Scale-teaching: Robust Multi-scale Training for Time Series Classification with Noisy Labels

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Abstract

Deep Neural Networks (DNNs) have been criticized because they easily overfit noisy (incorrect) labels. To improve the robustness of DNNs, existing methods for image data regard samples with small training losses as correctly labeled data (small-loss criterion). Nevertheless, time series' discriminative patterns are easily distorted by external noises (i.e., frequency perturbations) during the recording process. This results in training losses of some time series samples that do not meet the small-loss criterion. Therefore, this paper proposes a deep learning paradigm called *Scale-teaching* to cope with time series noisy labels. Specifically, we design a fine-to-coarse cross-scale fusion mechanism for learning discriminative patterns by utilizing time series at different scales to train multiple DNNs simultaneously. Meanwhile, each network is trained in a cross-teaching manner by using complementary information from different scales to select small-loss samples as clean labels. For unselected large-loss samples, we introduce multi-scale embedding graph learning via label propagation to correct their labels by using selected clean samples. Experiments on multiple benchmark time series datasets demonstrate the superiority of the proposed Scale-teaching paradigm over state-of-the-art methods in terms of effectiveness and robustness.

1 Introduction

Time series classification has recently received much attention in deep learning [1, 2]. Essentially, the success of Deep Neural Networks (DNNs) is driven by a large amount of well-labeled data. However, human errors [3] and sensor failures [4] produce noisy (incorrect) labels in time series datasets. For example, in electrocardiogram diagnosis [5], physicians with different experiences tend to make inconsistent category judgments. In recent studies [6, 7], DNNs have shown their powerful learning ability, which, however, makes it relatively easier to overfit noisy labels and inevitably degenerate

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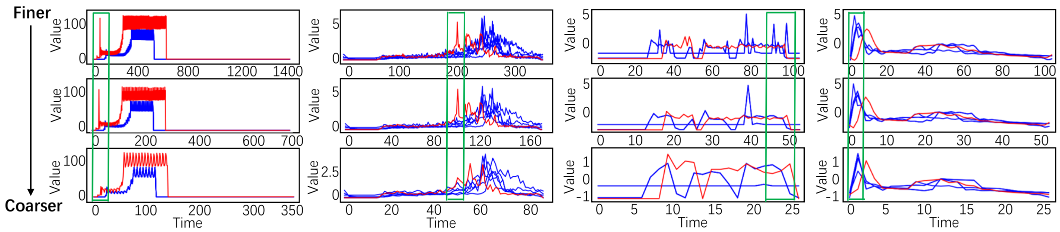


(a) PLAID (b) Lightning7 (c) ElectricDevices (d) MedicalImages

Figure 1: Illustration of time series samples *from the same category* at different time scales. Among all samples in the same category, red indicates the one with the largest variance, and blue indicates a few samples with the smallest variance.

the robustness of models. Moreover, time series data has complex temporal dynamics that make it challenging to manually correct noisy labels [8].

To cope with noisy labels, existing studies on label-noise learning [9, 10] use the memory effect of DNNs to select samples with small losses for training. DNNs memorize the data with clean labels first, and then those with noisy labels in classification training (small-loss criterion) [11]. It is worth noting that the small-loss criterion is not affected by the choice of training optimizations and network structures [12], and is widely utilized for label-noise learning in computer vision [13, 14]. However, the small loss criterion cannot always be applied to time series because the discriminative patterns of time series data are easily distorted by external noises [15, 16]. For example, in a smart grid, distortions may occur due to sampling frequency perturbations, imprecise sensors, or random differences in energy consumption [17]. Such distortions can make it difficult for DNNs to learn the appropriate discriminant patterns of time series, resulting in large training losses for some clean labeled samples. In addition, the small-loss criterion only utilizes the data's label information and does not consider the inherent properties of time series features (i.e., multi-scale information).

Multi-scale properties are crucial in time series classification tasks. In recent years, multi-scale convolution [16], dynamic skip connections [18, 19] and adaptive convolution kernel size [20] have been utilized to learn discriminative patterns of time series. Furthermore, according to related studies [2, 20, 21], the selection of appropriate time scales for time series data can facilitate DNNs to learn class-characteristic patterns. With correct labels, the above studies indicate that the multi-scale properties of time series data can help DNNs learn appropriate discriminative patterns for mitigating the negative effects of time series recording noises. Nevertheless, it remains an open challenge as to how the multi-scale properties of time series can be used for label-noise learning.

To this end, we propose a deep learning paradigm, named Scale-teaching, for time-series classification with noisy labels. In particular, we design a fine-to-coarse cross-scale fusion mechanism for obtaining robust time series embeddings in the presence of noisy labels. We select four time series datasets from the UCR archive [22] to explain our motivation. As shown in Figure 1, in the single scale case (top row), the red and blue samples from the same category have large differences in certain local regions (the green rectangle in Figure 1). By downsampling the time series from fine to coarse, some local regions between the red and blue samples did become similar. Meanwhile, existing studies [12, 23] show that multiple DNNs with random initialization have classification divergence for noisy labeled samples, but are consistent for clean labeled samples. The above findings inspire us to utilize multiple DNNs to combine robust embeddings at different scales to deal with noisy labels. Nonetheless, the coarse scale discards many local regions in the fine scale (as in Figure 1 (c)), which may degenerate the classification performance. Hence, we propose the Scale-teaching paradigm, which can better preserve the local discriminative patterns of fine scale while dealing with distortions.

More specifically, the proposed Scale-teaching paradigm performs the cross-scale embedding fusion in the finer-to-coarser direction by utilizing time series at different scales to train multiple DNNs simultaneously. The cross-scale embedding fusion exploits complementary information from different scales to learn discriminative patterns. This enables the learned embeddings to be more robust to distortions and noisy labels. During training, clean labels are selected through cross-teaching on those networks with the learned embeddings. The small-loss samples in training are used as (clean) labeled data, and the unselected large-loss samples are used as (noisy) unlabeled data. Moreover, multi-scale embedding graph learning is introduced to establish relationships between labeled and unlabeled samples for noisy label correction. Based on the multi-scale embedding graph, the label propagation theory [24] is employed to correct noisy labels. This drives the model to better fit time series category distribution. The contributions are summarized as follows:

- We propose a deep learning paradigm, called Scale-teaching, for time-series label-noise learning. In particular, a cross-scale fusion mechanism is designed to help the model select more reliable clean labels by exploiting complementary information from different scales.
- We further introduce multi-scale embedding graph learning for noisy label correction using the selected clean labels based on the label propagation theory. Unlike conventional image label-noise learning methods focused on sample loss levels, our approach uses well-learned multi-scale time series embeddings for noise label correction at sample feature levels.
- Extensive experiments on multiple benchmark time series datasets show that the proposed Scale-teaching paradigm achieves a state-of-the-art classification performance. In addition, multi-scale analyses and ablation studies indicate that the use of multi-scale information can effectively improve the robustness of Scale-teaching against noisy labels.

2 Related Work

Label-noise Learning. Existing label-noise learning studies focus mainly on image data [10]. These studies can be broadly classified into three categories: (1) designing noise-robust objective functions [25, 26] or regularization strategies [27, 28]; (2) detecting and correcting noisy labels [13, 29, 30]; (3) transition-matrix-based [31, 32] and semi-supervised-based [14, 33] methods. In contrast to the methodologies in the first and third categories, approaches categorized under the second category have received considerable attention in recent years [7, 34]. Methods of the second category can be further divided into sample selection and label correction. The common methods of sample selection are the Co-teaching family [12, 13, 23] and FINE [35]. Label correction [36, 37] attempts to correct noisy labels by either using prediction results of classifiers or pseudo-labeling techniques. Recently, SREA [4] utilizes pseudo-labels generated based on a clustering task to correct time-series noisy labels. Although the above methods can improve the robustness of DNNs, how the multi-scale properties of time series are exploited for label-noise learning has not been explored.

Multi-scale Time Series Modeling. In recent years, multi-scale properties have gradually gained attention in various time series downstream tasks [18, 38], such as time series classification, prediction, and anomaly detection [39]. For example, Cui et al. [16] employ multiple convolutional network channels of different scales to learn temporal patterns that facilitate time series classification. Chen et al. [19] design a time-aware multi-scale RNN model for human action prediction. Wang et al. [40] introduce a multi-scale one-class RNN for time series anomaly detection. Also, recent studies [41, 42, 43, 44] indicate that multi-scale properties can effectively improve the performance of long-term time series prediction. Unlike prior work, we utilize multiple DNNs with identical architectures to separately capture discriminative temporal patterns across various scales. This enables us to acquire robust embeddings for handling noisy labels via a cross-scale fusion strategy.

Label Propagation. Label propagation (LP) is a graph-based inductive inference method [24, 45] that can propagate pseudo-labels to unlabeled graph nodes using labeled graph nodes. Since LP can utilize the feature information of data to obtain pseudo-labels of unlabeled samples, related works employ LP in few-shot learning [46] and semi-supervised learning [47, 48]. Generally speaking, DNNs have the powerful capability for feature extraction, and the learned embeddings tend to be similar within classes and different between classes. Each sample contains feature and label information. Intuitively, the embeddings of samples with noisy labels obtained by DNNs closely align with the true class distribution when the DNNs do not fit noisy labels in the early training stages. Naturally, we create a nearest-neighbor graph based on well-learned multi-scale time series embeddings at the feature level. Subsequently, we employ LP theory to correct the labels of unselected noisy samples using the labels of clean samples chosen by the DNNs. This approach leverages robust multi-scale embeddings to address the issue of noisy labels.

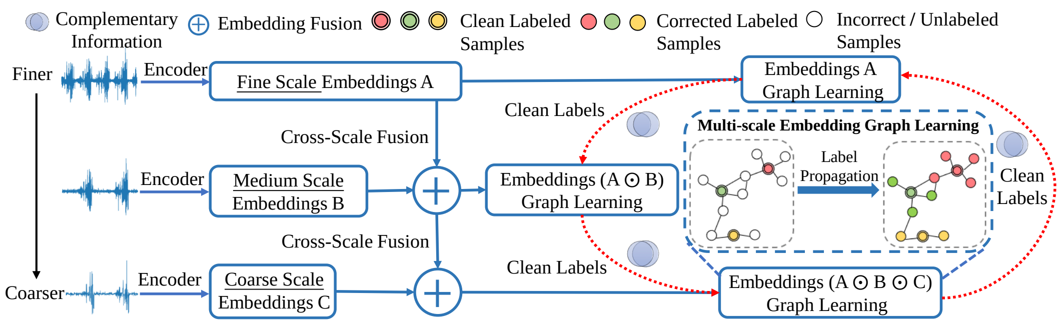


Figure 2: The Scale-teaching paradigm's general architecture comprises two core processes: (i) clean label selection and (ii) noisy label correction. In the clean label selection phase, networks A, B, and C engage in cross-scale fusion, moving from fine to coarse (A→B, B→C)). They employ clean labels acquired through cross-teaching (A→B, B→C, C→A) to guide their respective classification training. In the noisy label correction phase, pseudo labels derived from multi-scale embeddings graph learning are employed as corrected labels for time series not selected as clean labeled samples.

3 Proposed Approach

3.1 Problem Definition

Given a noisy labeled time series dataset $\mathcal{D} = \{(\mathcal{X}_i, \widehat{y}_i)\}_{i=1}^{N}$, it contains N time series, where $\mathcal{X}_i \in R^{L \times T}$, L denotes the number of variables, and T is the length of variable. $\widehat{y}_i \in \{1, \ldots, C\}$ is the observed label of $\mathcal{X}_i$ with η probability of being a noisy label. Our goal is to enable the DNNs trained on the noisy labeled training dataset $\mathcal{D}_{train}$ to correctly predict the ground-truth labels of the given time series in the test set. Specifically, the problem to be addressed in this paper consists of two steps. The first is to select clean labeled time series from $\mathcal{D}_{train}$, and the second is to perform noisy label correction for time series in $\mathcal{D}_{train}$ that have not been selected as clean labels.

3.2 Model Architecture

The overall architecture of Scale-teaching is shown in Figure 2. While this figure illustrates Scale-teaching with input time series at three scales, it can be extended to models with more scales, exceeding three. We utilize a consistent structural encoder to learn embeddings for each input scale sequence. Each encoder undergoes training at two levels: embedding learning for clean sample selection at the feature level and label correction with the multi-scale embeddings. For embedding learning, we propose a cross-scale fusion (Section 3.3) mechanism from fine to coarse to obtain robust embeddings. This approach enables the selection of more dependable clean labels through the small-loss criterion. Specifically, embeddings (A $\odot$ B $\odot$ C) encompass multi-scale information from fine, medium, and coarse scale sequences derived from the same time series. Regarding noisy label correction, we introduce multi-scale embedding graph learning (Section 3.4) based on label propagation, utilizing the selected clean samples to correct the labels of unselected large-loss samples.

3.3 Cross-scale Fusion for Clean Label Selection

After downsampling the original time series at different scales, it eliminates some of the differences in local regions between samples of the same category (as in Figure 1). However, the downsampled sequences (i.e., coarse scale) discard many local regions of the original time series. This tends to degrade the model's classification performance if the downsampled sequences are used directly for classification (please refer to Table 2 in the Experiments section). Meanwhile, existing studies [12, 23] on label-noise learning show that DNNs with different random initializations have high consistency in classification results for clean labeled samples in the early training period, while there is disagreement in the classification of noisy labeled samples. Based on the above findings, we utilize multiple DNNs (or encoders) with different random initializations to learn embeddings of different downsampled scale sequences separately, and perform cross-scale fusion. On the one hand, we exploit complementary information between adjacent scale embeddings to promote learned embeddings to be more robust for classification. On the other hand, we leverage the divergence in the classification of noisy labeled samples by different DNNs to mitigate the negative impact of noisy labels in training. In this way, we can utilize the cross-scale fusion embeddings for classification, thus better using the small loss criterion [11, 29] for clean label selection. Specifically, downsampling is employed to generate different scale sequences from the same time series. Given a time series $\mathcal{X}_i = \{x_1, x_2, \ldots, x_T\}$, supposing the downsampling ratio is k. Then, we only keep data points in $\mathcal{X}_i$ as follows:

$$\mathcal{X}_i^k = \{x_{k*j}\}, j = 1, 2, \ldots, \frac{T}{k}, \tag{1}$$

where $k \in [1, T/2]$, and a larger k indicates that $\mathcal{X}_i^k$ is coarser. As shown in Figure 2, time series with multiple downsampling intervals (i.e., k = 1, 2, 4) is treated as the input data for training. To better utilize the small-loss criterion for clean label selection, each time series sample performs cross-scale fusion from fine to coarse (i.e., A→B, B→C) in the embedding space, which is mathematically defined as:

$$v_i^k = f\left(r_i^k \left\|v_i^{k-t}\right\| \left(r_i^k - v_i^{k-t}\right) \| \left(r_i^k \cdot v_i^{k-t}\right)\right), \tag{2}$$

where r_i^k represents the single-scale embedding acquired by learning $\mathcal{X}_i^k$ through an encoder. Meanwhile, v_i^k (or v_i^{k-t}) denotes the embedding of the time series X_i^k (or X_i^{k-t}) after performing cross-scale fusion. Here, t denotes the interval between adjacent downsampling ratios, and $\|$ signifies the concatenation of two vectors to form a new vector. Notably, when $k = 1$, we employ the single-scale for classification training, resulting in $v_i^k = r_i^k$. By combining $(r_i^k - v_i^{k-t})$ and $(r_i^k \cdot v_i^{k-t})$ for vector concatenation, v_i^k can capture more nuanced discriminative information between r_i^k and v_i^{k-t} than that of simply concatenating r_i^k with v_i^{k-t}. The function $f(\cdot)$ represents a two-layer nonlinear network mapping function for fusing information of r_i^k and v_i^{k-t}. Additionally, v_i^k has the same dimension as r_i^k and serves as the input data for the multi-scale embedding graph learning process.

3.4 Multi-scale Embedding Graph Learning for Noisy Label Correction

We now present the multi-scale embedding graph learning module for correcting noisy labels. This module incorporates selected clean labels using label propagation theory. The process consists of two stages: graph construction and noisy label correction.

Graph Construction. It is assumed that the set of cross-fusion embeddings obtained from a batch of time series is defined as $V = \left\{v_1^k, v_2^k, \ldots, v_M^k\right\}$, where M is the batch size. Intuitively, samples close to each other in the feature space have a high probability of belonging to the same class. However, in label-noise learning, v_i^k obtained from the current iterative training of the model may have unstable information, resulting in large deviations in the information of the nearest-neighbor samples of v_i^k. To address this issue, the proposed approach performs a momentum update [49] on v_i^k during training, which is defined as:

$$\bar{v}_i^k[e] \quad = \quad \alpha v_i^k[e] + (1-\alpha)\bar{v}_i^k[e-1], \tag{3}$$

where e is the current training epoch and α denotes the momentum update parameter.

The multi-scale embeddings nearest-neighbor graph can be created by using Euclidean distance among different $\bar{v}_i^k$. A common approach is the use of the Gaussian similarity function [45] to obtain the nearest-neighbor graph edge weight, which is defined as:

$$W_{ij} \quad = \quad \exp\left(-\frac{1}{2} d\left(\frac{\bar{v}_i^k}{\sigma}, \frac{\bar{v}_j^k}{\sigma}\right)\right), \tag{4}$$

where $d(\cdot)$ is the Euclidean distance function and σ is a fixed parameter. $W \in R^{M \times M}$ is a symmetric adjacency matrix, and the element W_{ij} denotes the nearest-neighbor edge weight between the embedding v_i^k and v_j^k (note that larger values indicate closer proximity). Then, W is normalized based on the graph laplacians [50] to obtain $Q = D^{-1/2} W D^{-1/2}$, where $D = diag(W 1_n)$ is a diagonal matrix. Specifically, the K neighbors with the largest values in each row of Q are employed to create the nearest-neighbor graph. It is noteworthy that the embeddings in each mini-batch are utilized to generate the nearest-neighbor graph, thus obtaining Q within short computational time.

Noisy Label Correction. Specifically, small training loss samples acquired by DNNs in the early training period can be considered as clean samples, while samples with large training losses are considered as noisy ones [12, 14]. The above learning pattern of DNNs has been mathematically validated [11] (see Appendix A for details). Under this criterion, prior studies [12, 13, 23] have typically employed samples with small losses after a e_{warm} warm-up training as clean labels. Following [29], we extend the small-loss sample selection process to operate within each class, thereby enhancing the overall quality of the chosen clean labels. In our method, samples chosen with clean labels are considered labeled data, whereas unselected samples are treated as unlabeled data.

We utilize clean samples selected from time series at different scales in a cross-teaching manner (as in Figure 2). This could explore complementary information from different scale fusion embeddings to deal with noisy labels. It is supposed that there is a corresponding one-hot encoding matrix $Y \in R^{M \times C}$ ($Y_{ij} \in \{0, 1\}$) for the cross-fusion embeddings V. If y_i is identified as a clean label, we employ y_i to set Y_i as a one-hot encoded label. Otherwise, all the elements in Y_i are identified as zero. Through Y, the pseudo-label of each node in the nearest-neighbor graph Q can be obtained in an iterative way based on the label propagation theory. The specific solution formula is defined as:

$$F_{t+1} = \beta Q F_t + (1 - \beta) Y, \tag{5}$$

where $F_t \in R^{M \times C}$ denotes the predicted pseudo-label of the t-th iteration and $\beta \in (0, 1)$ is a hyperparameter. Naturally, F_t has a closed-form solution [24] defined as follows:

$$\mathcal{F} = (I - \beta Q)^{-1} Y, \tag{6}$$

where $\mathcal{F} \in R^{M \times C}$ is the final pseudo-labels and I denotes the identity matrix. Finally, the corrected label obtained for an unselected large-loss sample X_i is defined as:

$$y_i = \arg\max_{c} \mathcal{F}_i^c, \tag{7}$$

However, $\mathcal{F}$ is the estimated pseudo-labels, which inevitably contain some incorrect labels. To address this issue, two strategies are used to improve the quality of pseudo-labels in $\mathcal{F}$. For the first strategy, the model continues training e_{update} epochs by using small-loss samples after e_{warm} epochs warm-up training to improve the robustness of the multi-scale embeddings. Then, the noisy label correction is performed after $(e_{warm} + e_{update})$ epoch. For the second strategy, a dynamic threshold $\varphi_e(c) = \frac{\delta_e(c)}{\max(\delta_e)} \gamma$ is utilized for each class [51] to select the pseudo-labels with a high confidence for noisy label correction, where $\delta_e(c)$ is the number of labeled samples contained in class c in the e-th epoch, and γ is a constant threshold.

Overall Training. Finally, each encoder utilizes the selected clean samples in combination with multi-scale embedding graph learning to perform noisy label correction for unselected large-loss samples. Combining the training data of the selected clean labels and those of corrected labels, the proposed Scale-teaching paradigm utilizes cross-entropy for time-series label-noise learning. Please refer to Algorithm 1 in the Appendix for the specific pseudo-code of Scale-teaching.

4 Experiments

4.1 Experiment Setup

Datasets. We use three time series benchmarks (four individual large datasets [3, 52, 53], UCR 128 archive [22], and UEA 30 archive [54]) for experiments. Among the four individual large datasets, HAR [52] and UniMiB-SHAR [3] are human activity recognition scenarios; FD-A [53] is the mechanical fault diagnosis scenario; Sleep-EDF [52] belongs to the sleep stage classification scenario. The UCR archive [22] contains 128 univariate time series datasets from different real-world scenarios. The UEA archive [54] contains 30 multivariate time series datasets from real-world scenarios. For details on the above datasets, please refer to Appendix B. Since all the datasets in three time series benchmarks are correctly labeled, we utilize a label transformation matrix T to add noises to the original correct labels [4], where T_{ij} is the probability of label i being flipped to j. We use three types of noisy labels for evaluations, namely Symmetric (Sym) noise, Asymmetric (Asym) noise, and Instance-dependent (Ins) noise. Symmetric (Asymmetric) noise randomly replaces a true label with other labels with an equal (unequal) probability. Instance noise [55] means that the noisy label is instance-dependent. Like [4, 12, 23], we use the test set with correct labels for evaluations.

Table 1: Test classification accuracy results compared with baselines on three time series benchmarks. The best results are **bold**, and the second best results are underlined. When P-value < 0.05, it indicates that the performance of Scale-teaching is statistically significant than the baseline.

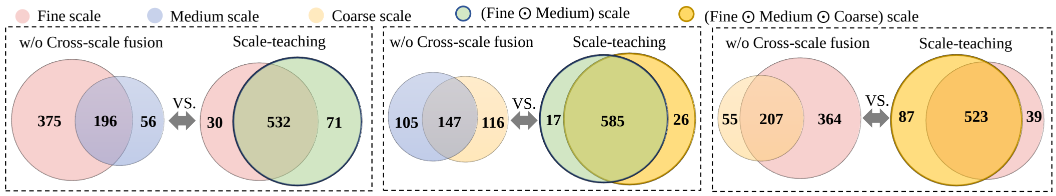
Dataset	Noise Ratio	Metric	Standard	Mixup	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
Four individual large datasets	Sym 20%	Avg Rank	4.75	4.75	4.50	7.50	6.50	4.50	2.50	**1.00**
	Sym 50%	Avg Rank	4.75	4.50	4.75	7.25	5.75	4.50	3.25	**1.25**
	Asym 40%	Avg Rank	5.00	5.50	3.75	7.50	5.75	4.00	3.25	**1.00**
	Ins 40%	Avg Rank	4.75	4.25	4.25	7.25	6.00	4.75	3.50	**1.00**
UCR 128 archive	Sym 20%	Avg Rank	4.15	4.33	3.61	7.50	6.16	3.48	3.54	**3.02**
		P-value	1.90E-04	4.06E-05	1.90E-03	1.49E-34	1.70E-17	3.04E-03	8.57E-03	-
	Sym 50%	Avg Rank	4.31	4.57	4.05	6.43	5.89	3.56	3.86	**3.11**
		P-value	3.15E-05	1.70E-05	4.02E-04	7.48E-19	1.22E-15	1.40E-02	4.93E-03	-
	Asym 40%	Avg Rank	4.38	4.80	3.93	6.91	5.91	3.30	3.67	**2.95**
		P-value	1.62E-05	3.53E-07	6.10E-04	1.93E-23	9.82E-14	1.89E-02	2.24E-02	-
	Ins 40%	Avg Rank	4.05	4.52	4.02	7.04	6.18	3.30	3.77	**2.95**
		P-value	1.43E-05	1.81E-06	2.43E-04	9.81E-26	2.36E-17	3.27E-02	1.54E-02	-
UEA 30 archive	Sym 20%	Avg Rank	5.03	5.20	3.83	6.37	4.77	3.73	4.00	**2.73**
		P-value	6.61E-04	3.33E-04	2.69E-02	2.37E-05	1.14E-02	2.63E-02	3.93E-02	-
	Sym 50%	Avg Rank	5.17	5.73	4.23	6.23	3.93	3.83	4.30	**2.43**
		P-value	2.98E-04	7.40E-05	1.59E-02	9.35E-05	1.67E-02	1.08E-02	3.75E-02	-
	Asym 40%	Avg Rank	5.60	4.77	4.40	6.13	4.20	4.00	3.97	**2.73**
		P-value	3.81E-03	6.17E-03	1.63E-02	9.33E-05	1.36E-02	2.62E-02	3.88E-02	-
	Ins 40%	Avg Rank	5.20	4.77	4.33	6.60	4.27	4.20	3.77	**2.60**
		P-value	6.08E-04	2.92E-03	1.20E-02	2.55E-05	5.52E-03	1.08E-02	3.47E-02	-

Baselines. We select seven methods for comparative analyses, namely 1) Standard: direct training of the model using cross-entropy with all noisy labels; 2) Mixup [56]; 3) Co-teaching [12]; 4) FINE [35]; 5) SREA [4]; 6) SELC [37]; and 7) CULCU [23]. Among them, Standard, Mixup, and Co-teaching are the benchmark methods for label-noise learning. FINE, SELC, and CULCU are the state-of-the-art methods that do not need to focus on data types, and SREA is the state-of-the-art method in time series domain. In addition, for fair comparisons, all the baselines and the proposed Scale-teaching paradigm use the same encoder and classifier. We focus on the ability of different label-noise learning paradigms to cope with time series noise labels, rather than the classification performance achieved by using fully correct labels. Hence, considering the trade-off between the running time and classification performance, we choose FCN [57] as the encoder of Scale-teaching. For more details of baselines, please refer to Appendix C.

Implementation Details. Based on the experience [19, 44] in time series modeling, we utilize three different sampling intervals 1, 2, 4 as the input muti-scale series data for Scale-teaching. We use Adam as the optimizer. The learning rate is set to 1e-3, the maximum batch size is set to 256, and the maximum epoch is set to 200. e_{warm} is set to 30 and e_{update} is set to 90. α in Eq. 3 is set to 0.9, σ in Eq. 4 is set to 0.25, β in Eq. 5 is set to 0.99, the largest neighbor K is set to 10, and γ is set to 0.99. In addition, following the parameter settings suggested in [23], we linearly decay the learning rate to zero from the 80-th epoch to 200-th epoch. For a comprehensive understanding of the hyperparameter selection and the implementation of the small-loss criterion applied to Scale-teaching, please consult Appendix C. To reduce random errors, we utilize the mean test classification accuracy of the last five epochs of the model on the test set as experimental results. All the experiments are independently conducted five times with five different seeds, and the average classification accuracy and rank are reported. Finally, we build our model using PyTorch 1.10 platform with 2 NVIDIA GeForce RTX 3090 GPUs. Our implementation of Scale-teaching is available at `https://github.com/qianlima-lab/Scale-teaching`.

4.2 Main Results

We evaluate each time series benchmack using four noise ratios, Sym 20%, Sym 50%, Asym 40%, and Ins 40%. Due to space constraints, we only give the average ranking of all the methods on each benchmark in Table 1. Please refer to Appendix D for the specific test classification accuracies. Besides, for UCR 128 and UEA 30 archives, we use the Wilcoxon signed rank test (P-value) [58] to analyze the classification performance of baselines. As shown in Table 1, the proposed Scale-teaching paradigm achieves the best Avg Rank in all the cases. It is found that Mixup [56] and FINE [35] perform worse than the Standard method in most cases. For Mixup, the complex dynamic properties



(a) Fine → Medium (b) Medium → Coarse (c) Coarse → Fine

Figure 3: Venn diagram of the average number of correctly classified samples for the different scale sequences of UCR 128 archive with Sym 20% noisy labels. The numbers in the figure indicate the complements and intersections of classification results at different scales.

Table 2: The test classification accuracy (%) results of different scale classifiers on UCR 128 archive. The best results are **bold**, and the second best results are underlined. When P-value < 0.05, it indicates that the performance of Scale-teaching's coarse scale classifier is significant than other classifiers.

Method		w/o Cross-scale fusion			Scale-teaching		
Noise Ratio	Metric	Fine	Medium	Coarse	Fine	Medium	Coarse
Sym 20%	Avg Acc	65.13	30.11	28.17	59.67	68.17	**68.70**
	Avg Rank	2.38	5.09	5.37	3.20	2.17	**2.11**
	P-value	1.89E-03	2.85E-37	2.07E-40	1.58E-09	3.74E-02	-
Asym 40%	Avg Acc	49.61	29.01	28.87	47.75	51.93	**52.87**
	Avg Rank	2.64	4.78	4.75	3.01	2.45	**2.27**
	P-value	1.94E-03	6.78E-25	1.59E-27	1.80E-07	2.80E-02	-

of the original time series are destroyed probably due to the mixture of two different time series mechanisms. FINE uses embeddings of the input data to select clean labels. Although FINE achieves advanced classification performance for image data, it is difficult to be used directly for time series data because its discriminative patterns are easily distorted by external noises. SREA [4] has a good performance on the UEA 30 archive, while it performs poorly on the other benchmarks. Meanwhile, Co-teaching [12], SELC [37], and CULCU [23] are more robust against time series noisy labels in different cases, further indicating that the small-loss criterion is also applicable to time series.

4.3 Multi-scale Analysis

To explain the multi-scale mechanism in the Scale-teaching paradigm, we add an ablation study based on Scale-teaching (w/o cross-scale fusion). We select the UCR 128 archive to analyze the classification results obtained by the fine, medium, and coarse scale classifiers. As shown in Figure 3, the classification results of different scale sequences have evident complementary information. Scale-teaching can effectively use complementary information between cross-scale to obtain more robust embeddings and clean labels. In response to the tendency of the coarse scale to ignore discriminative patterns in fine scale (please see Table 2), our proposed cross-scale fusion mechanism can effectively improve the classification performance of medium and coarse scales while retaining complementarity. Please refer to Appendix E for the specific classification results of Figure 3 and Table 2. In Appendix E, we also analyze the order and size of the downsampled input scale sequence for Scale-teaching.

Scale-teaching utilizes multi-scale embeddings to generate the nearest-neighbor graph, and uses clean labels selected for noisy label correction. To explore the distribution of different classes of embeddings, we employ t-SNE [59] for dimensionality reduction visualization. Specifically, we utilize the UniMiB-SHAR dataset containing Sym 20% noisy labels for visualization. As shown in Figure 4, we find that the embeddings learned by Scale-teaching are more discriminative across classes than the Standard and CULCU methods that use a single scale series for training. The above results suggest that Scale-teaching can effectively exploit the complementary information between different scales, prompting the learned embeddings to be more discriminative between classes. In addition, we choose the FD-A dataset for t-SNE visualization, and please refer to Appendix E.

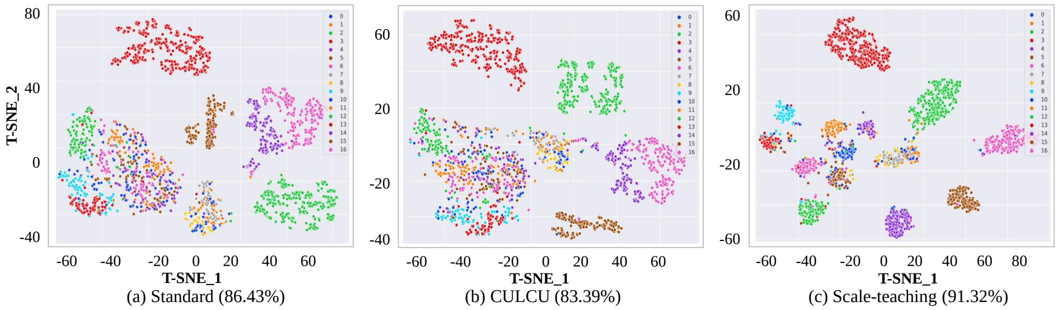


Figure 4: t-SNE visualization of the learned embeddings on the UnimiB-SHAR dataset with Sym 20% noisy labels (values in parentheses are the test classification accuracies).

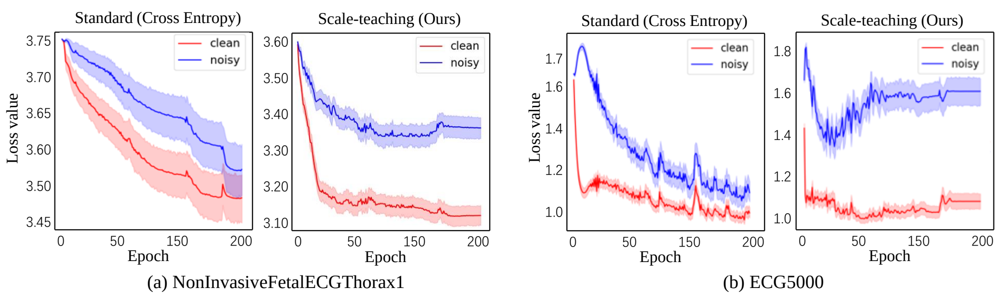


Figure 5: The change of loss values for clean and noisy time series samples under Aysm 40% noise labels. The solid line and shading indicate the mean and standard deviation loss values of all clean (or noisy) training samples within each epoch.

4.4 Small-loss Analysis

To analyze the application of the small-loss criterion to time series data, we visualize the change of loss values for ground-truth clean and noisy time series samples during training. Specifically, Figure 5 shows the change in loss values of the models trained by the Standard method and Scale-teaching on two UCR time series datasets. When the model is trained with the Standard method, differences can be found in the loss values of clean and noisy samples in the network early training, especially in Figure 5 (b). The Standard method makes the model gradually fit the noisy samples as the training proceeds, while Scale-teaching improves the ability of the model to handle noisy labels. To further prove its effectiveness, we selected two other UCR datasets for the loss value change analysis, which have the same pattern as Figure 5. Also, we report the HAR and UniMiB-SHAR dataset's loss value probability distributions of clean and noisy samples. For more details, please refer to Appendix F.

4.5 Ablation Study

To verify the robustness of each module in Scale-teaching, the ablation experiments have been conducted in the HAR and UniMiB-SHAR datasets, and the results are shown in Table 3. Specifically, (1) **w/o cross-scale fusion**: the cross-scale embedding fusion from fine to coarse mechanism is ablated; (2) **only single scale**: only the original time series is used for training; (3) **w/o graph learning**: the multi-scale embedding graph learning module for noisy label correction is ablated; (4) **w/o moment**: the embedding momentum update mechanism (Eq. 3) is ablated; (5) **w/o dynamic threshold**: using a dynamic threshold to select high-quality propagation pseudo-labels is ablated.

As shown in Table 3, the cross-scale fusion strategy (w/o cross-scale fusion) and the clean labels cross-teaching mechanism (only single scale) can effectively improve the classification performance of Scale-teaching, especially on the UniMiB-SHAR dataset with a large number of classes. Meanwhile, in terms of label correction based on multi-scale embedding graph learning, the results of the corresponding ablation module show that improving the stability of embedding (w/o moment) and

Table 3: The test classification accuracy (%) results of ablation study (values in parentheses denote drop accuracy).

Method	HAR		UniMiB-SHAR	
	Sym 50%	Asym 40%	Sym 50%	Asym 40%
Scale-teaching	**90.17**	**89.62**	**81.31**	**70.68**
w/o cross-scale fusion	88.47 (-1.70)	87.64 (-1.98)	73.32 (-7.99)	61.62 (-9.06)
only single scale	89.01 (-1.06)	88.11 (-1.51)	69.89 (-11.42)	60.32 (-10.36)
w/o graph learning	88.06 (-2.11)	87.65 (-1.97)	79.72 (-1.59)	68.87 (-1.81)
w/o moment	89.76 (-0.41)	88.76 (-0.86)	80.57 (-0.74)	69.85 (-0.83)
w/o dynamic threshold	89.12 (-1.05)	88.75 (-0.87)	77.42 (-3.89)	69.53 (-1.15)

Table 4: The test classification accuracy (%) results on four individual large datasets without noisy labels. The best results are **bold**, and the second best results are <u>underlined</u>.

Dataset	Standard	Mixup	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
HAR	93.29	95.42	93.77	93.13	93.02	93.76	**94.75**	<u>94.72</u>
UniMiB-SHAR	89.14	84.84	88.24	88.14	65.51	89.28	<u>89.46</u>	**93.61**
FD-A	99.93	99.91	**99.96**	68.22	90.25	99.82	<u>99.95</u>	**99.96**
Sleep-EDF	84.93	84.67	<u>85.37</u>	84.62	79.42	84.82	**85.54**	85.34

selecting high-quality pseudo-labels (w/o dynamic threshold) can effectively improve the performance of label correction based on graph learning.

Furthermore, we select the four individual large datasets without noisy labels for evaluation. As shown in Table 4, Scale-teaching's classification performance is still better than most baselines. It's worth mentioning that SREA [4] employs an unsupervised time series reconstruction loss as an auxiliary task, which reduces the model's classification performance without noisy labels. We also provide the corresponding test classification results for Tables 3 and 4 under the F1-score metric in Appendix G. Additionally, we find the running time of Scale-teaching, which is faster than FINE, SREA and CULCU for datasets with a larger number of samples or longer length of the sequence. We further analyze the classification performance of the proposed Scale-teaching paradigm and time series classification methods [15, 60] in Appendix G.

5 Conclusions

Limitations. The input scales of our proposed Scale-teaching paradigm can only select a fixed number of scales for training, and the running time will increase as the number of scales increases.

Conclusion. In this paper, we propose a deep learning paradigm for time-series classification with noisy labels called Scale-teaching. Experiments on the three time series benchmarks show that the Scale-teaching paradigm can utilize the multi-scale properties of time series to effectively handle noisy labels. Comprehensive analyses on multi-scale and ablation studies demonstrate the robustness of the Scale-teaching paradigm. In the future, we will explore the design of scale-adaptive time-series label-noise learning models.

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Supplementary Material: Scale-teaching: Robust Multi-scale Training for Time Series Classification with Noisy Labels

A Small-loss Criterion

DNNs have been widely known to first learn simple and generalized patterns, which is achieved by learning clean data. After that, the networks gradually overfit noisy ones. In other words, when we train a model with a dataset containing incorrectly labeled samples, we can consider the samples with small training losses as clean ones and use them to update the model. Formally, let f^* be the target concept which determines the true label of x and $\mathrm{model}\, g^* = g\left(\boldsymbol{x}; \Theta^*\right)$ minimizing the expected loss, i.e.,

$$\Theta^* = \arg\min_{\Theta} \mathbb{E}_{(\boldsymbol{x},\tilde{y})}\left[\ell_{CE}(g(\boldsymbol{x};\Theta),\tilde{y})\right]. \tag{8}$$

Then, the small-loss criterion can be stated as follows[1]:

Theorem 1. *Suppose g is ϵ-close to g^*, i.e., $\|g-g^*\|_\infty = \epsilon$, for two examples $(\boldsymbol{x}_1, \tilde{y})$ and $(\boldsymbol{x}_2, \tilde{y})$, assume $f^*\left(\boldsymbol{x}_1\right) = \tilde{y}$ and $f^*\left(\boldsymbol{x}_2\right) \neq \tilde{y}$, if T satisfies the diagonally-dominant condition $T_{ii} > \max\left\{\max_{j\neq i} T_{ij}, \max_{j\neq i} T_{ji}\right\}, \forall i$, and $\epsilon < \frac{1}{2}\cdot\left(T_{\tilde{y}\tilde{y}} - T_{f^*(\boldsymbol{x}_2)\tilde{y}}\right)$, then $\ell_{CE}\left(g\left(\boldsymbol{x}_1\right), \tilde{y}\right) < \ell_{CE}\left(g\left(\boldsymbol{x}_2\right), \tilde{y}\right)$.*

The work [11] provides the proof of this theorem. It shows that during training, the model can select clean samples according to the loss values. The reason is that the loss values of clean samples among the samples with the same observed labels are smaller. It is worth noting that the theorem is under the assumption of the class-dependent noise type and requires the transition matrix to satisfy the diagonally-dominant condition. Additionally, the finite data may also make the conditions of the theorem difficult to hold because the model g may be far away from g^*.

B Dataset Information

To evaluate the robustness of our proposed Scale-teaching and baselines on the time-series label-noise learning task, we selected three benchmark time-series datasets for experimental analysis.

B.1 Four individual large datasets

The statistical information of the four individual time series datasets is shown in Table 5. And the specific dataset information is as follows:

Human Activity Recognition (HAR)

The HAR dataset [52, 61] is collected from 30 students performing six human actions (i.e., walking, walking upstairs, downstairs, standing, sitting, and lying down) by wearing sensors.

University of Milano Bicocca Smartphone-based Human Activity Recognition (UniMiB SHAR)

The UniMiB SHAR dataset [3, 62] is human activity information collected at a sampling rate of 50 Hz from volunteers with a smartphone with an accelerometer sensor in the front pocket of their pants. Specifically, each accelerometer entry is labeled by specifying the type of ADL (e.g., walking, sitting, or standing) or the type of fall (e.g., forward, fainting, or backward).

Faulty Detection Condition A (FD-A)

The FD-A dataset [52, 63] is generated by an electromechanical drive system that monitors the condition of rolling bearings and detects their failure. Each rolling bearing can be classified into three categories: undamaged, inner damaged, and externally damaged.

Sleep Stage EEG Signal Classification (Sleep-EDF)

The Sleep-EDF dataset [52, 64] includes the whole night PSG sleep recordings, which contain five EEG sleep signal recordings: Wake (W), Non-rapid eye movement (N1, N2, N3), and Rapid Eye Movement (REM).

Table 5: A summary of four individual large time series datasets used in the experiments.

Dataset	# Train	# Test	Length	# Variables	# Classes
HAR	7352	2947	128	9	6
Sleep-EDF	25612	8910	3000	1	5
FD-A	8184	2728	5120	1	3
UniMiB-SHAR	9416	2354	453	1	17

B.2 UCR 128 Archive

The UCR time series archive [22] contains 128 univariate datasets and is widely used for classification in the time series mining community. Each UCR dataset includes a single training set and a single test set, and each time series sample has been z-normalized. In addition, we uniformly use the mean-imputation method to preprocess the datasets that contain missing values. For detailed information about UCR datasets, please refer to `https://www.cs.ucr.edu/~eamonn/time_series_data_2018/`.

B.3 UEA 30 Archive

The UEA time series archive [54] contains 30 multivariate datasets, mainly derived from Human Activity Recognition, Motion classification, ECG classification, EEG/MEG classification, Audio Spectra Classification, and other realistic scenarios. Each dataset contains a partitioned training set and a test set. In addition, we use the mean-imputation method to deal with datasets with missing values. For detailed information about UEA datasets, please refer to `https://www.timeseriesclassification.com/dataset.php`.

C Baselines

To analyze the performance and effectiveness of Scale-teaching on time-series label-noise learning, we selected seven baselines for comparative analysis. The specific information is as follows.

- Standard directly employs all samples in the training set containing noisy labels and performs supervised classification training using cross-entropy loss. Then, the trained model is used to make predictions on the test set.
- Mixup [56] trains a neural network on convex combinations of pairs of time series samples and their labels (whatever is clean or noisy). For the specific open source code, please refer to `https://github.com/facebookresearch/mixup-cifar10`.
- Co-teaching [12] trains two deep neural networks simultaneously, and lets them teach each other given every mini-batch with selected clean labels based on a small-loss criterion. For the specific open source code, please refer to `https://github.com/bhanML/Co-teaching`.
- FINE [35] utilizes a novel detector for clean label selection. Especially, FINE focus on each data point's latent representation dynamics and measures the alignment between the latent distribution and each representation using the eigen decomposition of the data gram matrix. For the specific open source code, please refer to `https://github.com/Kthyeon/FINE_official`.
- SREA [4] employs a novel multi-task deep learning approach for time series noisy label correction that jointly trains a classifier and an autoencoder with a shared embedding representation. For the specific open source code, please refer to `https://github.com/Castel44/SREA`.
- SELC [37] utilizes a simple and effective method self-ensemble label correction (SELC) to progressively correct noisy labels and refine the model. For the specific open source code, please refer to `https://github.com/MacLLL/SELC`.
- CULCU [23] incorporates the uncertainty of losses by adopting interval estimation instead of point estimation of losses to select clean labels based on Co-teaching. CULCU has two

versions: CNLCU-S and CNLCU-H, where CNLCU-S uses soft labels for training and CNLCU-H uses hard labels for training. According to the original paper's [23] experimental results, CNLCU-S has a better performance. Hence, we use CNLCU-S as a baseline. For the specific open source code, please refer to `https://github.com/xiaoboxia/CNLCU`.

Finally, based on the source code of the above baselines, we provide the reproduction source code of all baselines, as well as the source code of our proposed Scale-teaching (refer to Algorithm 1). For the specific open-source code, please refer to our GitHub repository `https://github.com/qianlima-lab/Scale-teaching`.

Our experiment contains 162 datasets. It would be time-consuming to perform hyperparameter selection for each dataset. Therefore, the hyperparameters of Scale-teaching are not carefully tuned for each dataset, and most of the hyperparameters are set based on the default hyperparameters of related works. The learning rate and maximum epoch are set based on the parameters of existing noise-label learning methods, such as FINE and CULCU. α in Eq. 3, σ in Eq. 4 and β in Eq. 5 are set based on the default hyperparameters of related label propagation works. e_{warm} is based on FINE settings. e_{update}, γ and batch size are based on manual empirical settings without specific hyperparameter analysis. The largest neighbor K is set based on human experience, and we had a simple test on several datasets, and found that a larger value of does not improve the classification performance, but instead increases the running time of the model.

For the implementation of small-loss criterion in Scale-teaching, we select small-loss samples within each class from the mini-batch data as clean labeled data. For stduies [12, 13], they use warm-up training to decrease $\lambda(e)$ from 1 to $1-\eta$. $\lambda(e)$ denotes the selection ratio of small-loss samples within the mini-batch data without considering the difference of class, and η is the ratio of noise labels in the training set. Based on the above criterion, the current work [29] uses the Jensen-Shannon divergence to calculate difference d between the classification result p_i of sample $\mathcal{X}_i^c$ and the observation label $\widehat{y}_i$. Following [29], for each class c, we consider the observed label of $\mathcal{X}_i^c$ as a clean label when the d of the training sample $\mathcal{X}_i^c$ is less than d_{avg}^e after a e_{warm} warm-up training. d_{avg}^e denotes the average of ds of all the training samples when the epoch is e. We observed that using the Jensen-Shannon divergence method [29] and directly employing stduies [12, 13] for clean sample selection within each class have distinct strengths and weaknesses when applied to various time series datasets. In our study, we implemented the strategy of stduies [12, 13] for clean sample selection within each class on four individual large datasets and the UCR 128 archive. Meanwhile, the Jensen-Shannon divergence method [29] was applied to the UEA 30 archive for clean sample selection within each class.

D Details of Main Results

For the four individual large time series datasets, the specific classification results of our proposed Scale-teaching paradigm and baselines are shown in Table 6. For the UCR 128 archive, the specific classification results for all methods with different noise ratios are shown in Table 11 (Sym 20%), 12 (Sym 50%), 13 (Asym 40%), and 14 (Ins 40%). For the UEA 30 archive, the specific classification results for all methods at different noise ratios are shown in Tables 15 (Sym 20%), 16 (Sym 50%), 17 (Asym 40%), and 18 (Ins 40%). For layout and reading convenience, we only give the average classification accuracy for multiple runs of all methods without standard deviation on the UCR 128 archive and UEA 30 archive.

E Details of Multi-scale Results

To analyze the multi-scale mechanism in the Scale-teaching paradigm, we provide the classification performance of classifiers corresponding to fine, medium and coarse scales, as shown in Tables 19 and 21. And the classification results by ablation cross-scale fusion mechanism based on the Scale-teaching are shown in Tables 20 and 22. For the abbreviations in Tables 19, 20, 21 and 22, such as a_t_b_f, b_f_c_t, and c_t_a_f, where a denotes fine classifier, b denotes medium classifier, and c denotes coarse classifier, and t and f represent correct and incorrect classification results, respectively. For example, a_t_b_f indicates the number of samples correctly predicted by the fine classifier and incorrectly predicted by the medium classifier. In addition, we provide t-SNE [59] visualization on the FD-A dataset with Sym 50% noisy labels (as in Figure 6) to explore the distribution of different classes of embeddings. Figure 6 shows that the cross-scale fusion mechanism in Scale-teaching for

Algorithm 1 The proposed Scale-teaching paradigm.

Input: encoders $[w_A, w_B, w_C]$, classifiers $[c_A, c_B, c_C]$, fine-scale series x_A, medium-scale series x_B, and coarse-scale series x_C

Output: $[w_A, w_B, w_C]$ and $[c_A, c_B, c_C]$

Note: For clarity, our analysis utilizes three distinct scales for training, but this approach can be extended to incorporate multiple scales.

1: **Step one:** Obtain single-scale embeddings r_A, r_B, r_C;
$r_A = w_A(x_A)$;
$r_B = w_B(x_B)$;
$r_C = w_C(x_C)$;

2: **Step two:** Obtain cross-scale embeddings v_A, v_B, v_C;
$v_A = r_A$;
v_B = Eq. $2(r_B, v_A)$;
v_C = Eq. $2(r_C, v_B)$;

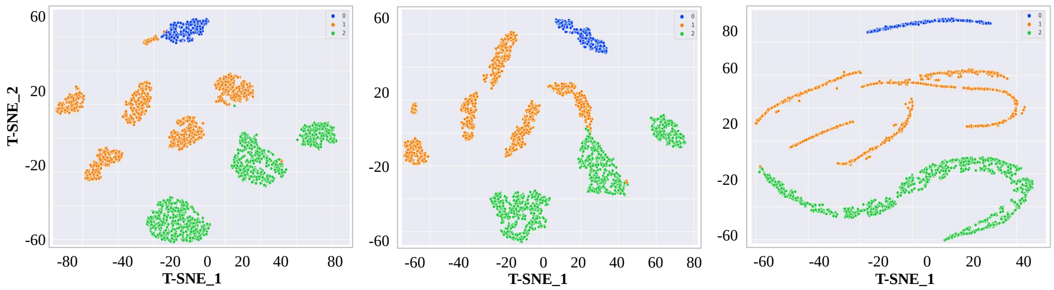
3: **Step three:** Obtain clean labels y_A, y_B, y_C for cross-teaching training;
$y_A = c_C(v_C)$ via small loss criterion;
$y_B = c_A(v_A)$ via small loss criterion;
$y_C = c_B(v_B)$ via small loss criterion;

4: **Step four:** Obtain corrected labels yc_A, yc_B, yc_C for classification training;
yc_A = Eq. $6(v_A, y_A)$ via label propagation;
yc_B = Eq. $6(v_B, y_B)$ via label propagation;
yc_C = Eq. $6(v_C, y_C)$ via label propagation;

5: **Step five:** Overall training;
Update encoder w_A and classifier c_A via cross-entropy loss(v_A, y_A & yc_A);
Update encoder w_B and classifier c_B via cross-entropy loss(v_B, y_B & yc_B);
Update encoder w_C and classifier c_C via cross-entropy loss(v_C, y_C & yc_C).

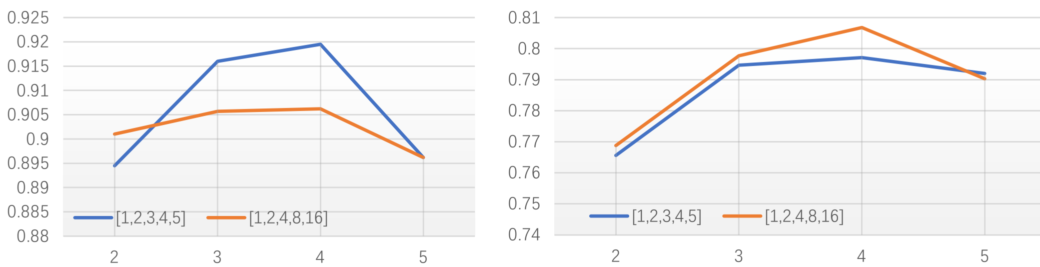
Table 6: The detailed test classification accuracy (%) compared with baselines on four individual large datasets (values in parentheses are standard deviations). The best results are in **bold**.

Dataset	Noise	Standard	Mixup	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
HAR	Sym 20%	92.13 (0.64)	92.52 (1.05)	92.28 (0.67)	92.15 (0.55)	92.53 (1.41)	92.88 (0.82)	92.66 (0.37)	**93.93 (0.66)**
	Sym 50%	83.99 (2.89)	76.75 (1.88)	89.90 (1.63)	88.42 (3.83)	**91.38 (0.59)**	90.37 (0.73)	89.91 (2.19)	90.17 (0.67)
	Asym 40%	75.59 (5.39)	66.91 (2.61)	87.67 (2.52)	83.87 (5.98)	88.98 (0.57)	87.67 (2.39)	87.22 (1.22)	**89.62 (0.73)**
	Ins 40%	83.56 (2.82)	73.86 (0.89)	90.98 (0.96)	90.77 (0.33)	91.25 (1.11)	91.02 (1.53)	91.15 (1.43)	**91.58 (1.47)**
UniMiB-SHAR	Sym 20%	87.07 (0.95)	82.13 (1.08)	80.54 (2.16)	26.63 (3.07)	51.48 (3.65)	68.52 (2.86)	82.80 (1.87)	**90.69 (1.02)**
	Sym 50%	79.37 (0.41)	77.77 (1.59)	66.33 (2.85)	18.92 (4.61)	47.62 (3.33)	67.65 (3.31)	66.36 (3.91)	**81.31 (0.67)**
	Asym 40%	63.59 (4.13)	66.32 (1.93)	60.25 (1.45)	19.18 (4.37)	51.16 (3.01)	55.65 (1.59)	60.45 (1.65)	**70.68 (2.15)**
	Ins 40%	55.83 (8.14)	56.97 (6.48)	54.09 (3.79)	11.18 (4.75)	51.5 (1.98)	54.62 (6.63)	53.90 (4.75)	**71.14 (3.99)**
FD-A	Sym 20%	98.89 (0.05)	99.78 (0.06)	99.83 (0.08)	78.13 (21.47)	89.92 (0.68)	99.67 (0.09)	99.85 (0.08)	**99.93 (0.04)**
	Sym 50%	96.63 (1.16)	98.73 (0.62)	99.04 (0.32)	70.65 (17.53)	82.18 (0.01)	98.59 (0.25)	99.06 (0.29)	**99.38 (0.53)**
	Asym 40%	96.12 (1.65)	93.50 (1.85)	97.06 (4.05)	61.04 (14.24)	90.23 (0.02)	98.24 (0.58)	98.91 (0.42)	**99.55 (0.36)**
	Ins 40%	99.36 (0.47)	99.55 (0.10)	99.51 (0.19)	67.81 (12.95)	88.63 (0.02)	99.36 (0.23)	99.53 (0.22)	**99.82 (0.06)**
Sleep-EDF	Sym 20%	85.01 (0.09)	84.31 (0.36)	84.81 (0.14)	81.21 (0.28)	72.79 (0.99)	84.32 (0.33)	85.23 (0.14)	**85.56 (0.35)**
	Sym 50%	83.58 (0.74)	83.61 (0.39)	83.39 (0.25)	78.17 (4.42)	72.78 (1.30)	83.06 (0.29)	84.02 (0.53)	**84.59 (0.97)**
	Asym 40%	79.62 (2.39)	77.40 (1.92)	82.87 (0.40)	64.77 (2.10)	72.23 (0.89)	82.50 (1.07)	83.05 (0.64)	**83.87 (0.38)**
	Ins 40%	84.35 (0.38)	84.25 (0.31)	84.62 (0.28)	79.68 (2.55)	71.99 (1.24)	83.78 (0.28)	84.86 (0.22)	**85.03 (0.61)**



(a) Standard (96.73%) (b) CULCU (98.77%) (c) Scale-teaching (99.79%)

Figure 6: t-SNE visualization of the learned embeddings on the FD-A dataset with Sym 50% noisy labels (values in parentheses are the test classification accuracies).



(a) HAR Dataset (b) UniMiB-SHAR Dataset

Figure 7: Multi-scale sampling strategies analysis under Sym 50% noisy labels.

time-series label-noise learning can make the embeddings of different classes more discriminative, thus facilitating clean sample selection and noisy label correction.

Impact of downsampling scale sequence list. Scale-teaching can be performed using a variety of different downsampling scales for label-noise learning. Based on the experience of [19, 44] on time series classification and prediction tasks, we utilize the downsampling scales of [1,2,4] for the experimental analyses of Scale-teaching. However, for real-world scenarios that actually contain noisy labels, it is generally not possible to perform hyperparametric analyses using a clean-labeled validation set. To facilitate the analysis, in this paper, we use the classification performance of the test set for multi-scale hyperparameter analyses. However, to avoid test set information leakage, we do not use the hyperparameter analysis result for Scale-teaching in our experiments. We use two multi-scale sampling strategies for analyses, which are (1) {[1,2], [1,2,3], [1,2,3,4], [1,2,3,4,5]}; (2) {[1,3], [1,2,4], [1,2,4,8], [1,2,4,8,16]}. From Figure 7, we find that Scale-teaching using four different scales for training has the highest classification accuracy, which indicates that more input scales do not necessarily make the classification performance better. In addition, using three or four scales of sequences can effectively improve the classification performance of Scale-teaching compared with using two different scales.

Impact of input scales of sequences order. Scale-teaching employs a finer-to-coarser strategy for cross-scale embedding fusion. Intuitively, when a single scale is used for classification, the original single scale (finer) time series is better overall because it does not discard the original sequence information compared to coarser scale time series. Therefore, Scale-teaching is trained using the finer-to-coarser cross-scale fusion strategy. To analyze the difference in classification performance between different fusion directions, we subtract the classification accuracy using the finer-to-coarser and coarser-to-finer training approaches, and the specific results are shown in Figure 8. We can find that the classification performance of finer-to-coarser is better overall, which is due to its ability to use a single fine-scale sequence with an excellent classification performance from the beginning to gradually promote the classification performance of multiscale fusion embeddings.

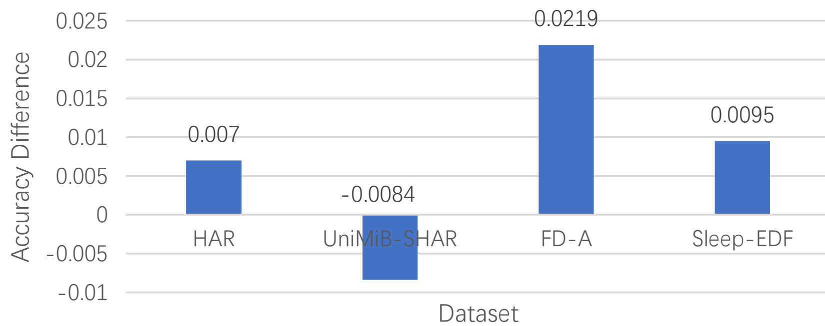


Figure 8: The cross fusion direction of input scale series analysis under Sym 50% noisy labels.

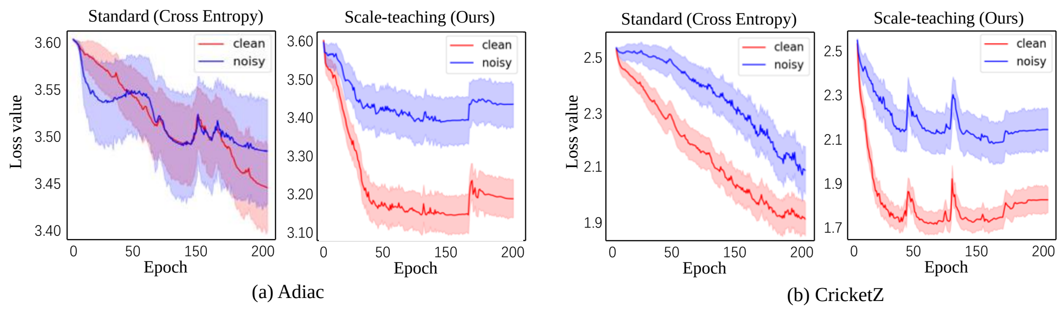


Figure 9: The change of loss values for clean and noisy time series samples under Aysm 40% noise labels. The solid line and shading indicate the mean and standard deviation loss values of all clean (or noisy) training samples within each epoch.

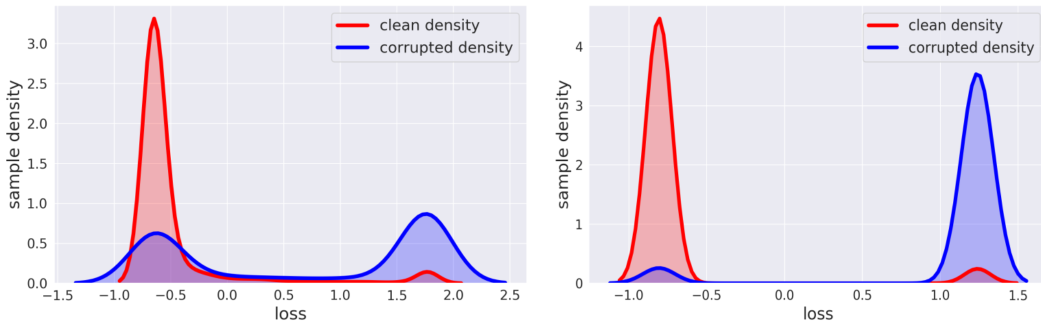
F Small-loss Visualization

The small-loss criterion has been extensively validated for clean label selection in label-noise learning for computer vision. To further analyze the application of the small-loss criterion in time series data, we provide the change of loss values of the models trained by the Standard method and Scale-teaching on Adiac and CricketZ UCR datasets (as in Figure 9). Also, we visualize the probability distributions of the ground-truth clean and noisy (corrupted) sample loss values on the test set with different training strategies. Specifically, Figures 10 and 11 show the loss probability distributions of the models trained by different strategies on the HAR dataset and UniMiB-SHAR with Aysm 40% noisy labels. Both red (clean) and blue (corrupted) in Figure 10 and Figure 11 contain two peaks, which indicate that some correctly labeled samples are still difficult to learn (large loss) and some incorrectly labeled samples are also easy to learn (small loss). Compared with the Standard method (Figure 10 (a) and Figure 11 (a)), Scale-teaching (Figure 10 (b) and Figure 11 (b)) can clearly distinguish clean and noisy samples by the loss value distribution, further validating the robustness of the multi-scale embeddings to cope with time-series noisy labels.

G Other Analysis

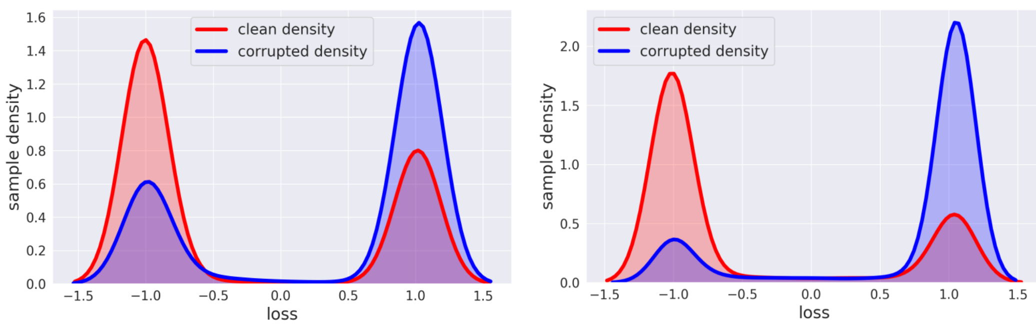
The test F1-score results of ablation study. Following [4], we select the averaged F1-score on the test set as a new metric for ablation analysis in Section 4.5. Hence, we give the corresponding test classification F1-score (%) in Tables 7 and 8.

Running time analysis. We select two datasets for running the time-consuming analysis, the FD-A dataset with the largest sequence length and the Sleep-EDF dataset with the largest samples. We performed the running time statistics on the NVIDIA GeForce RTX 3090 GPU using all baselines, and the results are shown in Table 9. On the FD-A dataset with the longest sequence length, Co-teaching and CULCU take essentially twice as long to run as the Stanard method because they use



(a) Standard (b) Scale-teaching

Figure 10: The loss value probability distributions visualization on HAR dataset with Asym 40% noisy labels.



(a) Standard (b) Scale-teaching

Figure 11: The loss value probability distributions visualization on UniMiB-SHAR dataset with Asym 40% noisy labels.

Table 7: The test classification F1-score (%) results of ablation study (values in parentheses denote drop F1-score).

Method	HAR		UniMiB-SHAR	
	Sym 50%	Asym 40%	Sym 50%	Asym 40%
Scale-teaching	**90.05**	**89.14**	**77.56**	**65.89**
w/o cross-scale fusion	88.16 (-1.89)	87.05 (-2.09)	68.23 (-9.33)	57.76 (-8.13)
only single scale	87.56 (-2.49)	86.75 (-2.39)	66.87 (-10.69)	54.12 (-11.77)
w/o graph learning	87.79 (-2.26)	87.41 (-1.73)	74.62 (-2.94)	63.15 (-2.74)
w/o moment	89.34 (-0.71)	88.27 (-0.87)	76.67 (-0.89)	64.92 (-0.97)
w/o dynamic threshold	88.93 (-1.12)	88.29 (-0.85)	73.11 (-4.45)	64.76 (-1.17)

Table 8: The test classification F1-score (%) results on four individual large datasets without noisy labels. The best results are **bold**, and the second best results are <u>underlined</u>.

Dataset	Standard	Mixup	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
HAR	93.27	**95.39**	93.75	93.19	92.91	93.71	<u>94.72</u>	94.18
UniMiB-SHAR	86.37	80.17	84.43	84.03	66.54	<u>89.19</u>	86.45	**93.62**
FD-A	99.93	99.91	**99.96**	64.05	90.14	99.82	<u>99.95</u>	**99.96**
Sleep-EDF	81.99	82.11	82.52	83.07	77.67	82.17	<u>83.26</u>	**84.76**

Table 9: Training time (hours) analysis using the FD-A and Sleep-EDF datasets with Asym 40% noisy labels.

Dataset	Standard	Mixup	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching		
								[1,2,4]	[1,4,16]	[1,8,32]
FD-A	**0.37**	0.42	0.79	0.63	0.90	0.42	0.87	1.06	0.86	0.82
Sleep-EDF	**0.54**	0.83	1.09	2.04	1.64	0.73	1.47	2.02	1.76	1.60

Table 10: Comparison with classification methods without label noise learning strategy. The best test classification accuracy (%) results are **bold**, and the second best results are underlined.

Dataset	HAR					FD-A				
Method	0	Sym 20%	Sym 50%	Asym 40%	Ins 40%	0	Sym 20%	Sym 50%	Asym 40%	Ins 40%
Boss [15]	72.34	62.55	56.11	53.29	52.34	69.75	64.75	57.95	61.99	62.25
Rocket [60]	**95.29**	92.93	90.04	82.53	90.43	**99.99**	99.71	97.01	89.75	97.98
FCN [57]	93.74	92.13	83.99	75.59	83.56	99.56	98.89	96.63	96.12	99.36
Scale-teaching	94.72	**93.93**	**90.17**	**89.62**	**91.58**	99.98	**99.93**	**99.38**	**99.55**	**99.82**

two encoders. Furthermore, although SREA uses a single network training, it utilizes a decoder for the unsupervised reconstruction task of the original time series, which significantly increases training time on the FD-A dataset with longer sequences. running time is higher than Co-teaching. The Scale-teaching paradigm uses multiple encoders for training and has an additional noisy label correction module, which is expected to increase the training time. Nevertheless, the larger the sampling scale (coarse scale) of the training data used by the Scale-teaching paradigm, the lower the training elapsed time of its model. For example, with input scales of [1, 8, 32], the training time of Scale-teaching is lower than that of CULCU and SREA. On the SleepEEG dataset with the largest number of samples, we find that FINE with an encoder has a higher running time because FINE using all training samples to select clean labels is time-consuming when the sample size is large. In contrast, the runtime of Scale-teaching is lower than FINE. Also, when the input scales are set to [1,8,32], the runtime of Scale-teaching is lower than SREA.

It is worth noting that when Scale-teaching is trained using two scales, such as [1,2] or [1,16], its training run time decreases further. From the analysis in Appendix E, it is clear that Scale-teaching using three different scales generally performs better than two scales for classification with noisy labels. In addition, the classification performance of [1,2,4], [1,4,16], and [1,8,32] when Scale-teaching is trained using three different scales has less difference in classification performance on datasets with longer sequences (e.g., FD-A and Sleep-EDF). The above results indicate that the Scale-teaching paradigm has a greater advantage in runtime on time-series datasets with longer sequences.

Robustness analysis. Three time-series supervised classification methods (Boss [15], Rocket [60] and FCN [57]) and the Scale-teaching paradigm are chosen for robustness analysis against time-series noise labels. Boss [15] is a time series classification method based on similarity search, which can effectively mitigate the negative impact of noise (e.g., adding Gaussian noise) in time series values on classification. Rocket [60] uses a large number of randomly initialized convolution kernels to extract time series features, and employs the extracted features to classify time series using a machine learning classifier (e.g., Ridge classifier). FCN [57] is the encoder used by Scale-teaching, which is a time series classification method based on DNNs. As shown in Table 10, the classification performance of the Scale-teaching paradigm using FCN as encoders is better than that of Boss, Rocket and FCN in the presence of noisy labels. It is worth noting that both Boss and Rocket training processes are independent of the optimization of DNNs. However, their classification performance is still reduced due to the influence of noisy labels. In addition, the encoder of the Scale-teaching paradigm can be designed flexibly, such as using ResNet [1], InceptionTime [65] and OS-CNN [20] in the field of time series classification. In other words, using better robustness encoders, the classification performance of Scale-teaching can be further improved with time-series noise labels.

Table 11: The test classification accuracy (%) on UCR archive with Sym 20% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ACSF1	71.44	73.28	67.00	10.00	54.00	70.40	**73.68**	66.20
2	Adiac	14.63	12.04	11.51	2.30	3.07	19.18	33.06	**52.43**
3	AllGestureWiimoteX	49.68	45.01	50.67	36.09	10.00	46.43	44.25	**56.66**
4	AllGestureWiimoteY	61.37	53.29	57.01	14.03	16.91	61.14	50.07	**64.94**
5	AllGestureWiimoteZ	55.09	50.13	52.34	18.20	20.09	51.00	47.42	**64.31**
6	ArrowHead	65.53	**67.77**	60.72	32.11	61.14	66.74	62.31	61.71
7	BME	48.05	51.73	47.77	47.47	50.67	49.87	48.73	**79.33**
8	Beef	46.67	47.33	**49.33**	20.00	33.33	46.67	44.47	38.00
9	BeetleFly	75.00	72.20	78.00	50.00	81.00	75.00	68.00	**85.00**
10	BirdChicken	86.00	86.80	89.50	50.00	75.00	86.00	83.50	**95.00**
11	CBF	82.47	83.82	**88.81**	33.38	84.18	83.53	76.75	87.24
12	Car	65.33	66.40	**68.67**	25.00	23.33	65.00	53.90	67.33
13	Chinatown	70.13	81.55	83.28	36.52	72.46	82.43	**83.54**	73.91
14	ChlorineConcentration	60.87	**61.19**	59.64	47.34	55.08	58.51	57.82	61.17
15	CinCECGTorso	62.90	61.62	63.27	27.06	39.07	**64.51**	54.59	55.06
16	Coffee	83.43	87.43	87.43	49.29	69.29	91.43	88.57	**100.00**
17	Computers	72.06	73.49	71.44	57.04	70.00	**74.40**	71.24	72.00
18	CricketX	57.10	46.46	46.35	9.95	33.33	53.59	62.91	**68.67**
19	CricketY	56.80	44.05	31.64	8.62	13.08	49.74	**59.88**	59.23
20	CricketZ	51.53	37.46	37.82	8.46	26.41	45.13	53.71	**69.95**
21	Crop	72.84	73.24	73.29	69.97	65.65	72.07	72.25	**74.44**
22	DiatomSizeReduction	63.05	71.27	61.54	69.72	67.32	70.13	59.29	**82.68**
23	DistalPhalanxOutlineAgeGroup	70.13	70.39	71.23	50.50	69.06	72.09	**72.83**	66.62
24	DistalPhalanxOutlineCorrect	72.10	69.20	75.91	48.33	42.75	75.22	75.22	**79.13**
25	DistalPhalanxTW	66.78	66.16	64.72	29.78	58.27	**67.34**	65.74	62.59
26	DodgerLoopDay	24.40	28.50	33.55	15.50	15.00	31.25	35.10	**36.25**
27	DodgerLoopGame	57.14	62.03	65.71	50.43	52.17	**68.84**	66.16	50.00
28	DodgerLoopWeekend	85.07	80.29	85.61	45.22	33.33	85.80	86.16	**86.96**
29	ECG200	79.00	78.32	**82.60**	58.40	79.20	79.80	82.10	77.00
30	ECG5000	92.37	91.23	92.93	44.55	90.92	92.76	93.13	**94.11**
31	ECGFiveDays	77.11	**77.19**	74.38	49.71	71.17	76.54	64.21	60.49
32	EOGHorizontalSignal	49.08	42.81	47.42	41.22	10.36	40.61	41.91	**52.49**
33	EOGVerticalSignal	34.34	30.57	33.12	30.39	11.48	30.66	30.06	**37.18**
34	Earthquakes	70.65	68.78	74.53	45.04	**74.82**	72.81	74.62	**74.82**
35	ElectricDevices	72.17	**72.97**	72.72	63.62	64.35	72.44	72.48	70.35
36	EthanolLevel	47.78	37.52	46.61	29.00	25.20	33.20	46.66	**57.12**
37	FaceAll	81.32	**85.84**	82.44	10.62	71.98	85.63	82.97	75.57
38	FaceFour	71.23	**78.68**	65.39	24.09	54.55	75.68	65.00	51.59
39	FacesUCR	77.40	60.71	65.10	10.35	34.73	69.41	75.38	**80.37**
40	FiftyWords	34.92	28.03	38.80	15.63	21.41	32.09	39.39	**50.95**
41	Fish	68.94	69.71	69.77	13.60	16.00	61.71	60.65	**72.11**
42	FordA	89.74	90.00	90.02	64.18	86.20	90.76	90.34	**92.35**
43	FordB	75.20	75.89	76.21	62.91	59.63	77.90	75.57	**80.00**
44	FreezerRegularTrain	91.76	**95.56**	92.97	61.60	76.21	88.20	93.81	84.07
45	FreezerSmallTrain	69.36	71.58	**76.13**	64.18	75.79	69.52	75.23	59.81
46	Fungi	39.87	22.11	24.62	24.52	23.66	31.18	**44.09**	26.34
47	GestureMidAirD1	31.31	28.62	25.31	24.00	19.23	33.85	32.20	**43.23**
48	GestureMidAirD2	29.23	23.42	21.92	3.85	13.08	26.92	27.51	**34.62**
49	GestureMidAirD3	16.31	14.49	14.52	14.00	8.46	15.38	20.08	**23.85**
50	GesturePebbleZ1	54.88	52.07	44.12	29.30	57.21	59.88	**78.35**	72.56
51	GesturePebbleZ2	73.39	73.11	74.44	32.78	57.72	75.95	75.09	**81.27**
52	GunPoint	71.79	76.53	69.47	49.87	57.33	**81.47**	70.24	76.00
53	GunPointAgeSpan	74.33	85.72	75.57	53.54	50.63	83.61	**89.11**	58.23
54	GunPointMaleVersusFemale	85.65	92.68	93.82	68.48	47.47	94.24	**96.65**	96.20
55	GunPointOldVersusYoung	95.96	99.62	98.90	**100.00**	47.62	99.56	**100.00**	**100.00**
56	Ham	63.62	65.18	67.24	49.71	57.90	**68.76**	65.62	63.81
57	HandOutlines	76.53	70.30	75.97	58.66	64.05	68.92	70.29	**82.05**
58	Haptics	38.61	**39.27**	38.06	19.87	26.62	37.27	36.81	38.70
59	Herring	54.94	62.69	59.69	55.63	59.38	62.81	59.38	**66.56**
60	HouseTwenty	79.52	83.13	83.12	48.40	57.98	84.03	**84.81**	67.39
61	InlineSkate	27.12	23.24	25.24	13.85	18.36	25.64	28.19	**29.49**
62	InsectEPGRegularTrain	99.37	95.98	**100.00**	96.63	**100.00**	96.63	**100.00**	**100.00**
63	InsectEPGSmallTrain	72.17	73.25	93.88	93.25	95.46	77.03	95.46	**100.00**
64	InsectWingbeatSound	31.69	28.82	30.47	9.09	11.10	32.07	29.18	**42.66**
65	ItalyPowerDemand	75.12	78.53	84.47	49.91	83.45	90.38	**90.79**	89.08
66	LargeKitchenAppliances	85.79	85.91	87.07	43.71	67.24	**87.20**	83.18	86.67
67	Lightning2	56.28	63.21	62.62	52.46	59.61	**64.26**	63.77	62.30
68	Lightning7	50.73	55.01	56.16	21.10	50.96	**56.44**	51.97	53.97
69	Mallat	49.13	43.14	47.91	12.48	13.76	59.28	50.63	**73.17**
70	Meat	73.40	72.00	66.67	35.33	33.33	71.67	61.73	**82.33**
71	MedicalImages	66.11	61.14	67.42	34.47	51.45	65.66	61.89	**70.45**
72	MelbournePedestrian	90.99	91.95	91.82	56.87	29.00	90.29	90.16	**95.18**
73	MiddlePhalanxOutlineAgeGroup	50.49	49.77	57.95	49.48	**61.69**	58.31	56.52	49.61
74	MiddlePhalanxOutlineCorrect	73.79	75.01	77.56	48.59	57.04	**77.87**	74.31	67.01
75	MiddlePhalanxTW	53.17	52.44	54.48	28.05	55.84	**55.97**	54.22	50.91
76	MixedShapesRegularTrain	93.09	93.43	93.10	21.87	54.62	92.54	92.11	**94.25**
77	MixedShapesSmallTrain	**80.06**	72.49	69.00	20.59	35.86	75.47	77.16	70.95
78	MoteStrain	75.20	78.42	80.15	50.78	79.85	80.38	**82.33**	53.91
79	NonInvasiveFetalECGThorax1	36.94	24.37	11.79	2.44	4.99	38.12	40.73	**87.54**
80	NonInvasiveFetalECGThorax2	39.71	24.79	13.56	2.24	10.52	31.65	42.42	**81.01**
81	OSULeaf	**88.94**	85.52	87.60	15.21	41.49	87.60	87.73	82.89
82	OliveOil	44.67	42.00	42.00	40.00	40.00	40.00	43.67	**66.67**
83	PLAID	36.09	38.13	38.73	25.88	25.88	37.09	**39.61**	22.72
84	PhalangesOutlinesCorrect	77.26	77.60	76.36	47.74	65.29	77.62	**77.69**	71.93
85	Phoneme	27.10	24.62	27.13	19.76	11.18	25.63	**27.60**	25.45
86	PickupGestureWiimoteZ	52.24	42.00	38.00	10.00	20.00	44.00	56.48	**66.00**
87	PigAirwayPressure	12.56	9.37	12.02	11.23	3.85	12.02	**20.82**	14.52
88	PigArtPressure	18.98	11.63	11.54	23.54	3.85	15.38	28.96	**29.23**
89	PigCVP	10.83	9.85	9.62	**18.79**	8.65	12.98	13.01	15.38
90	Plane	95.55	91.62	93.48	12.19	82.29	91.43	94.38	**100.00**
91	PowerCons	78.02	76.49	84.94	50.00	**85.22**	82.22	82.86	83.22
92	ProximalPhalanxOutlineAgeGroup	82.22	81.78	84.24	37.17	**85.37**	84.88	83.74	78.63
93	ProximalPhalanxOutlineCorrect	84.37	83.92	85.45	53.68	67.29	84.88	**85.79**	80.48
94	ProximalPhalanxTW	77.78	79.57	78.34	25.27	67.80	**79.80**	78.38	79.51
95	RefrigerationDevices	51.19	50.23	53.86	33.33	**54.36**	54.13	47.35	52.48
96	Rock	41.64	40.08	41.84	25.60	28.00	41.60	**43.28**	34.00
97	ScreenType	63.14	61.79	**63.66**	33.33	42.13	62.56	61.19	57.44
98	SemgHandGenderCh2	73.73	74.07	71.61	67.82	65.00	73.07	72.84	**74.10**
99	SemgHandMovementCh2	47.93	47.00	52.93	38.18	23.47	48.00	50.03	**57.47**
100	SemgHandSubjectCh2	61.80	58.77	60.73	32.18	28.00	60.44	58.02	**71.02**
101	ShakeGestureWiimoteZ	63.32	60.24	51.60	20.40	44.00	68.00	**73.72**	63.20
102	ShapeletSim	61.11	71.76	79.67	50.00	**85.20**	67.33	60.01	80.00
103	ShapesAll	45.85	32.73	45.33	1.67	1.67	36.67	37.96	**74.77**
104	SmallKitchenAppliances	73.53	78.66	78.86	54.77	75.81	**80.75**	77.91	80.00
105	SmoothSubspace	76.00	85.20	92.13	33.33	88.53	90.00	**92.67**	90.00
106	SonyAIBORobotSurface1	77.13	83.54	**87.07**	45.76	84.65	83.66	83.48	78.74
107	SonyAIBORobotSurface2	76.63	82.92	87.18	47.66	81.94	83.88	87.56	**92.24**
108	StarLightCurves	96.87	97.08	97.14	57.32	85.39	**97.19**	96.95	95.82
109	Strawberry	91.37	92.52	91.19	52.86	70.65	93.03	92.37	**93.41**
110	SwedishLeaf	89.89	83.71	90.64	6.27	33.88	88.83	85.42	**95.36**
111	Symbols	**76.37**	63.00	67.16	22.44	70.37	60.16	69.00	60.80
112	SyntheticControl	91.47	93.19	97.80	20.00	**98.48**	96.20	97.90	96.33
113	ToeSegmentation1	84.12	79.30	84.51	50.53	83.26	84.91	**85.48**	73.68
114	ToeSegmentation2	77.23	74.43	83.23	43.69	**84.74**	77.69	82.92	83.85
115	Trace	95.16	92.24	91.20	26.00	84.20	90.00	**98.60**	92.00
116	TwoLeadECG	86.50	83.13	83.63	49.96	84.27	**87.39**	84.11	69.39
117	TwoPatterns	80.00	67.35	86.35	24.95	86.07	85.31	85.68	**90.63**
118	UMD	83.08	83.19	81.60	53.47	50.00	**84.17**	77.58	78.06
119	UWaveGestureLibraryAll	74.12	68.99	72.08	12.38	12.62	61.99	67.12	**80.18**
120	UWaveGestureLibraryX	70.30	70.79	**74.35**	12.65	30.35	71.26	70.92	72.26
121	UWaveGestureLibraryY	62.03	61.03	61.43	12.53	42.08	60.30	60.20	**63.98**
122	UWaveGestureLibraryZ	68.63	67.50	68.23	12.42	48.92	65.36	65.78	**71.31**
123	Wafer	96.96	**97.69**	96.68	73.53	89.21	97.45	96.57	88.07
124	Wine	59.70	54.89	**61.11**	50.00	50.00	50.74	53.04	54.07
125	WordSynonyms	34.04	29.93	34.48	14.42	23.04	30.44	**39.42**	34.95
126	Worms	62.42	67.58	66.83	22.08	59.74	67.27	62.73	**75.32**
127	WormsTwoClass	72.83	73.25	76.84	42.86	57.14	76.10	77.27	**77.92**
128	Yoga	73.48	**73.56**	71.73	47.86	53.57	71.04	69.52	65.40
	Avg Acc	65.02	63.80	65.06	36.01	50.39	65.67	66.23	**68.70**
	Avg Rank	4.15	4.33	3.61	7.50	6.16	3.48	3.54	**3.02**
	P-value	1.90E-04	4.06E-05	1.90E-03	1.49E-34	1.70E-17	3.04E-03	8.57E-03	-

Table 12: The test classification accuracy (%) on UCR archive with Sym 50% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ACSF1	41.00	45.00	36.96	10.00	29.60	47.00	**47.20**	42.00
2	Adiac	12.48	8.56	6.39	2.20	4.09	9.97	23.55	**31.65**
3	AllGestureWiimoteX	33.14	22.89	29.32	31.29	18.09	32.17	26.40	**37.91**
4	AllGestureWiimoteY	36.51	31.00	32.46	19.05	16.97	35.00	31.64	**39.57**
5	AllGestureWiimoteZ	38.14	28.69	32.02	11.29	14.57	37.49	33.63	**42.95**
6	ArrowHead	34.29	31.31	31.43	33.94	30.29	38.40	37.83	**39.25**
7	BME	33.23	13.73	34.00	35.73	35.87	33.33	33.33	**36.80**
8	Beef	23.33	21.33	29.67	20.00	20.00	30.33	**31.00**	30.00
9	BeetleFly	51.00	40.00	49.00	50.00	46.00	**53.00**	52.00	50.00
10	BirdChicken	59.00	45.00	60.50	50.00	55.00	61.00	52.50	**71.00**
11	CBF	61.35	44.33	58.24	33.29	63.22	60.93	53.36	**64.30**
12	Car	49.33	38.33	42.50	23.33	23.33	**50.00**	38.17	30.67
13	Chinatown	60.79	58.71	62.15	**65.51**	36.52	59.54	55.30	57.22
14	ChlorineConcentration	43.88	41.59	46.69	29.47	**50.27**	41.63	44.85	49.17
15	CinCECGTorso	42.43	44.10	34.84	24.91	31.44	**45.55**	31.86	40.47
16	Coffee	60.00	54.29	55.36	47.86	46.43	55.71	52.50	**65.71**
17	Computers	49.74	51.47	**54.24**	47.76	50.48	51.76	47.60	54.16
18	CricketX	31.32	25.20	24.77	8.36	13.08	28.05	**43.39**	39.73
19	CricketY	33.67	29.13	23.85	8.46	8.46	31.69	36.77	**41.73**
20	CricketZ	29.19	24.71	26.90	7.49	20.77	26.92	**35.78**	33.10
21	Crop	67.58	68.22	68.04	44.52	64.11	67.81	68.23	**70.12**
22	DiatomSizeReduction	54.34	**63.23**	47.78	33.53	50.65	61.50	47.68	57.49
23	DistalPhalanxOutlineAgeGroup	50.85	53.96	64.26	38.71	62.30	62.16	**66.62**	63.57
24	DistalPhalanxOutlineCorrect	51.52	**52.32**	51.59	48.33	48.33	48.04	50.93	50.87
25	DistalPhalanxTW	55.65	55.57	56.97	29.78	51.65	59.14	58.27	**59.17**
26	DodgerLoopDay	19.15	21.40	26.37	14.50	15.00	23.00	21.90	**28.25**
27	DodgerLoopGame	49.71	48.70	50.88	49.57	50.72	50.29	**53.33**	50.06
28	DodgerLoopWeekend	62.46	64.46	71.59	64.35	37.83	62.17	54.71	**77.45**
29	ECG200	49.80	49.48	52.20	52.80	40.80	50.20	53.60	**58.40**
30	ECG5000	69.14	76.27	90.83	39.94	90.15	88.90	90.50	**91.58**
31	ECGFiveDays	50.46	51.34	**53.93**	49.71	51.86	50.31	50.71	44.87
32	EOGHorizontalSignal	38.43	34.56	37.76	35.30	13.65	31.82	30.34	**41.30**
33	EOGVerticalSignal	26.25	22.59	23.72	20.32	11.49	23.31	19.25	**29.73**
34	Earthquakes	53.32	54.10	66.98	**74.82**	64.75	51.94	61.37	60.78
35	ElectricDevices	67.65	66.58	68.36	64.03	57.10	67.89	**68.50**	64.91
36	EthanolLevel	32.62	28.57	31.75	25.38	25.20	27.76	32.60	**35.02**
37	FaceAll	56.62	46.70	50.99	10.62	10.12	**56.96**	52.02	53.53
38	FaceFour	40.68	50.45	42.16	23.18	32.00	**50.68**	38.98	35.05
39	FacesUCR	**44.98**	42.32	42.96	11.29	18.86	44.81	43.64	41.57
40	FiftyWords	31.64	29.46	33.14	28.54	12.97	30.99	30.30	**37.51**
41	Fish	48.69	**51.20**	35.93	13.71	16.00	47.77	35.41	32.55
42	FordA	49.46	49.33	**56.38**	52.47	51.59	54.58	49.19	54.83
43	FordB	50.39	49.81	47.09	46.53	50.10	**50.52**	45.95	48.54
44	FreezerRegularTrain	38.15	53.98	48.56	54.20	**55.21**	54.46	45.08	47.16
45	FreezerSmallTrain	32.25	47.09	50.30	51.39	50.47	43.63	50.17	**51.81**
46	Fungi	15.59	17.20	16.32	18.34	10.75	15.59	17.92	**19.18**
47	GestureMidAirD1	19.48	17.32	13.32	6.92	15.38	18.46	22.69	**24.18**
48	GestureMidAirD2	17.08	12.31	9.29	5.08	10.46	13.08	17.57	**25.29**
49	GestureMidAirD3	10.92	10.80	7.65	9.02	6.92	9.38	**13.42**	12.12
50	GesturePebbleZ1	41.67	37.16	49.58	23.02	35.37	41.30	**57.20**	47.81
51	GesturePebbleZ2	48.25	49.97	50.61	19.87	41.57	51.04	44.49	**55.39**
52	GunPoint	37.68	35.44	46.00	49.87	47.87	36.27	47.60	**52.80**
53	GunPointAgeSpan	50.09	50.30	48.34	49.05	50.13	50.00	46.30	**55.44**
54	GunPointMaleVersusFemale	46.68	44.89	55.09	49.30	49.49	48.61	51.14	**56.75**
55	GunPointOldVersusYoung	53.69	56.10	61.82	50.79	50.48	61.46	54.79	**70.54**
56	Ham	46.29	47.20	**54.19**	50.29	49.33	49.14	53.05	50.10
57	HandOutlines	38.01	35.18	**47.62**	46.97	47.19	35.51	35.25	47.14
58	Haptics	24.61	**29.77**	25.95	20.39	21.75	28.83	24.35	28.16
59	Herring	51.06	56.00	59.38	51.88	55.63	52.81	59.38	**59.69**
60	HouseTwenty	35.29	55.16	48.07	51.60	48.40	55.46	**55.50**	53.78
61	InlineSkate	20.43	19.03	19.79	15.64	18.36	19.24	**21.40**	18.78
62	InsectEPGRegularTrain	71.20	72.48	82.21	85.14	**93.25**	78.23	69.52	76.87
63	InsectEPGSmallTrain	58.68	55.71	**75.78**	51.97	**75.78**	75.50	64.90	**75.78**
64	InsectWingbeatSound	20.01	19.37	18.73	9.09	9.09	20.53	18.96	**23.04**
65	ItalyPowerDemand	48.54	47.88	50.46	50.03	**51.74**	48.92	49.49	49.18
66	LargeKitchenAppliances	57.01	62.35	64.25	36.75	40.27	**70.88**	57.23	60.23
67	Lightning2	55.08	52.00	52.62	50.82	47.61	52.46	51.15	**58.03**
68	Lightning7	38.41	38.41	40.19	13.70	32.33	41.37	**43.67**	41.81
69	Mallat	29.34	**39.77**	29.91	12.43	12.54	38.02	26.15	35.48
70	Meat	65.80	**66.07**	45.33	36.00	33.33	56.00	42.87	45.67
71	MedicalImages	53.02	52.82	57.34	42.74	51.45	56.39	54.61	**58.01**
72	MelbournePedestrian	84.49	84.78	**87.37**	48.33	29.05	86.96	86.85	87.17
73	MiddlePhalanxOutlineAgeGroup	43.79	40.70	35.79	34.16	37.92	42.60	**54.29**	46.42
74	MiddlePhalanxOutlineCorrect	46.21	47.64	46.63	42.96	45.77	47.63	45.99	**48.59**
75	MiddlePhalanxTW	48.73	48.60	51.36	23.38	**55.84**	52.34	54.25	53.38
76	MixedShapesRegularTrain	80.82	84.57	84.04	20.86	46.24	**86.16**	78.97	69.96
77	MixedShapesSmallTrain	58.86	57.25	41.97	21.19	23.96	57.84	**59.24**	46.12
78	MoteStrain	43.45	41.48	**50.14**	47.65	44.47	43.59	43.57	47.77
79	NonInvasiveFetalECGThorax1	20.65	13.78	8.20	2.50	2.95	15.37	27.85	**60.91**
80	NonInvasiveFetalECGThorax2	21.97	14.82	8.65	2.40	2.90	15.93	32.00	**61.47**
81	OSULeaf	66.60	57.31	47.21	19.09	40.17	56.12	**68.47**	48.46
82	OliveOil	36.53	35.60	34.67	38.00	34.67	35.33	32.67	**40.40**
83	PLAID	33.62	33.77	30.50	24.45	20.48	32.40	**34.63**	32.62
84	PhalangesOutlinesCorrect	52.63	53.25	52.19	50.73	51.86	**56.22**	47.93	49.03
85	Phoneme	20.13	18.93	19.15	17.54	9.44	20.22	**21.72**	19.73
86	PickupGestureWiimoteZ	26.72	25.28	30.80	10.00	16.80	29.60	31.76	**33.12**
87	PigAirwayPressure	9.52	7.00	7.69	3.42	3.85	7.69	**11.90**	9.90
88	PigArtPressure	9.90	8.27	9.38	4.52	2.88	8.17	17.21	**18.42**
89	PigCVP	7.21	6.00	7.93	2.67	5.58	5.96	8.94	**10.33**
90	Plane	78.13	81.75	67.57	14.10	73.14	**82.86**	81.52	68.76
91	PowerCons	50.56	**51.73**	50.06	48.11	50.31	50.56	49.17	37.33
92	ProximalPhalanxOutlineAgeGroup	65.13	67.98	69.06	29.07	71.71	73.56	**83.86**	72.70
93	ProximalPhalanxOutlineCorrect	53.92	49.73	59.49	**61.03**	46.32	48.73	45.60	**61.03**
94	ProximalPhalanxTW	73.01	73.89	69.22	22.34	67.80	75.51	**77.76**	72.49
95	RefrigerationDevices	42.30	41.14	44.64	37.33	45.55	43.36	**45.62**	43.77
96	Rock	29.60	27.20	25.40	19.20	28.40	26.80	**31.00**	26.40
97	ScreenType	47.13	**47.84**	43.20	36.11	39.73	46.45	43.76	41.29
98	SemgHandGenderCh2	47.51	49.70	46.14	**51.72**	41.00	49.93	48.03	46.95
99	SemgHandMovementCh2	42.62	38.52	**42.91**	35.11	27.16	40.40	38.93	39.84
100	SemgHandSubjectCh2	44.76	**49.64**	43.21	24.37	26.00	48.36	44.08	46.44
101	ShakeGestureWiimoteZ	39.12	32.16	29.84	15.60	16.40	34.00	**47.80**	28.48
102	ShapeletSim	51.78	52.18	49.94	50.00	57.02	52.00	48.09	**59.98**
103	ShapesAll	26.78	19.34	28.77	6.43	1.67	20.83	22.48	**43.24**
104	SmallKitchenAppliances	55.62	57.22	63.45	53.89	50.14	**63.47**	57.20	57.65
105	SmoothSubspace	51.60	51.01	68.33	33.33	50.64	51.47	**71.88**	56.40
106	SonyAIBORobotSurface1	56.49	54.22	**71.80**	51.41	52.45	56.84	54.74	48.42
107	SonyAIBORobotSurface2	48.29	48.87	46.92	47.66	47.94	47.97	48.67	**61.36**
108	StarLightCurves	86.01	89.49	87.59	63.60	85.41	**91.02**	89.15	86.81
109	Strawberry	48.92	47.99	45.65	**49.86**	41.41	47.46	43.03	45.33
110	SwedishLeaf	66.72	66.50	68.52	6.21	19.40	**69.28**	61.14	67.74
111	Symbols	44.22	50.24	43.06	28.52	**50.98**	47.20	44.68	**50.98**
112	SyntheticControl	62.23	64.69	**92.60**	16.67	80.07	72.93	89.60	88.32
113	ToeSegmentation1	41.23	42.93	46.04	**50.53**	47.58	43.07	41.32	49.47
114	ToeSegmentation2	51.54	56.89	52.38	43.69	55.91	54.92	**60.92**	41.78
115	Trace	73.64	**77.32**	53.42	43.80	46.60	76.20	62.96	63.60
116	TwoLeadECG	42.84	**54.34**	47.87	49.99	50.48	52.61	50.59	44.02
117	TwoPatterns	46.82	41.01	79.68	24.85	63.84	61.87	78.81	**85.17**
118	UMD	43.64	45.47	40.89	35.28	45.28	**47.08**	41.04	44.03
119	UWaveGestureLibraryAll	49.63	53.72	48.36	12.35	12.62	**54.17**	47.41	48.81
120	UWaveGestureLibraryX	55.67	59.71	55.62	12.65	20.70	**62.67**	55.72	53.63
121	UWaveGestureLibraryY	49.49	50.82	50.42	12.53	40.89	**51.35**	49.24	48.21
122	UWaveGestureLibraryZ	54.49	56.63	55.03	12.47	12.62	**57.65**	55.47	51.20
123	Wafer	50.91	48.13	43.45	**59.17**	32.14	46.39	50.25	46.52
124	Wine	46.30	48.15	**50.00**	**50.00**	**50.00**	47.78	**50.00**	**50.00**
125	WordSynonyms	30.15	13.82	18.33	9.31	14.80	20.91	**31.62**	30.57
126	Worms	58.70	56.36	57.01	26.23	48.57	**61.38**	60.91	57.71
127	WormsTwoClass	53.51	49.09	**61.56**	45.71	47.27	57.14	57.40	59.48
128	Yoga	52.81	49.67	49.59	**54.12**	49.29	53.21	50.22	49.13
	Avg Acc	45.27	44.59	46.03	32.83	37.80	46.91	46.86	**48.78**
	Avg Rank	4.31	4.57	4.05	6.43	5.89	3.56	3.86	**3.11**
	P-value	3.15E-05	1.70E-05	4.02E-04	7.48E-19	1.22E-15	1.40E-02	4.93E-03	-

Table 13: The test classification accuracy (%) results on UCR archive with Asym 40% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ACSF1	39.00	40.56	41.12	10.00	26.08	40.22	41.60	**42.00**
2	Adiac	4.35	8.85	7.80	2.76	2.30	9.46	24.37	**25.17**
3	AllGestureWiimoteX	34.60	39.66	35.47	28.15	12.32	38.83	38.33	**46.83**
4	AllGestureWiimoteY	35.14	39.87	36.20	17.48	12.81	37.17	36.79	**43.03**
5	AllGestureWiimoteZ	38.86	38.35	38.76	11.49	16.75	36.74	37.92	**42.29**
6	ArrowHead	47.80	52.89	48.01	32.11	45.42	**58.97**	49.95	39.20
7	BME	39.00	48.03	42.40	40.53	47.07	45.60	41.60	**49.33**
8	Beef	26.67	**35.47**	31.93	25.43	20.67	31.33	25.67	23.33
9	BeetleFly	43.00	51.40	**56.50**	50.00	55.00	53.00	55.50	40.00
10	BirdChicken	53.00	57.00	51.00	50.00	50.00	60.02	50.00	**75.00**
11	CBF	56.20	70.29	73.80	33.38	68.84	71.91	66.21	**74.22**
12	Car	57.12	**60.47**	54.83	24.67	23.00	54.33	53.47	44.00
13	Chinatown	59.47	55.11	57.26	45.51	63.48	55.42	58.41	**67.25**
14	ChlorineConcentration	**55.85**	49.69	49.52	41.18	47.22	49.48	48.58	51.10
15	CinCECGTorso	50.72	46.88	43.29	24.87	31.17	**52.93**	45.78	32.90
16	Coffee	47.84	52.00	**54.36**	52.14	52.14	51.43	52.50	53.57
17	Computers	53.14	59.36	60.72	55.84	**63.81**	60.32	59.38	48.80
18	CricketX	**58.64**	36.59	30.97	7.79	10.77	36.21	40.05	35.85
19	CricketY	**41.39**	28.52	25.95	11.03	9.20	29.44	37.49	34.72
20	CricketZ	37.46	30.15	20.82	9.69	11.38	30.62	**37.82**	35.49
21	Crop	37.17	48.29	49.58	42.13	**60.29**	51.29	50.04	55.57
22	DiatomSizeReduction	50.16	36.08	42.32	38.45	34.58	36.54	40.65	**54.50**
23	DistalPhalanxOutlineAgeGroup	37.44	63.65	62.79	36.98	64.03	65.04	**65.14**	46.76
24	DistalPhalanxOutlineCorrect	59.68	58.04	65.69	45.00	48.99	63.04	**66.45**	64.39
25	DistalPhalanxTW	55.32	56.83	57.84	25.18	47.05	58.71	58.56	**64.03**
26	DodgerLoopDay	21.75	21.25	28.07	14.50	14.75	33.75	31.87	**33.85**
27	DodgerLoopGame	50.22	41.30	52.97	49.57	51.30	54.20	49.13	**64.78**
28	DodgerLoopWeekend	62.61	70.64	**80.87**	64.35	35.94	73.48	70.43	70.61
29	ECG200	46.80	40.80	65.80	41.60	**68.80**	46.20	60.60	61.00
30	ECG5000	60.72	65.88	87.36	33.26	84.25	68.84	87.44	**89.18**
31	ECGFiveDays	63.06	54.75	61.29	50.06	57.21	65.85	53.39	**66.52**
32	EOGHorizontalSignal	40.13	35.14	36.88	34.48	8.57	33.87	30.62	**42.32**
33	EOGVerticalSignal	31.88	23.48	30.46	23.65	10.72	26.24	26.51	**34.81**
34	Earthquakes	57.37	54.82	74.32	35.11	**74.82**	59.86	72.59	**74.82**
35	ElectricDevices	56.76	54.86	61.18	53.42	55.35	**62.86**	62.20	61.98
36	EthanolLevel	40.46	25.08	31.04	27.26	25.04	27.88	27.26	**40.76**
37	FaceAll	47.52	40.04	46.85	4.76	15.21	49.74	**50.91**	45.74
38	FaceFour	48.09	50.50	41.14	49.32	41.36	50.23	43.86	**57.73**
39	FacesUCR	50.18	41.29	44.42	8.71	20.75	50.51	50.36	**51.02**
40	FiftyWords	22.20	13.71	24.20	27.43	9.32	23.38	20.59	**30.90**
41	Fish	46.40	**53.49**	49.04	13.49	13.14	51.66	48.67	44.57
42	FordA	67.73	73.05	73.37	72.43	68.46	82.33	82.69	**86.59**
43	FordB	53.11	55.56	62.88	55.45	57.99	**63.47**	62.81	60.20
44	FreezerRegularTrain	65.85	72.20	60.40	62.23	62.31	71.78	61.32	**75.44**
45	FreezerSmallTrain	53.80	41.11	46.34	46.24	44.85	49.98	53.62	**54.60**
46	Fungi	**36.88**	20.43	23.60	21.54	11.40	24.30	22.53	29.03
47	GestureMidAirD1	22.31	16.15	17.31	9.85	7.69	20.15	23.77	**43.23**
48	GestureMidAirD2	20.46	14.31	21.15	4.00	6.92	17.85	24.26	**28.46**
49	GestureMidAirD3	11.54	7.69	12.69	6.92	5.54	12.92	12.51	**15.38**
50	GesturePebbleZ1	40.91	35.58	32.48	28.60	31.05	46.63	50.26	**51.07**
51	GesturePebbleZ2	41.04	36.46	40.19	30.00	25.82	44.56	44.16	**48.99**
52	GunPoint	52.43	50.13	52.13	50.93	46.53	**62.33**	60.67	56.67
53	GunPointAgeSpan	50.81	47.15	54.03	51.65	49.87	58.13	55.22	**59.71**
54	GunPointMaleVersusFemale	61.90	70.76	70.43	58.42	47.47	70.06	71.65	**81.65**
55	GunPointOldVersusYoung	68.90	66.81	77.03	**85.46**	47.62	72.44	82.76	82.79
56	Ham	47.39	44.19	48.46	50.29	47.81	50.29	50.53	**51.43**
57	HandOutlines	64.49	61.41	**65.95**	59.03	64.05	63.08	65.40	58.65
58	Haptics	32.53	**32.95**	30.08	20.65	21.36	30.84	29.51	31.62
59	Herring	51.38	52.94	49.22	51.88	48.13	**55.00**	49.69	43.75
60	HouseTwenty	55.21	58.79	65.80	57.98	51.60	61.34	62.99	**90.76**
61	InlineSkate	25.35	23.04	23.24	17.02	17.13	21.67	**28.08**	25.09
62	InsectEPGRegularTrain	92.37	95.31	99.80	96.63	96.63	98.80	95.86	**100.00**
63	InsectEPGSmallTrain	67.72	60.59	75.74	65.86	76.35	73.01	**79.00**	35.74
64	InsectWingbeatSound	18.96	18.37	23.88	9.09	9.09	22.58	22.57	**26.31**
65	ItalyPowerDemand	57.46	46.03	71.85	51.74	68.64	63.97	67.80	**86.98**
66	LargeKitchenAppliances	48.89	51.36	61.29	42.45	49.75	**63.68**	55.92	55.52
67	Lightning2	60.66	55.41	61.31	50.82	60.66	61.64	52.46	**62.66**
68	Lightning7	34.25	38.93	35.59	23.56	30.41	40.27	35.32	**41.64**
69	Mallat	36.98	41.82	36.69	12.40	12.45	39.82	34.62	**44.43**
70	Meat	61.47	**62.47**	56.43	40.33	33.33	59.67	49.77	58.33
71	MedicalImages	50.07	47.26	53.24	34.37	51.45	53.03	47.31	**59.66**
72	MelbournePedestrian	62.07	67.72	69.20	34.30	23.03	**71.67**	68.21	67.41
73	MiddlePhalanxOutlineAgeGroup	37.40	36.36	50.73	28.57	**60.78**	47.92	51.71	17.92
74	MiddlePhalanxOutlineCorrect	60.78	53.54	58.49	54.23	57.04	**63.44**	57.56	60.14
75	MiddlePhalanxTW	46.29	38.83	44.17	22.86	50.39	50.13	**51.36**	47.40
76	MixedShapesRegularTrain	72.19	69.94	71.95	20.86	34.27	**78.54**	70.65	66.09
77	MixedShapesSmallTrain	57.22	**58.54**	43.23	19.14	38.38	54.99	56.72	40.49
78	MoteStrain	54.76	**54.80**	51.66	50.78	52.50	54.06	48.68	46.09
79	NonInvasiveFetalECGThorax1	23.77	17.39	7.20	2.25	3.34	17.69	27.93	**55.65**
80	NonInvasiveFetalECGThorax2	29.06	18.38	8.22	2.33	3.84	22.69	32.04	**55.02**
81	OSULeaf	59.69	64.18	51.38	16.86	27.02	62.31	53.23	**72.89**
82	OliveOil	37.33	36.00	36.00	30.67	35.33	35.33	35.33	**40.00**
83	PLAID	29.13	28.23	23.36	21.38	12.51	29.24	**33.02**	18.44
84	PhalangesOutlinesCorrect	61.56	59.63	59.69	62.43	56.78	65.22	64.63	**66.43**
85	Phoneme	21.21	17.78	18.80	19.76	6.12	19.51	**22.14**	19.63
86	PickupGestureWiimoteZ	35.44	23.20	22.16	10.00	11.60	34.40	35.48	**49.20**
87	PigAirwayPressure	12.71	5.87	7.86	6.51	4.23	9.71	**18.04**	12.98
88	PigArtPressure	15.31	9.62	8.64	7.87	1.92	10.96	22.12	**30.38**
89	PigCVP	11.63	4.33	8.17	6.57	6.15	9.52	13.01	**14.33**
90	Plane	70.29	65.87	61.14	13.52	69.71	**70.81**	69.52	49.52
91	PowerCons	60.04	58.60	77.33	50.00	**80.42**	63.33	74.67	63.56
92	ProximalPhalanxOutlineAgeGroup	58.65	59.43	45.77	38.34	67.22	65.17	**73.59**	71.71
93	ProximalPhalanxOutlineCorrect	63.31	64.52	**74.13**	60.41	68.38	70.58	71.90	72.03
94	ProximalPhalanxTW	60.04	61.83	56.26	28.59	50.73	66.34	**70.82**	68.39
95	RefrigerationDevices	36.92	38.93	42.13	33.33	**44.58**	39.73	41.52	39.47
96	Rock	45.80	40.00	47.40	40.80	37.60	**48.00**	46.40	38.00
97	ScreenType	48.79	**49.29**	42.51	34.67	38.24	47.25	38.57	34.24
98	SemgHandGenderCh2	57.31	57.87	53.92	49.59	53.00	58.30	53.72	**62.27**
99	SemgHandMovementCh2	40.74	38.34	40.29	29.73	23.94	37.91	39.29	**40.89**
100	SemgHandSubjectCh2	42.55	**45.12**	42.98	26.62	21.76	41.69	41.03	41.07
101	ShakeGestureWiimoteZ	39.92	42.72	31.08	15.84	24.80	40.00	40.40	**52.00**
102	ShapeletSim	53.22	50.98	50.89	50.00	**53.36**	52.78	51.80	50.00
103	ShapesAll	30.23	19.95	25.54	2.13	1.67	20.60	24.84	**49.00**
104	SmallKitchenAppliances	58.25	61.06	67.06	47.93	60.85	64.48	68.20	**69.01**
105	SmoothSubspace	61.87	60.29	72.67	33.33	59.17	61.07	71.89	**73.87**
106	SonyAIBORobotSurface1	69.88	70.49	70.67	51.41	75.13	70.18	69.55	**78.37**
107	SonyAIBORobotSurface2	60.08	60.90	**63.00**	57.02	57.31	59.62	62.61	46.90
108	StarLightCurves	75.55	76.10	85.10	45.38	56.47	80.35	82.89	**95.26**
109	Strawberry	71.12	74.83	74.65	41.41	64.32	**76.03**	69.16	66.92
110	SwedishLeaf	67.77	64.08	68.43	6.82	21.98	69.94	63.31	**70.29**
111	Symbols	55.45	48.60	49.18	52.31	**56.72**	50.05	50.50	45.29
112	SyntheticControl	67.81	68.20	78.87	16.67	72.91	70.73	**78.95**	75.13
113	ToeSegmentation1	51.96	52.39	**62.72**	49.47	59.42	53.07	47.96	41.67
114	ToeSegmentation2	54.15	53.69	64.69	56.31	66.89	54.62	65.92	**78.46**
115	Trace	51.52	53.36	46.32	29.20	50.00	59.60	**60.34**	42.40
116	TwoLeadECG	72.26	70.47	71.84	49.97	74.96	72.96	71.98	**86.11**
117	TwoPatterns	63.84	46.01	**78.65**	24.54	67.94	68.04	77.95	78.33
118	UMD	60.44	63.39	47.43	40.56	49.44	**64.28**	54.24	60.42
119	UWaveGestureLibraryAll	50.56	52.06	47.51	12.46	12.28	**53.14**	47.51	52.60
120	UWaveGestureLibraryX	50.72	52.96	52.39	12.48	16.35	52.88	52.41	**56.58**
121	UWaveGestureLibraryY	47.23	49.15	47.58	12.59	30.97	**50.76**	47.93	48.40
122	UWaveGestureLibraryZ	52.53	**52.82**	51.28	12.56	28.83	52.70	51.08	52.29
123	Wafer	79.93	84.06	88.69	70.43	89.21	90.19	88.26	**90.37**
124	Wine	51.41	45.19	**52.19**	50.00	50.00	51.48	50.44	50.00
125	WordSynonyms	29.20	26.53	19.82	14.58	21.36	25.30	**29.80**	27.59
126	Worms	52.31	55.01	53.32	25.19	40.52	56.48	49.64	**58.96**
127	WormsTwoClass	56.83	50.91	58.05	54.29	49.09	58.70	**59.04**	51.17
128	Yoga	55.17	55.77	55.66	47.86	50.71	**57.82**	50.58	51.89
	Avg Acc	48.60	47.31	49.36	34.11	40.37	50.75	50.98	**52.87**
	Avg Rank	4.38	4.80	3.93	6.91	5.91	3.30	3.67	**2.95**
	P-value	1.62E-05	3.53E-07	6.10E-04	1.93E-23	9.82E-14	1.89E-02	2.24E-02	-

Table 14: The test classification accuracy (%) results on UCR archive with Ins 40% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ACSF1	35.40	39.08	43.00	14.80	29.20	41.40	42.70	**45.00**
2	Adiac	8.33	9.73	7.29	4.57	2.35	9.77	19.93	**27.16**
3	AllGestureWiimoteX	36.80	38.15	32.91	24.82	10.00	36.92	32.78	**43.78**
4	AllGestureWiimoteY	39.82	39.10	37.02	23.39	10.03	38.80	37.83	**46.49**
5	AllGestureWiimoteZ	31.95	31.15	33.87	15.43	11.51	33.91	32.04	**38.78**
6	ArrowHead	42.27	45.97	**48.32**	32.11	38.51	41.26	34.06	42.03
7	BME	36.93	40.81	41.49	40.27	36.13	41.73	38.13	**42.21**
8	Beef	31.33	33.00	35.67	20.00	22.67	**36.33**	33.93	29.33
9	BeetleFly	55.40	55.00	60.50	50.00	50.00	59.00	68.00	**70.00**
10	BirdChicken	64.00	70.80	55.00	50.00	50.00	**71.00**	67.00	68.00
11	CBF	61.00	59.97	58.34	33.20	64.45	**65.31**	58.66	51.31
12	Car	49.80	49.80	50.50	24.67	26.33	**50.67**	40.03	45.60
13	Chinatown	62.96	62.11	58.87	54.49	45.51	62.94	59.10	**64.53**
14	ChlorineConcentration	41.58	43.47	43.05	35.27	35.96	44.63	43.55	**45.55**
15	CinCECGTorso	37.14	49.42	41.05	35.70	30.52	**50.39**	45.08	46.80
16	Coffee	61.43	66.57	62.86	49.29	53.57	66.43	65.71	**75.00**
17	Computers	41.92	54.16	51.12	47.28	51.60	54.00	54.28	**54.48**
18	CricketX	33.79	35.04	23.45	7.95	10.62	38.26	44.06	**46.39**
19	CricketY	44.24	36.55	31.28	8.77	9.33	35.38	42.40	**47.48**
20	CricketZ	41.57	32.33	28.08	8.92	11.33	33.38	44.99	**45.27**
21	Crop	52.52	53.74	56.48	44.00	**63.37**	54.45	56.94	63.25
22	DiatomSizeReduction	63.35	71.07	55.82	30.00	30.20	**72.12**	45.77	67.36
23	DistalPhalanxOutlineAgeGroup	47.25	49.29	59.12	45.04	**62.30**	49.35	57.99	51.83
24	DistalPhalanxOutlineCorrect	53.12	56.22	**66.17**	51.67	55.87	64.42	59.57	63.12
25	DistalPhalanxTW	50.76	52.23	56.63	25.47	49.35	52.23	57.77	**59.42**
26	DodgerLoopDay	26.20	29.05	30.07	13.75	15.00	30.25	26.00	**31.25**
27	DodgerLoopGame	55.22	56.87	53.64	49.57	52.17	56.23	52.01	**56.93**
28	DodgerLoopWeekend	58.84	56.29	68.84	45.22	54.78	58.99	**69.90**	57.19
29	ECG200	61.40	63.20	61.40	52.80	64.52	61.40	67.30	**67.40**
30	ECG5000	73.57	71.83	89.10	49.16	90.76	82.03	90.46	**91.12**
31	ECGFiveDays	54.18	52.99	56.27	50.06	51.91	55.08	50.88	**59.77**
32	EOGHorizontalSignal	37.19	29.45	35.52	31.96	10.70	28.73	28.86	**39.51**
33	EOGVerticalSignal	26.15	26.60	25.62	23.43	9.83	23.59	21.59	**27.16**
34	Earthquakes	60.12	58.76	71.24	**74.82**	**74.82**	60.29	72.50	72.09
35	ElectricDevices	68.39	**69.51**	68.90	67.86	60.71	68.57	68.82	64.59
36	EthanolLevel	25.15	31.18	**32.74**	24.88	25.12	27.76	32.14	32.40
37	FaceAll	56.89	57.38	52.60	7.87	17.49	**59.91**	53.41	57.25
38	FaceFour	57.36	**60.00**	38.07	21.36	31.50	58.41	38.75	47.68
39	FacesUCR	48.81	42.41	48.23	7.53	14.25	**50.26**	46.51	48.29
40	FiftyWords	32.49	27.16	35.93	28.56	10.73	29.80	29.78	**40.44**
41	Fish	37.99	40.66	37.71	19.43	13.94	37.49	37.70	**40.94**
42	FordA	68.92	71.77	80.55	59.04	69.17	82.76	**83.39**	81.52
43	FordB	60.70	62.61	**70.78**	61.02	57.93	68.99	67.27	66.54
44	FreezerRegularTrain	71.31	**74.21**	54.41	59.09	52.78	71.61	61.98	62.43
45	FreezerSmallTrain	55.52	55.64	57.34	44.18	44.88	52.60	**58.16**	52.53
46	Fungi	23.28	14.41	**24.48**	20.51	11.08	14.52	19.78	18.09
47	GestureMidAirD1	28.15	16.92	19.23	19.14	12.12	23.54	25.17	**39.17**
48	GestureMidAirD2	13.51	6.46	13.46	4.92	7.78	11.85	15.82	**22.58**
49	GestureMidAirD3	12.77	9.08	11.15	11.23	5.08	11.85	12.58	**13.91**
50	GesturePebbleZ1	50.65	44.05	47.09	26.77	38.63	44.77	51.41	**52.12**
51	GesturePebbleZ2	56.73	50.56	53.35	36.20	33.80	56.48	54.16	**59.27**
52	GunPoint	60.05	**66.69**	55.13	48.40	47.73	60.00	56.40	52.40
53	GunPointAgeSpan	59.49	**60.59**	57.06	51.58	49.62	60.57	57.51	53.11
54	GunPointMaleVersusFemale	66.18	63.11	67.59	49.87	47.47	65.63	71.22	**76.27**
55	GunPointOldVersusYoung	87.24	90.18	93.52	78.29	48.57	90.79	96.10	**99.56**
56	Ham	59.81	57.45	56.23	48.57	49.71	**59.90**	56.57	51.24
57	HandOutlines	65.57	**66.36**	65.38	64.32	64.05	66.16	66.35	64.28
58	Haptics	27.40	**28.70**	26.19	19.81	20.06	28.53	26.92	27.97
59	Herring	53.50	55.88	54.06	51.88	51.88	56.56	52.53	**58.56**
60	HouseTwenty	70.39	57.14	63.24	48.40	54.79	**71.26**	48.35	69.41
61	InlineSkate	19.67	15.75	19.49	16.00	14.18	18.62	20.16	**21.11**
62	InsectEPGRegularTrain	69.43	71.18	83.90	85.38	**87.15**	72.45	71.53	65.06
63	InsectEPGSmallTrain	67.34	71.52	89.88	56.63	72.57	74.70	**93.10**	86.84
64	InsectWingbeatSound	20.47	14.26	22.87	9.09	9.32	18.90	19.40	**25.99**
65	ItalyPowerDemand	67.35	65.55	61.10	49.91	69.69	69.23	**84.53**	63.76
66	LargeKitchenAppliances	72.12	69.65	77.86	46.08	46.59	**78.36**	72.84	73.00
67	Lightning2	56.72	54.10	56.89	54.43	55.74	**60.98**	58.69	55.08
68	Lightning7	36.15	35.62	33.15	19.18	26.03	35.62	38.77	**39.12**
69	Mallat	35.91	26.42	33.05	15.43	12.47	33.39	31.37	**40.87**
70	Meat	46.60	**49.73**	45.63	33.33	33.33	47.67	43.17	46.20
71	MedicalImages	52.91	44.42	53.83	51.45	49.08	52.29	50.81	**55.41**
72	MelbournePedestrian	68.53	62.94	69.50	39.53	22.90	71.26	70.95	**71.68**
73	MiddlePhalanxOutlineAgeGroup	46.52	36.88	51.09	27.53	**61.69**	49.09	44.71	47.53
74	MiddlePhalanxOutlineCorrect	59.27	52.51	55.14	48.59	51.41	**60.10**	53.33	51.07
75	MiddlePhalanxTW	43.71	39.64	40.52	21.30	34.16	45.97	**50.82**	45.06
76	MixedShapesRegularTrain	79.62	78.52	71.27	22.80	38.91	**83.27**	71.35	67.12
77	MixedShapesSmallTrain	59.86	51.69	49.41	21.01	21.18	62.99	**63.29**	51.54
78	MoteStrain	73.52	73.10	70.78	49.22	72.73	72.83	**76.43**	67.14
79	NonInvasiveFetalECGThorax1	16.24	8.66	9.92	2.39	2.92	12.31	18.02	**44.45**
80	NonInvasiveFetalECGThorax2	20.81	8.60	11.22	2.15	3.21	13.57	18.03	**41.88**
81	OSULeaf	63.10	62.63	59.86	16.03	27.01	60.25	**65.83**	61.97
82	OliveOil	44.13	40.00	40.00	40.00	40.00	38.00	38.00	**48.67**
83	PLAID	29.83	25.33	27.60	15.12	13.61	29.24	**34.59**	28.27
84	PhalangesOutlinesCorrect	61.60	62.49	59.80	63.26	57.18	63.62	59.61	**64.61**
85	Phoneme	21.55	16.32	19.59	17.21	7.01	19.76	**22.79**	20.79
86	PickupGestureWiimoteZ	31.68	19.20	27.16	10.53	11.20	31.20	30.08	**33.92**
87	PigAirwayPressure	11.88	7.46	7.88	8.21	3.08	6.92	11.13	**12.04**
88	PigArtPressure	15.13	6.15	11.54	6.98	2.31	9.13	17.62	**21.46**
89	PigCVP	9.79	4.33	10.14	9.14	5.62	7.69	10.26	**13.73**
90	Plane	62.48	62.48	64.48	16.19	55.62	63.81	**65.33**	60.95
91	PowerCons	63.16	59.78	82.72	57.78	83.13	66.44	78.78	**83.36**
92	ProximalPhalanxOutlineAgeGroup	56.55	56.20	65.85	40.68	**71.61**	63.41	70.54	52.37
93	ProximalPhalanxOutlineCorrect	63.20	57.94	70.27	38.97	67.29	71.75	71.62	**72.01**
94	ProximalPhalanxTW	65.05	65.37	65.71	28.39	59.90	71.41	**78.99**	67.61
95	RefrigerationDevices	45.06	44.21	48.03	33.33	**48.37**	46.61	45.90	48.17
96	Rock	27.60	22.00	30.20	30.45	28.40	25.60	**31.40**	24.00
97	ScreenType	52.44	**52.54**	46.09	33.33	36.76	51.57	41.09	44.11
98	SemgHandGenderCh2	56.55	57.53	56.38	51.73	53.00	**58.67**	53.10	53.46
99	SemgHandMovementCh2	37.29	38.23	39.48	31.37	19.76	39.29	38.61	**41.26**
100	SemgHandSubjectCh2	45.22	**46.83**	42.37	32.09	21.56	44.58	39.74	45.29
101	ShakeGestureWiimoteZ	40.72	36.32	34.76	29.87	26.40	46.80	**47.20**	35.20
102	ShapeletSim	50.64	48.11	45.98	50.00	50.67	49.89	49.83	**54.40**
103	ShapesAll	21.13	8.83	23.58	5.17	1.67	17.93	21.32	**46.39**
104	SmallKitchenAppliances	64.45	63.04	**75.88**	42.99	68.84	71.41	71.08	71.25
105	SmoothSubspace	59.87	59.84	66.68	33.33	59.33	59.07	**67.87**	55.17
106	SonyAIBORobotSurface1	52.88	41.55	47.93	48.59	58.26	51.81	**61.59**	51.20
107	SonyAIBORobotSurface2	55.56	50.47	56.68	57.02	58.35	55.91	60.81	**61.90**
108	StarLightCurves	75.50	83.51	88.16	62.79	76.77	86.72	89.08	**89.53**
109	Strawberry	66.81	74.49	73.24	58.71	52.86	**76.27**	60.43	56.30
110	SwedishLeaf	63.31	52.42	62.11	6.50	19.81	65.02	56.70	**65.67**
111	Symbols	43.34	**47.40**	41.84	41.31	42.72	46.63	39.23	44.29
112	SyntheticControl	70.73	73.53	86.83	16.67	82.20	78.73	**88.07**	82.87
113	ToeSegmentation1	66.02	64.84	71.32	52.63	**71.75**	64.82	67.96	65.09
114	ToeSegmentation2	69.38	72.49	71.54	43.69	**73.88**	71.38	68.15	69.35
115	Trace	63.48	**73.64**	51.00	20.00	46.80	69.80	65.16	52.16
116	TwoLeadECG	61.86	57.53	50.69	49.99	**62.05**	59.74	53.03	51.71
117	TwoPatterns	58.48	49.17	84.69	24.87	85.27	73.59	83.81	**87.37**
118	UMD	45.67	57.58	42.14	50.69	40.00	**58.06**	53.75	47.50
119	UWaveGestureLibraryAll	52.41	49.83	50.04	12.42	12.38	49.94	45.61	**53.34**
120	UWaveGestureLibraryX	57.60	55.68	57.21	12.49	14.75	**58.80**	57.05	56.88
121	UWaveGestureLibraryY	46.65	45.77	43.90	12.39	32.02	45.31	43.71	**46.92**
122	UWaveGestureLibraryZ	49.46	49.37	48.47	12.56	21.39	50.09	47.72	**50.23**
123	Wafer	81.09	85.23	90.20	38.77	89.21	90.08	88.03	**91.01**
124	Wine	51.63	50.89	50.00	50.00	50.00	**51.85**	48.89	50.22
125	WordSynonyms	34.70	30.36	31.46	18.56	22.19	30.66	35.56	**36.46**
126	Worms	61.36	63.58	62.26	27.27	48.83	**64.68**	58.21	59.01
127	WormsTwoClass	53.38	55.16	54.94	48.57	50.91	**59.48**	53.90	50.39
128	Yoga	54.77	55.85	54.87	53.57	50.71	**56.03**	53.09	54.14
	Avg Acc	49.57	48.39	50.11	34.24	39.80	51.21	51.12	**52.57**
	Avg Rank	4.05	4.52	4.02	7.04	6.18	3.30	3.77	**2.95**
	P-value	1.43E-05	1.81E-06	2.43E-04	9.81E-26	2.36E-17	3.27E-02	1.54E-02	-

Table 15: The detailed test classification accuracy (%) results on UEA 30 archive with Sym 20% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ArticularyWordRecognition	89.33	81.04	81.77	41.07	90.13	87.87	84.33	**92.73**
2	AtrialFibrillation	26.67	25.67	26.67	**33.33**	26.67	26.67	22.67	28.00
3	BasicMotions	97.10	97.40	**99.25**	91.00	97.50	98.00	97.50	95.50
4	CharacterTrajectories	98.16	98.49	92.59	7.45	96.54	**98.93**	98.66	**98.93**
5	Cricket	94.72	94.17	91.53	41.11	**97.50**	96.67	93.89	97.28
6	DuckDuckGeese	48.40	**52.48**	48.60	24.40	46.80	50.00	49.60	45.60
7	EigenWorms	53.56	55.42	62.88	34.66	61.80	**64.58**	64.10	61.25
8	Epilepsy	84.96	80.28	**93.33**	82.46	88.70	86.38	**93.33**	87.59
9	EthanolConcentration	24.15	25.48	26.43	24.71	25.11	24.87	24.39	**27.42**
10	ERing	73.11	**73.70**	70.04	16.67	64.59	72.59	61.70	72.77
11	FaceDetection	52.90	51.93	52.36	51.96	50.93	52.30	52.69	**53.09**
12	FingerMovements	50.80	50.44	52.76	52.20	50.20	52.80	52.30	**54.68**
13	HandMovementDirection	28.92	32.22	35.14	24.05	19.46	28.11	29.16	**35.35**
14	Handwriting	35.71	28.55	30.71	25.31	16.63	28.19	34.12	**41.35**
15	Heartbeat	52.00	52.93	57.46	**72.10**	62.75	50.17	66.39	51.76
16	InsectWingbeat	62.31	53.90	64.74	63.92	51.56	64.63	**64.75**	63.85
17	JapaneseVowels	88.99	87.61	94.70	49.73	**97.41**	93.51	97.19	95.62
18	Libras	74.60	70.07	77.00	10.78	73.22	76.78	70.83	**79.67**
19	LSST	49.68	48.91	50.23	51.61	35.53	50.48	51.91	**55.16**
20	MotorImagery	51.00	50.88	51.60	50.80	**55.92**	52.80	50.10	50.84
21	NATOPS	80.78	80.40	90.56	25.78	89.33	82.67	87.17	**91.11**
22	PenDigits	96.04	97.58	97.33	**98.30**	97.90	98.27	98.16	98.12
23	PEMS-SF	62.08	62.87	60.06	14.91	**64.97**	62.08	61.10	63.05
24	PhonemeSpectra	21.89	23.46	22.25	18.00	6.23	22.82	23.74	**26.50**
25	RacketSports	76.84	73.50	78.64	25.00	75.74	77.24	**79.41**	76.87
26	SelfRegulationSCP1	76.81	77.49	78.91	56.86	49.83	78.43	77.55	**81.28**
27	SelfRegulationSCP2	47.47	49.24	48.32	50.89	50.00	47.44	50.66	**51.78**
28	SpokenArabicDigits	96.17	96.21	98.83	27.79	98.52	98.67	98.71	**99.18**
29	StandWalkJump	44.00	40.00	36.00	33.33	**45.33**	42.67	33.40	34.13
30	UWaveGestureLibrary	76.90	76.97	74.61	12.50	74.29	77.75	66.97	**78.12**
	Avg Acc	63.87	62.98	64.84	40.42	62.04	64.81	64.55	**66.29**
	Avg Rank	5.03	5.20	3.83	6.37	4.77	3.73	4.00	**2.73**
	P-value	6.61E-04	3.33E-04	2.69E-02	2.37E-05	1.14E-02	2.63E-02	3.93E-02	-

Table 16: The detailed test classification accuracy (%) results on UEA 30 archive with Sym 50% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ArticularyWordRecognition	66.64	55.57	52.12	7.53	67.33	57.40	49.63	**68.68**
2	AtrialFibrillation	28.00	26.67	29.33	33.33	29.33	30.67	32.00	**36.00**
3	BasicMotions	56.00	58.20	70.75	54.50	**81.00**	59.00	71.25	60.20
4	CharacterTrajectories	90.62	87.56	67.75	6.73	95.28	93.82	97.03	**97.23**
5	Cricket	67.44	60.00	68.89	8.33	84.28	66.67	68.06	**87.27**
6	DuckDuckGeese	32.00	**36.64**	29.60	26.00	34.00	33.20	33.20	33.84
7	EigenWorms	49.62	45.37	55.65	32.98	38.78	**56.79**	56.09	49.28
8	Epilepsy	57.39	57.25	64.16	36.38	62.62	60.00	63.55	**64.36**
9	EthanolConcentration	25.20	25.32	26.05	25.02	**27.56**	25.62	24.58	26.27
10	ERing	44.30	44.39	40.63	16.67	39.35	44.52	38.54	**45.10**
11	FaceDetection	48.54	49.81	49.30	49.51	48.94	49.11	48.58	**50.72**
12	FingerMovements	50.40	50.20	51.80	51.40	50.60	50.80	51.30	**54.40**
13	HandMovementDirection	26.22	25.51	25.41	26.11	23.51	26.57	24.35	**27.08**
14	Handwriting	19.54	19.53	19.99	13.41	7.53	19.18	18.28	**21.06**
15	Heartbeat	55.32	53.52	52.20	54.44	**55.40**	54.63	53.27	48.62
16	InsectWingbeat	49.30	32.34	58.02	52.25	31.07	53.97	**58.13**	52.01
17	JapaneseVowels	60.14	59.28	73.97	15.03	70.65	66.43	78.11	**79.23**
18	Libras	47.09	43.98	**51.39**	6.67	44.78	50.11	40.06	49.78
19	LSST	47.29	44.58	46.21	47.89	34.35	46.33	47.92	**48.75**
20	MotorImagery	50.84	51.48	50.10	51.40	**52.00**	50.60	49.70	49.80
21	NATOPS	54.33	52.53	**60.17**	16.67	59.80	53.44	58.06	59.56
22	PenDigits	93.38	85.29	95.92	92.85	92.74	**96.80**	96.53	93.89
23	PEMS-SF	41.20	40.55	32.96	14.45	42.43	**43.24**	37.57	41.27
24	PhonemeSpectra	19.08	19.11	19.94	11.48	3.92	19.69	19.23	**20.09**
25	RacketSports	52.50	51.03	52.80	24.08	53.29	52.89	**56.58**	54.21
26	SelfRegulationSCP1	47.41	42.68	48.86	48.60	49.97	48.33	57.93	**58.08**
27	SelfRegulationSCP2	48.13	48.22	47.61	48.78	**50.00**	49.22	**50.00**	48.73
28	SpokenArabicDigits	85.64	69.95	96.55	96.16	**99.23**	95.66	97.59	97.69
29	StandWalkJump	38.67	37.87	40.67	33.33	42.67	42.67	37.33	**44.00**
30	UWaveGestureLibrary	50.41	48.60	45.45	12.50	**53.91**	49.00	37.94	52.61
	Avg Acc	50.09	47.43	50.81	33.82	50.88	51.55	51.75	**53.99**
	Avg Rank	5.17	5.73	4.23	6.23	3.93	3.83	4.30	**2.43**
	P-value	2.98E-04	7.40E-05	1.59E-02	9.35E-05	1.67E-02	1.08E-02	3.75E-02	-

Table 17: The detailed test classification accuracy (%) results on UEA 30 archive with Asym 40% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ArticularyWordRecognition	66.33	62.40	55.87	17.27	69.40	63.67	53.73	**70.44**
2	AtrialFibrillation	21.67	33.33	33.33	33.33	11.33	33.67	32.67	**34.67**
3	BasicMotions	66.00	62.30	67.25	49.50	**69.00**	64.00	61.75	65.10
4	CharacterTrajectories	61.08	60.01	57.42	19.05	87.78	64.29	61.35	**88.34**
5	Cricket	72.22	71.56	70.97	50.00	73.44	72.78	68.61	**80.56**
6	DuckDuckGeese	43.20	42.96	44.80	24.00	43.68	**45.20**	44.60	38.24
7	EigenWorms	41.75	34.75	**51.34**	37.86	43.56	41.68	50.38	42.47
8	Epilepsy	62.32	63.01	63.48	47.25	61.01	61.45	**64.71**	58.70
9	EthanolConcentration	23.04	23.85	23.61	25.02	24.78	24.33	25.57	**27.70**
10	ERing	60.30	60.37	42.74	39.47	45.56	59.11	43.96	**61.74**
11	FaceDetection	49.88	50.64	51.12	51.06	50.32	51.07	50.12	**51.61**
12	FingerMovements	47.76	49.92	48.50	49.80	49.00	48.20	50.19	**50.96**
13	HandMovementDirection	28.97	31.24	30.41	28.38	**31.46**	29.19	29.73	29.03
14	Handwriting	21.61	23.92	24.74	21.03	10.67	22.99	25.69	**26.98**
15	Heartbeat	55.22	57.46	55.61	**72.20**	61.52	55.12	55.51	56.68
16	InsectWingbeat	43.40	38.07	45.34	46.32	48.78	47.81	50.34	**51.87**
17	JapaneseVowels	61.62	58.63	62.46	36.81	65.97	64.27	**73.76**	70.02
18	Libras	57.47	57.00	53.39	8.67	54.33	59.44	45.72	**63.22**
19	LSST	42.11	42.77	41.70	43.67	32.79	43.67	**43.74**	29.10
20	MotorImagery	48.80	50.24	51.32	53.00	52.60	49.60	49.70	**53.20**
21	NATOPS	57.00	55.29	58.65	16.67	64.89	55.89	63.22	**65.13**
22	PenDigits	78.76	67.36	92.78	84.05	91.07	89.18	92.23	**93.57**
23	PEMS-SF	50.20	51.38	42.60	14.45	50.87	50.76	47.86	**51.45**
24	PhonemeSpectra	17.71	19.05	18.70	14.41	5.11	18.02	18.65	**19.52**
25	RacketSports	57.50	**59.13**	54.30	27.50	55.26	58.16	56.32	54.21
26	SelfRegulationSCP1	63.47	66.21	64.94	60.96	49.83	66.42	**68.10**	66.30
27	SelfRegulationSCP2	49.04	51.24	51.20	**52.16**	50.00	52.11	51.26	51.22
28	SpokenArabicDigits	64.19	60.64	79.13	72.11	**99.04**	79.42	88.10	93.85
29	StandWalkJump	38.67	34.67	39.33	33.33	33.33	**40.00**	39.33	36.27
30	UWaveGestureLibrary	53.56	53.36	55.38	12.50	**57.81**	53.69	45.53	55.84
	Avg Acc	50.16	49.76	51.08	38.06	51.47	52.17	51.75	**54.60**
	Avg Rank	5.60	4.77	4.40	6.13	4.20	4.00	3.97	**2.73**
	P-value	3.81E-03	6.17E-03	1.63E-02	9.33E-05	1.36E-02	2.62E-02	3.88E-02	-

Table 18: The detailed test classification accuracy (%) results on UEA 30 archive with Ins 40% noisy labels.

ID	Dataset	Standard	MixUp	Co-teaching	FINE	SREA	SELC	CULCU	Scale-teaching
1	ArticularyWordRecognition	67.27	57.39	60.93	9.20	68.67	61.73	57.10	**75.40**
2	AtrialFibrillation	28.00	29.33	30.00	33.33	32.00	28.00	**34.67**	32.00
3	BasicMotions	77.00	73.00	**81.75**	39.00	80.90	77.50	74.75	78.50
4	CharacterTrajectories	82.52	69.46	66.33	5.22	85.38	81.92	83.48	**87.47**
5	Cricket	80.28	78.28	79.31	26.11	92.50	81.11	76.81	**92.78**
6	DuckDuckGeese	38.80	41.60	36.40	20.00	39.20	39.60	**42.00**	37.20
7	EigenWorms	33.44	54.63	**60.38**	32.67	43.66	43.21	60.31	54.81
8	Epilepsy	65.80	64.55	72.03	67.10	73.04	71.74	78.64	**79.36**
9	EthanolConcentration	24.82	26.40	27.75	24.71	25.17	26.69	26.81	**28.37**
10	ERing	53.69	52.48	48.48	36.79	49.82	**56.44**	44.59	54.15
11	FaceDetection	50.05	50.04	50.80	50.57	49.81	50.22	50.93	**51.00**
12	FingerMovements	51.40	**51.60**	51.10	51.20	49.60	51.40	48.60	49.60
13	HandMovementDirection	25.31	30.11	26.49	19.73	19.73	28.92	25.95	**31.62**
14	Handwriting	21.35	22.54	22.92	17.93	6.17	21.51	**23.19**	23.01
15	Heartbeat	56.39	58.01	**66.63**	57.69	58.50	56.20	59.02	51.00
16	InsectWingbeat	47.94	39.18	57.07	55.93	36.95	57.12	**59.40**	58.32
17	JapaneseVowels	68.05	66.46	65.36	27.89	77.03	73.35	78.97	**81.54**
18	Libras	46.04	**51.56**	47.00	9.33	48.67	49.44	41.11	50.18
19	LSST	48.16	47.72	46.43	49.04	33.58	48.78	49.11	**50.47**
20	MotorImagery	49.20	51.00	49.90	50.00	51.00	**52.00**	51.90	47.80
21	NATOPS	57.78	56.80	58.78	26.67	**67.24**	57.67	58.34	59.98
22	PenDigits	81.99	70.68	93.43	91.81	92.59	91.18	93.29	**96.69**
23	PEMS-SF	42.89	43.86	35.14	16.42	**47.86**	43.82	41.49	44.35
24	PhonemeSpectra	16.50	15.82	17.37	8.40	3.22	17.15	**17.48**	17.42
25	RacketSports	59.08	59.55	**64.68**	27.50	60.11	58.55	58.62	59.89
26	SelfRegulationSCP1	60.63	60.38	56.02	48.12	49.90	65.80	**66.00**	54.54
27	SelfRegulationSCP2	51.69	50.87	50.63	51.11	50.00	51.89	50.22	**52.11**
28	SpokenArabicDigits	74.85	67.24	89.70	83.37	**98.76**	86.68	87.87	97.53
29	StandWalkJump	40.00	**42.67**	39.33	32.00	**42.67**	38.67	42.00	40.00
30	UWaveGestureLibrary	67.19	67.90	60.56	12.50	67.74	67.69	55.69	**69.96**
	Avg Acc	52.27	51.70	53.76	36.04	53.38	54.53	54.61	**56.90**
	Avg Rank	5.20	4.77	4.33	6.60	4.27	4.20	3.77	**2.60**
	P-value	6.08E-04	2.92E-03	1.20E-02	2.55E-05	5.52E-03	1.08E-02	3.47E-02	-

Table 19: Multi-scale analysis of Scale-teaching using UCR 128 archive with Sym 20% noisy labels.

ID	Dataset	fine	medium	coarse	a_t_b_f	a_f_b_t	a_t_b_t	b_t_c_f	b_f_c_t	b_t_c_t	c_t_a_f	c_f_a_t	c_t_a_t
1	ACSF1	0.6080	0.6640	0.6620	8	14	52	4	4	63	16	11	50
2	Adiac	0.0281	0.4890	0.5243	11	191	0	18	32	173	205	11	0
3	AllGestureWiimoteX	0.4089	0.5526	0.5666	34	135	252	22	31	365	149	39	247
4	AllGestureWiimoteY	0.4526	0.6643	0.6494	47	196	269	27	17	438	188	50	266
5	AllGestureWiimoteZ	0.4863	0.6449	0.6431	39	150	301	31	30	420	164	55	286
6	ArrowHead	0.4194	0.5886	0.6171	11	41	62	2	7	101	46	11	62
7	BME	0.5347	0.7333	0.7933	6	36	74	0	9	110	45	6	74
8	Beef	0.2667	0.4000	0.3800	0	4	8	1	0	11	3	0	8
9	BeetleFly	0.6000	0.8500	0.8500	0	5	12	0	0	17	5	0	12
10	BirdChicken	0.9600	0.8500	0.9500	3	1	16	1	3	16	1	1	18
11	CBF	0.7611	0.8311	0.8724	23	86	662	2	40	746	109	8	677
12	Car	0.4033	0.6633	0.6733	3	18	22	1	2	39	19	3	22
13	Chinatown	0.7304	0.7391	0.7391	5	8	247	8	8	247	3	0	252
14	ChlorineConcentration	0.5724	0.6120	0.6117	265	417	1933	92	91	2258	484	333	1865
15	CinCECGTorso	0.5097	0.5007	0.5506	148	136	555	34	102	657	145	89	614
16	Coffee	1.0000	1.0000	1.0000	0	0	28	0	0	28	0	0	28
17	Computers	0.6824	0.7280	0.7200	2	14	168	4	2	178	12	3	168
18	CricketX	0.3923	0.6733	0.6867	16	126	137	9	14	254	132	18	135
19	CricketY	0.4549	0.5990	0.5923	25	81	152	16	13	218	85	31	146
20	CricketZ	0.4764	0.6949	0.6995	23	108	163	11	12	260	118	31	155
21	Crop	0.7035	0.7443	0.7444	545	1231	11273	215	217	12289	1292	604	11214
22	DiatomSizeReduction	0.8105	0.8333	0.8268	0	7	248	2	0	253	5	0	248
23	DistalPhalanxOutlineAgeGroup	0.6619	0.6647	0.6662	13	14	79	5	5	88	18	17	75
24	DistalPhalanxOutlineCorrect	0.7949	0.7986	0.7913	12	13	208	3	1	217	14	15	205
25	DistalPhalanxTW	0.6806	0.6806	0.6259	8	8	87	11	3	84	9	16	78
26	DodgerLoopDay	0.3500	0.3750	0.3625	12	14	16	3	2	27	14	13	15
27	DodgerLoopGame	0.5942	0.5087	0.5000	20	8	62	19	18	51	22	35	47
28	DodgerLoopWeekend	0.8826	0.8957	0.8696	1	3	120	5	1	119	0	2	120
29	ECG200	0.7500	0.7600	0.7700	1	2	74	0	1	76	2	0	75
30	ECG5000	0.9313	0.9415	0.9411	50	96	4141	15	13	4221	103	59	4132
31	ECGFiveDays	0.6039	0.6139	0.6049	14	23	506	15	7	513	11	10	510
32	EOGHorizontalSignal	0.3994	0.4608	0.5249	28	50	117	8	32	158	76	30	114
33	EOGVerticalSignal	0.2790	0.3315	0.3718	13	32	88	5	20	115	44	10	91
34	Earthquakes	0.7482	0.7468	0.7482	3	3	101	4	5	99	7	7	97
35	ElectricDevices	0.6540	0.6774	0.7035	289	470	4754	136	337	5087	718	336	4707
36	EthanolLevel	0.2520	0.5628	0.5712	46	202	80	15	19	267	208	48	78
37	FaceAll	0.6820	0.7729	0.7557	92	246	1060	40	11	1266	225	101	1052
38	FaceFour	0.3182	0.5023	0.5159	5	21	23	2	3	42	19	2	26
39	FacesUCR	0.5544	0.8270	0.8037	36	594	1101	111	63	1584	575	64	1073
40	FiftyWords	0.2725	0.4295	0.5095	2	73	122	21	58	174	112	4	120
41	Fish	0.4114	0.7074	0.7211	2	53	70	7	9	117	58	4	68
42	FordA	0.9124	0.9189	0.9235	25	34	1179	4	10	1209	42	27	1177
43	FordB	0.7719	0.7968	0.8000	37	57	588	8	11	637	65	42	583
44	FreezerRegularTrain	0.9062	0.8516	0.8407	220	65	2363	43	12	2384	72	258	2324
45	FreezerSmallTrain	0.6724	0.7077	0.5981	87	188	1829	434	122	1583	72	283	1633
46	Fungi	0.0591	0.3430	0.2634	0	53	11	24	9	40	38	0	11
47	GestureMidAirD1	0.2492	0.4108	0.4323	5	26	27	6	9	47	31	7	25
48	GestureMidAirD2	0.2154	0.3215	0.3462	7	21	21	5	8	37	24	7	21
49	GestureMidAirD3	0.1308	0.1631	0.2385	1	5	16	2	12	19	16	2	15
50	GesturePebbleZ1	0.8233	0.7116	0.7256	25	6	117	3	6	119	8	24	117
51	GesturePebbleZ2	0.8025	0.8228	0.8127	8	11	119	4	2	126	13	11	116
52	GunPoint	0.8293	0.7840	0.7600	25	19	99	5	1	113	20	30	94
53	GunPointAgeSpan	0.4937	0.5127	0.5823	1	7	155	3	25	159	32	4	152
54	GunPointMaleVersusFemale	0.9968	0.9671	0.9620	9	0	306	2	0	304	0	11	304
55	GunPointOldVersusYoung	1.0000	1.0000	1.0000	0	0	315	0	0	315	0	0	315
56	Ham	0.5905	0.6286	0.6381	3	7	59	3	4	63	9	4	58
57	HandOutlines	0.6405	0.7870	0.8205	34	88	203	7	20	284	99	33	204
58	Haptics	0.2851	0.3890	0.3870	35	67	53	11	10	109	72	41	47
59	Herring	0.5938	0.6719	0.6656	7	12	31	2	2	41	13	8	30
60	HouseTwenty	0.6202	0.6773	0.6739	1	8	73	2	2	78	7	0	73
61	InlineSkate	0.1585	0.2691	0.2949	30	91	57	20	34	128	119	44	43
62	InsectEPGRegularTrain	1.0000	1.0000	1.0000	0	0	249	0	0	249	0	0	249
63	InsectEPGSmallTrain	1.0000	1.0000	1.0000	0	0	249	0	0	249	0	0	249
64	InsectWingbeatSound	0.2799	0.4133	0.4266	131	395	423	109	135	710	467	176	378
65	ItalyPowerDemand	0.8871	0.8892	0.8908	4	6	909	2	4	913	8	4	909
66	LargeKitchenAppliances	0.8747	0.8645	0.8667	13	9	315	6	7	318	10	13	315
67	Lightning2	0.6393	0.6066	0.6230	3	1	36	1	2	36	0	1	38
68	Lightning7	0.3562	0.5068	0.5397	6	17	20	2	4	35	20	7	19
69	Mallat	0.2473	0.7108	0.7317	3	1090	577	109	158	1558	1204	69	511
70	Meat	0.3333	0.7100	0.8233	1	24	19	2	8	41	31	2	18
71	MedicalImages	0.5797	0.7153	0.7045	56	159	384	33	25	511	172	77	364
72	MelbournePedestrian	0.8996	0.9343	0.9518	11	96	2193	11	53	2278	146	18	2186
73	MiddlePhalanxOutlineAgeGroup	0.6104	0.5260	0.4961	26	13	68	10	5	71	16	34	60
74	MiddlePhalanxOutlineCorrect	0.5704	0.6227	0.6701	8	23	158	16	30	165	53	24	142
75	MiddlePhalanxTW	0.5195	0.5351	0.5091	12	14	68	8	4	75	17	19	61
76	MixedShapesRegularTrain	0.9326	0.9485	0.9425	47	85	2215	17	3	2283	81	57	2205
77	MixedShapesSmallTrain	0.4317	0.7070	0.7095	151	819	896	106	112	1609	874	200	847
78	MoteStrain	0.5391	0.6193	0.5391	102	202	573	202	102	573	0	0	675
79	NonInvasiveFetalECGThorax1	0.0249	0.7906	0.8754	1	1506	48	44	211	1509	1680	9	40
80	NonInvasiveFetalECGThorax2	0.0249	0.7719	0.8101	1	1469	48	140	215	1377	1544	1	48
81	OSULeaf	0.8372	0.8132	0.8289	12	6	190	2	6	195	8	10	192
82	OliveOil	0.4000	0.6000	0.6667	1	7	11	1	3	17	9	1	11
83	PLAID	0.3289	0.2205	0.2272	61	3	116	5	9	113	7	62	115
84	PhalangesOutlinesCorrect	0.6720	0.6911	0.7193	27	43	550	14	38	579	80	39	537
85	Phoneme	0.2346	0.2684	0.2545	114	178	330	86	60	423	179	141	304
86	PickupGestureWiimoteZ	0.3480	0.6600	0.6600	3	19	14	7	7	26	23	7	10
87	PigAirwayPressure	0.0654	0.1933	0.1452	4	31	10	17	7	23	23	7	7
88	PigArtPressure	0.0673	0.2663	0.2923	5	47	9	12	17	44	50	3	11
89	PigCVP	0.0721	0.1885	0.1538	8	32	7	15	8	24	22	5	10
90	Plane	1.0000	1.0000	1.0000	0	0	105	0	0	105	0	0	105
91	PowerCons	0.8422	0.8367	0.8322	5	4	147	3	2	148	5	6	145
92	ProximalPhalanxOutlineAgeGroup	0.8537	0.8224	0.7863	10	4	165	7	0	161	3	17	158
93	ProximalPhalanxOutlineCorrect	0.7216	0.8082	0.8048	8	33	202	5	4	230	37	13	197
94	ProximalPhalanxTW	0.8098	0.7951	0.7951	5	2	161	0	0	163	2	5	161
95	RefrigerationDevices	0.5061	0.5429	0.5248	9	23	181	15	8	188	26	19	171
96	Rock	0.4400	0.3880	0.3400	4	1	18	3	1	16	0	5	17
97	ScreenType	0.6325	0.5888	0.5744	41	24	197	17	11	204	25	47	190
98	SemgHandGenderCh2	0.6970	0.7277	0.7410	25	43	394	7	15	429	52	26	392
99	SemgHandMovementCh2	0.4622	0.5933	0.5747	28	87	180	24	16	243	87	37	171
100	SemgHandSubjectCh2	0.5556	0.6929	0.7102	29	91	221	18	25	294	112	42	208
101	ShakeGestureWiimoteZ	0.3400	0.6400	0.6320	1	16	16	2	2	30	17	2	15
102	ShapeletSim	0.9367	0.8833	0.8000	12	2	157	25	10	134	7	32	137
103	ShapesAll	0.1863	0.7257	0.7477	7	331	105	26	39	409	343	6	106
104	SmallKitchenAppliances	0.8091	0.8000	0.8000	22	19	281	2	2	298	21	24	279
105	SmoothSubspace	0.9067	0.8933	0.9000	5	3	131	0	1	134	3	4	132
106	SonyAIBORobotSurface1	0.9621	0.8133	0.7874	97	8	481	20	4	469	8	113	465
107	SonyAIBORobotSurface2	0.9318	0.9328	0.9224	16	17	872	19	9	870	15	24	864
108	StarLightCurves	0.8559	0.9372	0.9582	96	765	6953	68	241	7651	998	155	6894
109	Strawberry	0.9216	0.9351	0.9341	3	8	338	2	2	344	8	3	338
110	SwedishLeaf	0.8416	0.9600	0.9536	6	80	520	7	3	593	78	8	518
111	Symbols	0.5809	0.6036	0.6080	1	24	577	1	5	600	28	1	577
112	SyntheticControl	0.9667	0.9667	0.9633	2	2	288	1	0	289	2	3	287
113	ToeSegmentation1	0.8596	0.7851	0.7368	25	8	171	12	1	167	3	31	165
114	ToeSegmentation2	0.8692	0.8215	0.8385	8	2	105	0	2	107	3	7	106
115	Trace	0.9600	0.8900	0.9200	9	2	87	0	3	89	2	6	90
116	TwoLeadECG	0.6673	0.6939	0.6939	18	48	742	11	11	780	54	24	736
117	TwoPatterns	0.8599	0.8959	0.9063	66	210	3374	11	53	3572	239	53	3387
118	UMD	0.5653	0.6875	0.7806	3	21	78	0	13	99	33	2	79
119	UWaveGestureLibraryAll	0.5499	0.7699	0.8018	112	900	1858	87	201	2671	1058	156	1814
120	UWaveGestureLibraryX	0.7054	0.7208	0.7226	229	284	2297	109	115	2473	363	302	2225
121	UWaveGestureLibraryY	0.5842	0.6321	0.6398	212	384	1880	111	138	2154	468	269	1823
122	UWaveGestureLibraryZ	0.6245	0.6887	0.7131	197	427	2040	139	227	2328	605	287	1950
123	Wafer	0.8921	0.8834	0.8807	95	41	5404	68	51	5377	81	151	5348
124	Wine	0.5000	0.5556	0.5407	6	9	21	3	2	27	11	9	18
125	WordSynonyms	0.2429	0.3210	0.3495	31	80	124	10	28	195	98	30	125
126	Worms	0.6623	0.7714	0.7532	4	12	47	1	0	58	12	5	46
127	WormsTwoClass	0.8052	0.7792	0.7792	3	1	59	4	4	56	5	7	55
128	Yoga	0.6559	0.6507	0.6540	163	147	1805	18	28	1934	150	156	1812
	Avg Value	0.5967	0.6817	0.6870	38	126	629	26	32	729	141	47	620

Table 20: Multi-scale analysis of w/o cross-scale fusion based on Scale-teaching using UCR 128 archive with Sym 20% noisy labels.

ID	Dataset	fine	medium	coarse	a_t_b_f	a_f_b_t	a_t_b_t	b_t_c_f	b_f_c_t	b_t_c_t	c_t_a_f	c_f_a_t	c_t_a_t
1	ACSF1	0.5500	0.0100	0.2500	54	0	1	1	25	0	7	37	18
2	Adiac	0.1074	0.0327	0.0077	34	5	8	13	3	0	1	40	2
3	AllGestureWiimoteX	0.4697	0.1337	0.0980	280	45	49	43	18	51	32	293	36
4	AllGestureWiimoteY	0.5503	0.0543	0.0994	360	13	25	38	70	0	5	321	65
5	AllGestureWiimoteZ	0.5723	0.1109	0.0977	348	25	53	77	68	1	68	400	0
6	ArrowHead	0.6366	0.3029	0.4114	93	34	19	34	53	19	8	48	64
7	BME	0.4747	0.3467	0.5653	21	2	50	8	41	44	41	27	44
8	Beef	0.3667	0.2000	0.2000	10	5	1	6	6	0	3	8	3
9	BeetleFly	0.8000	0.5000	0.5000	10	4	6	0	0	10	4	10	6
10	BirdChicken	0.8500	0.5000	0.5000	9	2	8	0	0	10	2	9	8
11	CBF	0.8978	0.3311	0.4153	510	0	298	0	76	298	21	455	353
12	Car	0.6667	0.0833	0.2167	35	0	5	5	13	0	1	28	12
13	Chinatown	0.7438	0.7391	0.7246	8	6	249	5	0	250	4	11	246
14	ChlorineConcentration	0.5973	0.2367	0.5326	2091	707	202	909	2045	0	377	625	1668
15	CinCECGTorso	0.4768	0.0845	0.1759	588	46	70	115	241	2	38	453	205
16	Coffee	1.0000	0.4643	0.4643	15	0	13	0	0	13	0	15	13
17	Computers	0.6960	0.5984	0.5000	54	30	120	43	18	107	46	95	79
18	CricketX	0.4769	0.1723	0.0949	125	6	61	67	37	0	33	182	4
19	CricketY	0.4785	0.0846	0.1149	155	1	32	33	45	0	22	163	23
20	CricketZ	0.4769	0.1564	0.1631	142	17	44	45	48	16	8	131	55
21	Crop	0.6986	0.1058	0.0225	10215	256	1522	1767	368	11	193	11551	186
22	DiatomSizeReduction	0.7320	0.2915	0.2039	194	59	30	81	54	8	17	179	45
23	DistalPhalanxOutlineAgeGroup	0.7626	0.5122	0.4604	46	11	60	58	51	13	18	60	46
24	DistalPhalanxOutlineCorrect	0.7826	0.5971	0.5833	68	17	148	8	4	157	21	76	140
25	DistalPhalanxTW	0.7065	0.2806	0.2806	63	4	35	0	0	39	4	63	35
26	DodgerLoopDay	0.2450	0.1125	0.2000	19	8	1	8	15	1	16	20	0
27	DodgerLoopGame	0.7261	0.4783	0.4783	51	16	50	0	0	66	16	51	50
28	DodgerLoopWeekend	0.9029	0.2609	0.2609	99	10	26	0	0	36	10	99	26
29	ECG200	0.6940	0.6440	0.6400	6	1	63	0	0	64	1	6	63
30	ECG5000	0.9396	0.2929	0.0191	2940	30	1288	1314	82	4	63	4205	23
31	ECGFiveDays	0.6156	0.5029	0.5029	375	278	155	0	0	433	278	375	155
32	EOGHorizontalSignal	0.4779	0.1492	0.0304	134	15	39	53	10	1	8	170	3
33	EOGVerticalSignal	0.3265	0.0657	0.0801	100	6	18	11	16	13	15	104	14
34	Earthquakes	0.7511	0.2518	0.2518	104	35	0	0	0	35	35	104	0
35	ElectricDevices	0.7407	0.0929	0.0929	5458	463	254	642	641	75	187	5182	530
36	EthanolLevel	0.4480	0.2392	0.2408	121	17	103	118	118	2	120	223	1
37	FaceAll	0.9155	0.0643	0.0095	1447	8	100	109	16	0	5	1536	11
38	FaceFour	0.4545	0.0455	0.1591	40	4	0	3	13	1	5	31	9
39	FacesUCR	0.8332	0.1257	0.0474	1456	6	252	258	97	0	10	1621	87
40	FiftyWords	0.3143	0.0088	0.0400	142	3	1	4	18	0	4	128	15
41	Fish	0.6629	0.0457	0.2571	111	3	5	7	44	1	2	73	43
42	FordA	0.9098	0.6244	0.4841	425	48	776	200	15	624	60	622	579
43	FordB	0.7788	0.5521	0.5049	275	91	356	47	9	400	100	322	309
44	FreezerRegularTrain	0.9882	0.5004	0.5000	1409	19	1407	1	0	1425	19	1410	1406
45	FreezerSmallTrain	0.6216	0.4220	0.5000	1167	598	605	164	387	1038	705	1052	720
46	Fungi	0.1882	0.0710	0.0806	35	13	0	13	15	0	15	35	0
47	GestureMidAirD1	0.2631	0.0308	0.0385	31	1	3	4	5	0	3	32	2
48	GestureMidAirD2	0.2385	0.0231	0.0185	28	0	3	3	2	0	0	29	2
49	GestureMidAirD3	0.1538	0.0308	0.0323	19	3	1	3	3	1	2	18	2
50	GesturePebbleZ1	0.7395	0.1919	0.3198	114	20	13	1	23	32	21	93	34
51	GesturePebbleZ2	0.8139	0.1329	0.2595	109	1	20	18	38	3	19	106	22
52	GunPoint	1.0000	0.9533	0.4933	7	0	143	69	0	74	0	76	74
53	GunPointAgeSpan	0.7506	0.5544	0.4937	67	5	170	84	65	91	70	151	86
54	GunPointMaleVersusFemale	0.9968	0.4399	0.4747	176	0	139	4	15	135	0	165	150
55	GunPointOldVersusYoung	1.0000	0.9873	0.5238	4	0	311	146	0	165	0	150	165
56	Ham	0.6381	0.5143	0.5143	35	22	32	0	0	54	22	35	32
57	HandOutlines	0.7741	0.6405	0.6405	81	31	206	0	0	237	31	81	206
58	Haptics	0.3662	0.1883	0.2370	77	22	36	58	73	0	27	67	46
59	Herring	0.7188	0.4062	0.4062	31	11	15	0	0	26	11	31	15
60	HouseTwenty	0.9328	0.4202	0.4202	62	1	49	0	0	50	1	62	49
61	InlineSkate	0.1880	0.1509	0.1793	99	79	4	23	39	60	85	90	14
62	InsectEPGRegularTrain	0.8313	0.6426	0.0008	89	42	118	160	0	0	0	207	0
63	InsectEPGSmallTrain	1.0000	0.4739	0.0161	131	0	118	114	0	4	0	245	4
64	InsectWingbeatSound	0.3357	0.1285	0.0943	519	109	146	240	173	14	70	548	116
65	ItalyPowerDemand	0.9499	0.5015	0.5015	481	20	496	0	0	516	20	481	496
66	LargeKitchenAppliances	0.8240	0.3333	0.2880	205	21	104	125	108	0	22	223	86
67	Lightning2	0.6066	0.6393	0.5410	0	2	37	9	3	30	5	9	28
68	Lightning7	0.4110	0.3178	0.0849	11	4	19	23	6	0	6	30	0
69	Mallat	0.5092	0.2370	0.1454	674	36	520	509	294	47	0	853	341
70	Meat	0.6633	0.3333	0.1500	22	2	18	15	4	5	0	31	9
71	MedicalImages	0.6405	0.4261	0.1800	206	43	281	261	74	62	51	401	85
72	MelbournePedestrian	0.9030	0.0079	0.1012	2198	5	14	17	246	2	7	1972	241
73	MiddlePhalanxOutlineAgeGroup	0.5870	0.5714	0.1883	21	19	69	88	29	0	20	81	9
74	MiddlePhalanxOutlineCorrect	0.7993	0.6852	0.5704	51	18	182	40	7	159	23	90	143
75	MiddlePhalanxTW	0.5506	0.2506	0.1883	69	22	16	19	9	20	19	75	10
76	MixedShapesRegularTrain	0.9509	0.0134	0.1340	2277	3	29	32	325	0	7	1988	318
77	MixedShapesSmallTrain	0.6786	0.3753	0.1295	914	178	732	910	314	0	18	1350	296
78	MoteStrain	0.8997	0.4617	0.4609	632	84	494	9	8	569	92	641	485
79	NonInvasiveFetalECGThorax1	0.2532	0.0193	0.0165	462	2	36	38	32	0	4	469	28
80	NonInvasiveFetalECGThorax2	0.1859	0.0220	0.0025	324	2	41	43	5	0	5	365	0
81	OSULeaf	0.9628	0.1860	0.1322	188	0	45	45	32	0	1	202	31
82	OliveOil	0.4000	0.4000	0.4000	0	0	12	0	0	12	0	0	12
83	PLAID	0.3158	0.1713	0.1456	83	5	87	14	0	78	0	91	78
84	PhalangesOutlinesCorrect	0.7683	0.7536	0.6131	38	25	622	150	29	497	32	165	494
85	Phoneme	0.2429	0.0216	0.0195	448	29	12	40	36	1	23	447	14
86	PickupGestureWiimoteZ	0.3760	0.1000	0.1000	14	0	5	2	2	3	0	14	5
87	PigAirwayPressure	0.1058	0.0000	0.0385	22	0	0	0	8	0	4	18	4
88	PigArtPressure	0.1250	0.0058	0.0192	26	1	0	1	4	0	4	26	0
89	PigCVP	0.0577	0.0202	0.0192	12	4	0	4	4	0	4	12	0
90	Plane	1.0000	0.1238	0.2000	92	0	13	13	21	0	0	84	21
91	PowerCons	0.8389	0.5167	0.5000	67	9	84	3	0	90	9	70	81
92	ProximalPhalanxOutlineAgeGroup	0.8263	0.4293	0.1883	105	24	64	49	0	39	6	137	33
93	ProximalPhalanxOutlineCorrect	0.8165	0.7113	0.6838	32	1	206	9	1	198	2	41	197
94	ProximalPhalanxTW	0.8049	0.1951	0.1951	136	11	29	0	0	40	11	136	29
95	RefrigerationDevices	0.5296	0.3413	0.3120	142	71	57	114	103	14	85	167	32
96	Rock	0.3600	0.1920	0.3000	12	4	6	8	13	2	9	12	6
97	ScreenType	0.6240	0.3333	0.3237	144	35	90	90	86	35	47	159	75
98	SemgHandGenderCh2	0.7017	0.3777	0.3500	267	73	154	17	0	210	72	283	138
99	SemgHandMovementCh2	0.4862	0.1169	0.2138	215	49	3	44	88	9	23	146	73
100	SemgHandSubjectCh2	0.5711	0.2116	0.2000	184	23	73	88	83	7	42	209	48
101	ShakeGestureWiimoteZ	0.4800	0.0840	0.1000	21	1	3	4	5	0	0	19	5
102	ShapeletSim	0.8944	0.5000	0.5000	74	3	87	0	0	90	3	74	87
103	ShapesAll	0.3500	0.0263	0.0000	205	11	5	16	0	0	0	210	0
104	SmallKitchenAppliances	0.7787	0.3621	0.2629	195	39	97	63	26	72	39	233	59
105	SmoothSubspace	0.9400	0.3333	0.3800	93	2	48	23	30	27	2	86	55
106	SonyAIBORobotSurface1	0.8985	0.4725	0.4293	259	3	281	26	0	258	3	285	255
107	SonyAIBORobotSurface2	0.9003	0.6252	0.6170	294	32	564	8	0	588	32	302	556
108	StarLightCurves	0.9740	0.2799	0.5517	5739	22	2283	2305	4544	0	45	3524	4499
109	Strawberry	0.9405	0.6432	0.6432	121	11	227	0	0	238	11	121	227
110	SwedishLeaf	0.9072	0.0640	0.0822	527	0	40	38	49	2	0	516	51
111	Symbols	0.5648	0.0000	0.1749	562	0	0	0	174	0	0	388	174
112	SyntheticControl	0.9733	0.1867	0.1827	236	0	56	49	48	7	1	238	54
113	ToeSegmentation1	0.9342	0.4737	0.4737	110	5	103	0	0	108	5	110	103
114	ToeSegmentation2	0.8123	0.1846	0.1846	88	6	18	0	0	24	6	88	18
115	Trace	0.9500	0.0800	0.3000	87	0	8	8	30	0	5	70	25
116	TwoLeadECG	0.7489	0.5004	0.5004	568	285	285	0	0	570	285	568	285
117	TwoPatterns	0.8628	0.0251	0.2523	3382	32	69	96	1005	4	214	2656	795
118	UMD	0.5861	0.3333	0.3681	36	0	48	0	5	48	4	35	49
119	UWaveGestureLibraryAll	0.6949	0.1428	0.0367	2037	59	452	491	111	20	37	2395	94
120	UWaveGestureLibraryX	0.7059	0.1940	0.1095	1944	110	584	683	380	12	144	2280	248
121	UWaveGestureLibraryY	0.5853	0.1704	0.0959	1660	174	437	609	342	1	88	1841	256
122	UWaveGestureLibraryZ	0.6559	0.1788	0.1128	1835	126	514	640	404	0	66	2012	338
123	Wafer	0.9639	0.8921	0.8921	559	117	5382	0	0	5499	117	559	5382
124	Wine	0.6000	0.5000	0.5000	25	20	7	0	0	27	20	25	7
125	WordSynonyms	0.3323	0.2223	0.1589	77	7	135	120	79	22	42	153	59
126	Worms	0.6701	0.1688	0.1818	43	4	9	13	14	0	8	46	6
127	WormsTwoClass	0.8052	0.5714	0.5714	22	4	40	0	0	44	4	22	40
128	Yoga	0.6902	0.5357	0.5357	867	403	1204	0	0	1607	403	867	1204
	Avg Value	0.6513	0.3011	0.2817	512	44	217	119	113	142	41	516	213

Table 21: Multi-scale analysis of Scale-teaching using UCR 128 archive with Asym 50% noisy labels.

ID	Dataset	fine	medium	coarse	a_t_b_f	a_f_b_t	a_t_b_t	b_t_c_f	b_f_c_t	b_t_c_t	c_t_a_f	c_f_a_t	c_t_a_t
1	ACSF1	0.4380	0.5400	0.5000	0	10	44	6	2	48	7	1	43
2	Adiac	0.0179	0.1857	0.2517	2	68	5	1	26	72	93	2	5
3	AllGestureWiimoteX	0.3714	0.4643	0.4683	31	96	229	16	19	309	99	31	229
4	AllGestureWiimoteY	0.3514	0.4494	0.4603	32	101	214	13	21	302	115	39	207
5	AllGestureWiimoteZ	0.3429	0.4494	0.4829	20	94	220	17	41	297	127	29	211
6	ArrowHead	0.3531	0.3760	0.3920	13	17	48	1	4	65	20	13	48
7	BME	0.4867	0.5000	0.4933	0	2	73	2	1	73	2	1	72
8	Beef	0.2000	0.2000	0.2333	1	1	5	0	1	6	2	1	5
9	BeetleFly	0.4000	0.4500	0.4000	2	3	6	3	2	6	0	0	8
10	BirdChicken	0.8000	0.8000	0.7500	0	0	16	1	0	15	0	1	15
11	CBF	0.7727	0.9398	0.9422	42	192	653	2	4	844	194	41	654
12	Car	0.4000	0.4433	0.4400	4	7	20	5	4	22	9	7	17
13	Chinatown	0.5681	0.6841	0.6725	10	50	186	16	12	220	58	22	174
14	ChlorineConcentration	0.5141	0.5090	0.5110	198	178	1776	15	23	1940	195	207	1767
15	CinCECGTorso	0.3372	0.3342	0.3290	114	109	352	28	21	433	119	131	335
16	Coffee	0.5357	0.5357	0.5357	0	0	15	0	0	15	0	0	15
17	Computers	0.5120	0.4976	0.4880	7	3	121	3	1	121	3	9	119
18	CricketX	0.2744	0.3431	0.3585	10	37	97	12	18	122	52	19	88
19	CricketY	0.2533	0.3318	0.3472	32	62	67	14	20	116	78	42	57
20	CricketZ	0.2154	0.3554	0.3549	9	64	75	11	10	128	71	17	67
21	Crop	0.4823	0.5471	0.5557	578	1666	7525	358	503	8833	1956	724	7380
22	DiatomSizeReduction	0.5850	0.5850	0.5850	0	0	179	0	0	179	0	0	179
23	DistalPhalanxOutlineAgeGroup	0.4676	0.4676	0.4676	0	0	65	0	0	65	0	0	65
24	DistalPhalanxOutlineCorrect	0.6043	0.5942	0.5964	7	4	160	1	2	163	6	8	159
25	DistalPhalanxTW	0.6691	0.6921	0.6403	6	9	87	8	1	88	10	14	79
26	DodgerLoopDay	0.2325	0.3500	0.3350	1	10	18	2	1	26	8	0	18
27	DodgerLoopGame	0.5623	0.7362	0.7478	7	31	70	2	3	100	34	8	69
28	DodgerLoopWeekend	0.7826	0.8261	0.6783	1	7	107	20	0	94	1	16	92
29	ECG200	0.6280	0.6360	0.6100	0	1	63	4	1	60	2	4	59
30	ECG5000	0.8978	0.8909	0.8918	51	20	3989	5	9	4004	23	50	3990
31	ECGFiveDays	0.5029	0.5145	0.5419	1	11	432	51	75	392	85	51	382
32	EOGHorizontalSignal	0.3354	0.4006	0.4232	13	37	108	9	17	136	40	8	113
33	EOGVerticalSignal	0.3033	0.3271	0.3481	11	20	99	6	14	112	31	15	95
34	Earthquakes	0.7482	0.7482	0.7482	0	0	104	0	0	104	0	0	104
35	ElectricDevices	0.6258	0.5982	0.5976	334	121	4492	126	122	4486	210	428	4398
36	EthanolLevel	0.2480	0.3632	0.4076	107	164	17	16	38	166	190	110	14
37	FaceAll	0.4463	0.4531	0.4574	48	60	706	35	42	731	79	61	694
38	FaceFour	0.4545	0.4614	0.5773	2	3	38	3	14	37	14	3	37
39	FacesUCR	0.3937	0.4758	0.4802	73	241	734	68	77	908	272	94	713
40	FiftyWords	0.1934	0.2901	0.3090	5	49	83	14	23	118	63	10	78
41	Fish	0.1371	0.3406	0.4457	5	41	19	1	19	59	60	6	18
42	FordA	0.8623	0.8608	0.8659	14	12	1124	5	12	1131	24	19	1119
43	FordB	0.5914	0.5916	0.6020	6	7	473	2	10	477	15	7	472
44	FreezerRegularTrain	0.7446	0.7595	0.7544	21	64	2101	46	31	2119	69	41	2081
45	FreezerSmallTrain	0.5000	0.4947	0.4996	17	2	1408	3	17	1407	0	1	1424
46	Fungi	0.1022	0.3226	0.2903	9	50	10	26	20	34	42	7	12
47	GestureMidAirD1	0.1692	0.3385	0.4323	2	24	20	6	18	38	39	5	17
48	GestureMidAirD2	0.1462	0.2785	0.2846	1	18	18	8	9	28	22	4	15
49	GestureMidAirD3	0.1154	0.1385	0.1538	2	5	13	3	5	15	8	3	12
50	GesturePebbleZ1	0.3605	0.2942	0.2988	19	8	43	3	3	48	10	21	41
51	GesturePebbleZ2	0.5190	0.5013	0.4899	13	10	69	5	4	74	8	13	69
52	GunPoint	0.5067	0.5933	0.5667	0	13	76	4	0	85	9	0	76
53	GunPointAgeSpan	0.5057	0.4937	0.5671	33	29	127	2	25	154	30	11	149
54	GunPointMaleVersusFemale	0.8544	0.8165	0.8165	12	0	258	0	0	258	0	12	258
55	GunPointOldVersusYoung	1.0000	0.9524	0.8279	15	0	300	48	9	252	0	54	261
56	Ham	0.5143	0.5524	0.5143	2	6	52	6	2	52	0	0	54
57	HandOutlines	0.6589	0.6097	0.5865	37	19	206	26	17	200	36	63	181
58	Haptics	0.2292	0.3325	0.3162	30	62	40	8	3	94	60	34	37
59	Herring	0.4062	0.4531	0.4375	1	4	25	2	1	27	3	1	25
60	HouseTwenty	0.8756	0.9076	0.9076	4	8	100	1	1	107	8	4	100
61	InlineSkate	0.1636	0.2302	0.2509	45	82	45	30	42	96	112	64	26
62	InsectEPGRegularTrain	1.0000	1.0000	1.0000	0	0	249	0	0	249	0	0	249
63	InsectEPGSmallTrain	0.5606	0.5261	0.3574	14	5	126	42	0	89	5	56	84
64	InsectWingbeatSound	0.1376	0.2653	0.2631	70	323	202	109	105	416	351	103	170
65	ItalyPowerDemand	0.8707	0.8688	0.8698	16	14	880	5	6	889	18	19	877
66	LargeKitchenAppliances	0.5973	0.5600	0.5552	19	5	205	4	2	206	6	22	202
67	Lightning2	0.6557	0.6230	0.6066	4	2	36	2	1	36	2	5	35
68	Lightning7	0.4247	0.4110	0.4164	6	5	25	0	0	30	5	6	25
69	Mallat	0.2473	0.4583	0.4443	199	693	381	56	23	1018	678	216	364
70	Meat	0.5700	0.6167	0.5833	0	3	34	2	0	35	1	0	34
71	MedicalImages	0.4997	0.5987	0.5966	23	98	357	20	19	435	105	32	348
72	MelbournePedestrian	0.6867	0.6840	0.6741	24	18	1658	31	7	1645	20	50	1632
73	MiddlePhalanxOutlineAgeGroup	0.1883	0.1623	0.1792	5	1	24	2	5	23	6	7	22
74	MiddlePhalanxOutlineCorrect	0.5704	0.5883	0.6014	0	5	166	1	5	170	10	1	165
75	MiddlePhalanxTW	0.5675	0.4727	0.4740	22	8	65	1	1	72	8	22	65
76	MixedShapesRegularTrain	0.6712	0.6626	0.6609	85	64	1543	26	22	1581	82	107	1521
77	MixedShapesSmallTrain	0.2851	0.3651	0.4049	15	209	676	28	125	857	332	42	649
78	MoteStrain	0.4609	0.4609	0.4609	0	0	577	0	0	577	0	0	577
79	NonInvasiveFetalECGThorax1	0.0244	0.4365	0.5565	1	811	47	15	251	843	1047	1	47
80	NonInvasiveFetalECGThorax2	0.0461	0.4595	0.5502	1	813	90	20	198	883	992	1	90
81	OSULeaf	0.7545	0.7248	0.7289	9	1	174	4	5	171	4	10	172
82	OliveOil	0.4000	0.4333	0.4000	1	2	11	1	0	12	2	2	10
83	PLAID	0.2127	0.1534	0.1844	48	16	66	23	40	59	49	64	50
84	PhalangesOutlinesCorrect	0.6410	0.6522	0.6643	13	23	537	5	15	555	35	15	535
85	Phoneme	0.2013	0.1972	0.1963	91	84	290	55	53	319	96	105	277
86	PickupGestureWiimoteZ	0.2600	0.5000	0.4920	1	13	12	2	2	23	14	2	11
87	PigAirwayPressure	0.1058	0.0894	0.1298	11	7	11	6	15	12	15	10	12
88	PigArtPressure	0.0625	0.2077	0.3038	7	37	6	5	25	38	52	2	11
89	PigCVP	0.0337	0.0692	0.1433	4	11	3	4	20	10	26	3	4
90	Plane	0.4952	0.4952	0.4952	0	0	52	0	0	52	0	0	52
91	PowerCons	0.6578	0.6278	0.6356	8	3	110	2	3	111	1	5	113
92	ProximalPhalanxOutlineAgeGroup	0.7463	0.7395	0.7171	7	5	146	5	0	147	5	11	142
93	ProximalPhalanxOutlineCorrect	0.6838	0.7223	0.7203	6	17	193	10	9	201	26	16	183
94	ProximalPhalanxTW	0.5463	0.6537	0.6839	0	22	112	5	11	129	33	5	107
95	RefrigerationDevices	0.3995	0.4107	0.3947	11	15	139	8	2	146	15	17	133
96	Rock	0.3000	0.3000	0.3800	1	1	14	1	5	14	6	2	13
97	ScreenType	0.3733	0.3483	0.3424	17	8	123	8	6	122	11	22	118
98	SemgHandGenderCh2	0.6227	0.6137	0.6227	13	8	361	8	14	360	12	12	361
99	SemgHandMovementCh2	0.3733	0.4120	0.4089	14	32	154	16	14	170	44	28	140
100	SemgHandSubjectCh2	0.3542	0.3791	0.4107	14	25	145	4	18	167	39	14	145
101	ShakeGestureWiimoteZ	0.3400	0.5800	0.5200	1	13	16	3	0	26	10	1	16
102	ShapeletSim	0.5000	0.5000	0.5000	0	0	90	0	0	90	0	0	90
103	ShapesAll	0.0633	0.4350	0.4900	2	225	36	23	56	238	259	3	35
104	SmallKitchenAppliances	0.6971	0.6939	0.6901	15	14	246	5	3	256	15	17	244
105	SmoothSubspace	0.7067	0.7467	0.7387	3	9	103	2	1	110	10	5	101
106	SonyAIBORobotSurface1	0.6922	0.7544	0.7837	36	73	380	10	28	443	81	26	390
107	SonyAIBORobotSurface2	0.6031	0.4716	0.4690	171	46	404	25	23	424	49	177	398
108	StarLightCurves	0.9613	0.9538	0.9526	96	35	7821	19	9	7836	36	107	7810
109	Strawberry	0.6432	0.6389	0.6692	13	11	225	4	15	232	25	16	222
110	SwedishLeaf	0.4800	0.6861	0.6829	28	157	272	30	28	398	182	55	245
111	Symbols	0.3176	0.4253	0.4529	1	108	315	46	73	377	137	2	314
112	SyntheticControl	0.8233	0.7573	0.7513	36	16	211	8	6	220	21	43	204
113	ToeSegmentation1	0.4175	0.4219	0.4167	3	4	92	2	1	94	3	3	92
114	ToeSegmentation2	0.7692	0.7385	0.7846	5	1	95	1	7	95	2	0	100
115	Trace	0.3900	0.3800	0.4240	3	2	36	0	4	38	5	2	37
116	TwoLeadECG	0.8520	0.8820	0.8611	5	39	965	31	8	973	32	21	949
117	TwoPatterns	0.7693	0.7747	0.7833	122	144	2955	12	46	3087	165	109	2968
118	UMD	0.3333	0.3472	0.6042	0	2	48	3	40	47	41	2	46
119	UWaveGestureLibraryAll	0.4893	0.5109	0.5260	148	226	1604	103	157	1727	344	213	1540
120	UWaveGestureLibraryX	0.5281	0.5540	0.5658	72	165	1820	71	113	1914	251	117	1775
121	UWaveGestureLibraryY	0.4818	0.4797	0.4840	213	205	1513	90	105	1628	279	272	1454
122	UWaveGestureLibraryZ	0.5240	0.5247	0.5229	93	96	1784	94	88	1786	167	171	1706
123	Wafer	0.8921	0.8933	0.9037	0	8	5499	0	64	5507	72	0	5499
124	Wine	0.5000	0.5000	0.5000	0	0	27	0	0	27	0	0	27
125	WordSynonyms	0.2313	0.2906	0.2759	10	47	138	27	18	158	50	22	126
126	Worms	0.5325	0.4987	0.5896	4	1	37	0	7	38	7	3	38
127	WormsTwoClass	0.5091	0.4935	0.5117	4	3	35	1	2	37	5	5	34
128	Yoga	0.5177	0.5190	0.5189	33	37	1520	24	24	1533	27	23	1530
	Avg Value	0.4775	0.5204	0.5281	31	71	532	18	26	585	88	39	524

Table 22: Multi-scale analysis of w/o cross-scale fusion based on Scale-teaching using UCR 128 archive with Asym 40% noisy labels.

ID	Dataset	fine	medium	coarse	a_t_b_f	a_f_b_t	a_t_b_t	b_t_c_f	b_f_c_t	b_t_c_t	c_t_a_f	c_f_a_t	c_t_a_t
1	ACSF1	0.6000	0.0100	0.3000	59	0	1	1	30	0	1	31	29
2	Adiac	0.0665	0.0588	0.0205	22	19	4	23	8	0	8	26	0
3	AllGestureWiimoteX	0.3863	0.0917	0.0923	247	41	23	35	35	29	47	253	17
4	AllGestureWiimoteY	0.4200	0.1354	0.0383	227	28	67	83	15	12	21	288	6
5	AllGestureWiimoteZ	0.3811	0.1000	0.0894	208	11	59	50	42	20	38	242	25
6	ArrowHead	0.5097	0.3029	0.3029	89	53	0	53	53	0	1	37	52
7	BME	0.4867	0.3333	0.1387	23	0	50	49	20	1	20	72	1
8	Beef	0.2333	0.2000	0.1867	7	6	0	6	6	0	1	2	5
9	BeetleFly	0.4000	0.5000	0.5000	7	9	1	0	0	10	9	7	1
10	BirdChicken	0.6000	0.5000	0.5000	8	6	4	0	0	10	6	8	4
11	CBF	0.5589	0.3311	0.3311	205	0	298	0	0	298	0	205	298
12	Car	0.4000	0.2533	0.1200	23	14	1	15	7	0	3	20	4
13	Chinatown	0.5275	0.7275	0.7246	4	73	178	2	1	249	74	6	176
14	ChlorineConcentration	0.4660	0.3694	0.5380	904	533	885	399	1046	1020	769	493	1297
15	CinCECGTorso	0.3338	0.1733	0.2696	455	233	6	233	366	6	43	131	329
16	Coffee	0.5357	0.4643	0.4643	15	13	0	0	0	13	13	15	0
17	Computers	0.5024	0.4840	0.5000	8	3	118	1	5	120	2	3	123
18	CricketX	0.2790	0.0974	0.1308	73	2	36	38	51	0	47	105	4
19	CricketY	0.2738	0.1077	0.1149	83	18	24	42	45	0	35	97	10
20	CricketZ	0.2144	0.1364	0.1590	61	30	23	53	62	0	31	52	31
21	Crop	0.4882	0.0619	0.0342	7332	170	870	1040	574	0	386	8014	188
22	DiatomSizeReduction	0.3007	0.0974	0.3497	92	30	0	13	90	17	107	92	0
23	DistalPhalanxOutlineAgeGroup	0.6619	0.3655	0.5324	58	17	34	42	65	9	20	38	54
24	DistalPhalanxOutlineCorrect	0.5333	0.5978	0.5833	38	56	109	9	5	156	61	47	100
25	DistalPhalanxTW	0.6763	0.2806	0.3525	55	0	39	0	10	39	0	45	49
26	DodgerLoopDay	0.2700	0.1075	0.1625	13	0	8	0	4	9	1	10	12
27	DodgerLoopGame	0.5290	0.4783	0.4783	72	65	1	0	0	66	65	72	1
28	DodgerLoopWeekend	0.7739	0.2609	0.2609	72	1	35	0	0	36	1	72	35
29	ECG200	0.6700	0.6400	0.6400	15	12	52	0	0	64	12	15	52
30	ECG5000	0.8888	0.1998	0.0191	3115	14	885	897	84	2	86	4000	0
31	ECGFiveDays	0.5970	0.5029	0.5029	283	202	231	0	0	433	202	283	231
32	EOGHorizontalSignal	0.3138	0.0961	0.1320	96	17	18	35	48	0	13	78	35
33	EOGVerticalSignal	0.2873	0.0746	0.0801	84	7	20	20	22	7	25	100	4
34	Earthquakes	0.7482	0.2518	0.2518	104	35	0	0	0	35	35	104	0
35	ElectricDevices	0.6009	0.0691	0.1126	4578	477	56	533	868	0	487	4253	381
36	EthanolLevel	0.2528	0.2520	0.2544	56	56	70	125	126	1	71	70	56
37	FaceAll	0.5088	0.0677	0.0182	795	50	64	114	31	0	5	834	26
38	FaceFour	0.4705	0.0000	0.2045	41	0	0	0	18	0	4	27	14
39	FacesUCR	0.4839	0.1740	0.0062	661	26	331	357	13	0	3	982	10
40	FiftyWords	0.2382	0.1253	0.0659	77	26	31	57	30	0	22	100	8
41	Fish	0.4583	0.0834	0.1314	66	0	15	15	23	0	19	76	4
42	FordA	0.8917	0.7006	0.4932	365	113	812	289	15	636	111	637	540
43	FordB	0.6407	0.5568	0.5049	112	44	407	51	9	400	53	163	356
44	FreezerRegularTrain	0.6327	0.6138	0.5000	59	5	1744	482	157	1268	160	538	1265
45	FreezerSmallTrain	0.5004	0.7038	0.5000	192	772	1234	773	192	1233	4	5	1421
46	Fungi	0.0968	0.0591	0.1290	7	0	11	0	13	11	13	7	11
47	GestureMidAirD1	0.1769	0.0138	0.0385	23	2	0	1	4	1	2	20	3
48	GestureMidAirD2	0.1708	0.0385	0.0462	17	0	5	5	6	0	5	21	1
49	GestureMidAirD3	0.1385	0.0615	0.0431	15	5	3	5	3	3	4	16	2
50	GesturePebbleZ1	0.4814	0.1802	0.1453	53	1	30	31	25	0	7	65	18
51	GesturePebbleZ2	0.5089	0.0481	0.1861	73	0	7	7	29	0	10	61	19
52	GunPoint	0.6133	0.5973	0.4933	22	20	70	53	37	37	57	75	17
53	GunPointAgeSpan	0.3829	0.4342	0.4937	72	88	49	2	21	135	90	55	66
54	GunPointMaleVersusFemale	0.8576	0.7266	0.4747	43	2	228	80	0	150	2	123	148
55	GunPointOldVersusYoung	1.0000	0.6540	0.5238	109	0	206	41	0	165	0	150	165
56	Ham	0.4381	0.5143	0.5143	20	28	26	0	0	54	28	20	26
57	HandOutlines	0.6200	0.6546	0.6405	104	117	126	5	0	237	117	109	120
58	Haptics	0.2591	0.2292	0.2338	67	58	13	70	71	1	20	28	52
59	Herring	0.4688	0.4062	0.4062	5	1	25	0	0	26	1	5	25
60	HouseTwenty	0.6353	0.4034	0.4202	28	1	47	0	2	48	1	26	49
61	InlineSkate	0.2073	0.1691	0.1873	109	88	5	44	54	49	88	99	15
62	InsectEPGRegularTrain	1.0000	0.4739	0.6426	131	0	118	0	42	118	0	89	160
63	InsectEPGSmallTrain	0.5719	0.4739	0.1687	131	107	11	118	42	0	0	100	42
64	InsectWingbeatSound	0.1622	0.0962	0.1188	283	152	39	177	222	14	133	219	102
65	ItalyPowerDemand	0.9261	0.5015	0.5015	463	26	490	0	0	516	26	463	490
66	LargeKitchenAppliances	0.6016	0.3557	0.2224	105	12	121	118	68	15	25	167	58
67	Lightning2	0.6393	0.5410	0.5410	15	9	24	0	0	33	9	15	24
68	Lightning7	0.3836	0.2575	0.2466	23	14	5	3	2	16	15	25	3
69	Mallat	0.2479	0.1243	0.0198	581	291	1	276	30	16	46	581	0
70	Meat	0.6000	0.3333	0.3167	20	4	16	1	0	19	3	20	16
71	MedicalImages	0.5503	0.4468	0.2171	99	21	319	234	59	106	61	314	104
72	MelbournePedestrian	0.7768	0.0600	0.0199	1772	16	131	133	35	14	15	1869	34
73	MiddlePhalanxOutlineAgeGroup	0.6169	0.5714	0.2143	7	0	88	84	29	4	22	84	11
74	MiddlePhalanxOutlineCorrect	0.6220	0.5918	0.5704	17	8	164	7	1	165	9	24	157
75	MiddlePhalanxTW	0.5065	0.1494	0.1455	63	8	15	7	6	16	12	68	10
76	MixedShapesRegularTrain	0.7980	0.0851	0.1298	1735	6	200	206	315	0	7	1627	308
77	MixedShapesSmallTrain	0.4144	0.1195	0.2501	997	282	8	286	603	4	23	422	583
78	MoteStrain	0.4609	0.4612	0.4609	2	2	575	2	2	575	0	0	577
79	NonInvasiveFetalECGThorax1	0.1186	0.0214	0.0422	192	1	41	42	83	0	40	190	43
80	NonInvasiveFetalECGThorax2	0.1445	0.0261	0.0453	233	0	51	51	89	0	1	196	88
81	OSULeaf	0.6901	0.1694	0.0950	129	3	38	36	18	5	4	148	19
82	OliveOil	0.4000	0.4000	0.4000	0	0	12	0	0	12	0	0	12
83	PLAID	0.2134	0.1088	0.1233	74	18	41	13	21	46	27	76	39
84	PhalangesOutlinesCorrect	0.6452	0.6142	0.6131	145	119	408	1	0	526	119	146	407
85	Phoneme	0.1786	0.0188	0.0179	336	33	2	35	33	1	30	335	4
86	PickupGestureWiimoteZ	0.1320	0.0360	0.2680	7	2	0	2	13	0	9	2	4
87	PigAirwayPressure	0.0788	0.0096	0.0192	16	2	0	0	2	2	4	16	0
88	PigArtPressure	0.0894	0.0192	0.0192	15	0	4	4	4	0	0	15	4
89	PigCVP	0.0577	0.0192	0.0337	9	1	3	4	7	0	4	9	3
90	Plane	0.4952	0.2152	0.1733	40	11	12	11	7	12	6	40	12
91	PowerCons	0.5833	0.5000	0.5056	61	46	44	0	1	90	46	60	45
92	ProximalPhalanxOutlineAgeGroup	0.7844	0.4098	0.5122	98	21	63	81	102	3	9	65	96
93	ProximalPhalanxOutlineCorrect	0.7491	0.6838	0.6838	23	4	195	0	0	199	4	23	195
94	ProximalPhalanxTW	0.7873	0.1951	0.1863	130	9	31	33	31	7	9	132	29
95	RefrigerationDevices	0.4299	0.3333	0.3333	112	76	49	125	125	0	89	125	36
96	Rock	0.4800	0.3000	0.1800	15	6	9	14	8	1	7	22	2
97	ScreenType	0.3899	0.3333	0.3280	65	44	81	92	90	33	97	121	26
98	SemgHandGenderCh2	0.6033	0.3500	0.3777	230	78	132	0	17	210	78	213	149
99	SemgHandMovementCh2	0.3409	0.1702	0.1236	109	33	44	77	56	0	25	122	31
100	SemgHandSubjectCh2	0.2933	0.1418	0.2298	125	57	7	64	103	0	42	71	61
101	ShakeGestureWiimoteZ	0.2200	0.1400	0.1400	6	2	5	7	7	0	7	11	0
102	ShapeletSim	0.5000	0.5000	0.5000	90	90	0	0	0	90	90	90	0
103	ShapesAll	0.2513	0.0280	0.0133	139	5	12	17	8	0	1	144	7
104	SmallKitchenAppliances	0.6816	0.3333	0.2912	213	82	43	94	78	31	47	194	62
105	SmoothSubspace	0.6133	0.3333	0.2933	59	17	33	46	40	4	23	71	21
106	SonyAIBORobotSurface1	0.5990	0.4293	0.4293	132	30	228	0	0	258	30	132	228
107	SonyAIBORobotSurface2	0.2661	0.6233	0.6170	171	511	83	9	3	585	514	180	74
108	StarLightCurves	0.9631	0.2799	0.5772	5707	80	2225	2305	4754	0	24	3202	4730
109	Strawberry	0.7957	0.6432	0.6432	110	54	184	0	0	238	54	110	184
110	SwedishLeaf	0.5763	0.0672	0.0304	318	0	42	42	19	0	1	342	18
111	Symbols	0.4750	0.1648	0.2553	316	7	157	73	163	91	1	220	253
112	SyntheticControl	0.9280	0.0713	0.1307	260	3	18	13	31	8	2	241	37
113	ToeSegmentation1	0.4000	0.4605	0.4737	58	72	33	0	3	105	75	58	33
114	ToeSegmentation2	0.8923	0.1846	0.1846	99	7	17	0	0	24	7	99	17
115	Trace	0.7300	0.1100	0.3000	62	0	11	11	30	0	3	46	27
116	TwoLeadECG	0.8386	0.5004	0.5004	408	23	547	0	0	570	23	408	547
117	TwoPatterns	0.7727	0.0150	0.2976	3084	53	7	58	1189	2	328	2228	863
118	UMD	0.3347	0.3333	0.3333	48	48	0	48	48	0	19	19	29
119	UWaveGestureLibraryAll	0.4907	0.1680	0.0878	1213	56	545	600	313	1	83	1527	231
120	UWaveGestureLibraryX	0.5207	0.1304	0.1235	1445	47	420	464	439	3	186	1609	256
121	UWaveGestureLibraryY	0.4638	0.1439	0.0749	1279	134	382	482	235	34	92	1485	176
122	UWaveGestureLibraryZ	0.5313	0.1359	0.1161	1468	51	436	482	411	5	126	1613	290
123	Wafer	0.8734	0.8569	0.8921	158	57	5225	73	290	5209	132	16	5367
124	Wine	0.5000	0.5000	0.5000	27	27	0	0	0	27	27	27	0
125	WordSynonyms	0.2442	0.1398	0.0737	70	3	86	88	46	1	39	148	8
126	Worms	0.6442	0.0909	0.2078	44	1	6	7	16	0	9	43	7
127	WormsTwoClass	0.6234	0.5714	0.5714	15	11	33	0	0	44	11	15	33
128	Yoga	0.5539	0.5357	0.5357	587	532	1075	0	0	1607	532	587	1075
	Avg Value	0.4961	0.2901	0.2887	376	56	196	106	116	147	56	365	207