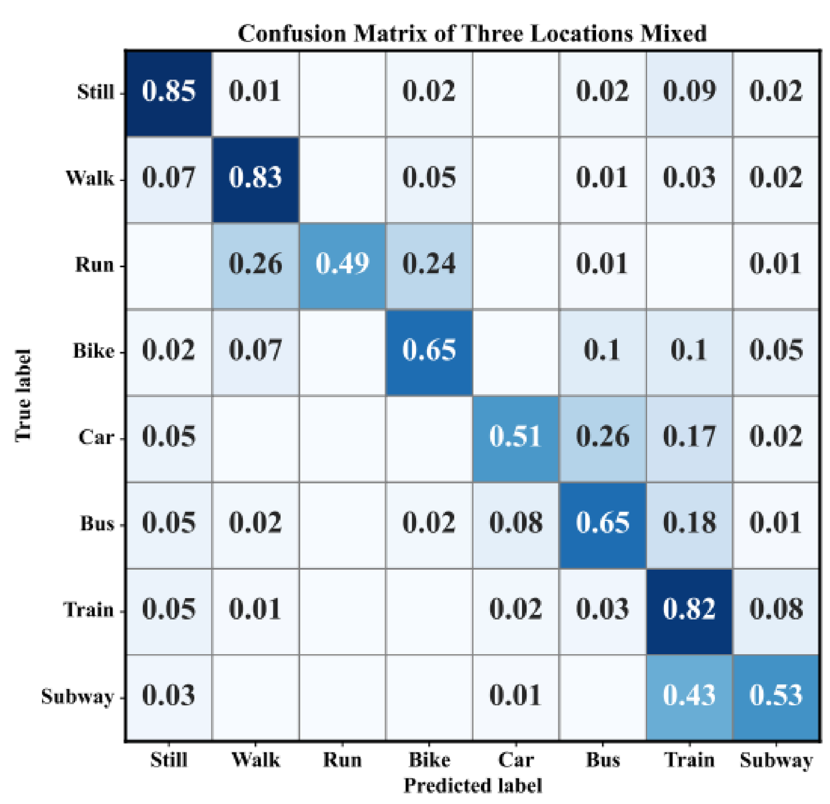
Confusion matrix of bag location



Confusion matrix of hips location



Confusion matrix of torso location



Confusion matrix of three locations mixed.

Conclusion

Main Contribution: This paper proposes a robust HAR framework based on hand-crafted features and a CatBoost classifier, effectively addressing the challenges of varying device placements and missing sensor data.

- The unified pipeline avoids complex stages or multiple classifiers.
- Achieved competitive results on the challenging SHL dataset.
- The model maintains stable prediction performance even with partial data loss.

Reference

[1] The University of Sussex-Huawei locomotion and transportation dataset for multimodal analytics with mobile devices, IEEE Access 6 (2018): 42592-42604.

[2] Enabling reproducible research in sensor-based transportation mode recognition with the Sussex-Huawei dataset, IEEE Access 7 (2019): 10870-10891.

[3] Tsfel: Time series feature extraction library, SoftwareX, vol. 11, p. 100456, 2020.