ALLEVIATING OVERCONFIDENCE IN LONG-TAILED TIME SERIES CLASSIFICATION WITH HIERARCHICAL REVERSE DISTILLATION

1. EXPERIMENT

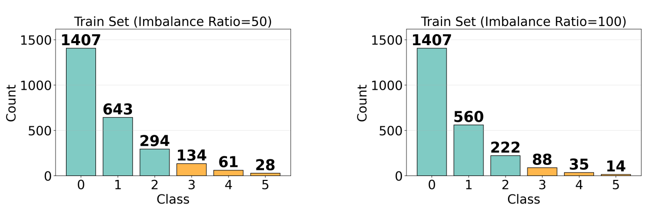
1.1. Datasets

The effectiveness of HRD-LT was evaluated on three long-tailed datasets: HAR, ISRUC, and Epilepsy. The following section presents detailed introductions to these datasets.

Human Activity Recognition (HAR). The UCI HAR dataset (Anguita et al., 2013) comprises sensor data collected from 30 participants aged between 19 and 48. Each subject performed six distinct activities, and the recordings were obtained using a Samsung Galaxy S2 smartphone with a sampling frequency of 50 Hz. Figure 1 illustrates the class distributions of the long-tailed HAR datasets under imbalance ratios of 50 and 100.

Sleep Stage Classification (ISRUC-S3). The ISRUC-S3 dataset (Khalighi et al., 2016) contains recordings from 10 healthy subjects, including electrophysiological and respiratory signals as well as background information. All data were visually examined by two experts. Figure 2 shows the class distributions of the long-tailed ISRUC datasets under imbalance ratios of 50 and 100.

Epileptic Seizure Prediction (Epilepsy). The Epileptic Seizure Recognition dataset (Andrzejak et al., 2001) consists of EEG recordings from 500 subjects, with each sample covering 23.6 seconds of brain activity. Figure 3 presents the class distributions of the long-tailed Epilepsy datasets generated under imbalance ratios of 50 and 100.

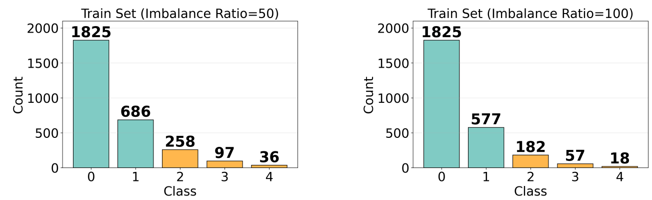


(a) HAR-LT-50 (b) HAR-LT-100

Fig. 1: Class distributions of HAR-LT datasets.

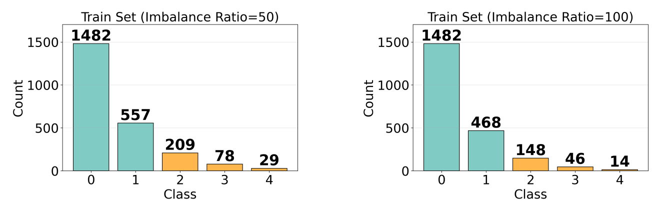
1.2. Evaluation Metrics

Model performance is evaluated using accuracy (ACC), F1-score (F1), and Matthews correlation coefficient (MCC). The



(a) ISRUC-LT-50 (b) ISRUC-LT-100

Fig. 2: Class distributions of ISRUC-LT datasets.



(a) Epilepsy-LT-50 (b) Epilepsy-LT-100

Fig. 3: Class distributions of Epilepsy-LT datasets.

definitions of these metrics are given as follows:

$$\mathrm{ACC} = \frac{TP + TN}{TP + FP + FN + TN},$$

$$\mathrm{F1} = \frac{2 \cdot P \cdot R}{P + R},$$

$$\mathrm{MCC} = \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}. \quad (1)$$

where P and R represent the precision and recall, respectively. TP, FN, TN, and FP denote true positives, false negatives, true negatives, and false positives, respectively.

2. BASELINES

We conduct comparisons with 7 widely recognized state-of-the-art methods:

PatchTST (Nie et al. 2022) This method partitions time series into equal-length segments (patches) and employs a vanilla Transformer encoder to model inter-patch dependencies. It operates in a channel-independent manner, where each variable sequence is encoded separately, thereby improving the flexibility of feature representation.

iTransformer (Liu et al. 2023) This model embeds temporal observations of each variable into tokens, upon which attention and feed-forward networks are applied to capture multivariate dependencies. Without altering the core Transformer architecture, it substantially enhances both predictive accuracy and generalization in time series forecasting.

Timemixer++(Wang et al. 2024) It extends TimeMixer by incorporating hybrid modules that further enhance multi-scale temporal decomposition. Through refined MLP-based operators and residual integration, it achieves stronger representation of both global and local temporal dependencies.

DisMS-TS (Liu et al. 2025)It tackles long-tailed time series classification with a disentangled multi-scale framework. By separating global trends from local variations and introducing collaborative distillation between scales, it improves feature discriminability under severe imbalance.

Hybrid-PSC (Wang et al. 2024)It combines prototype-based supervision with contrastive learning for imbalanced time series. By dynamically updating class prototypes and aligning tail samples with both head prototypes and contrastive signals, it ensures balanced performance across classes.

IWB (Dang et al. 2024)It introduces instance-wise balancing for long-tailed time series data. By re-weighting samples at the instance level rather than class level, it adaptively emphasizes informative tail examples, mitigating overconfidence and improving generalization.

DGMSCL (Qian et al. 2025)It addresses imbalanced time series classification via dynamic graph reconstruction and a mixed contrast loss. The loss combines weight-augmented inter-graph supervision and minority class-aware contrast to enhance representation.

3. REFERENCES

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