

Appendix:

Diffusion Language-Shapelets for Semi-supervised Time-Series Classification

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A Details of Datasets

The UCR time series archive (Dau et al. 2019) is widely utilized in time series classification studies (Ismail Fawaz et al. 2019; Middlehurst, Schäfer, and Bagnall 2023), which collects 128 time series datasets from various real-world scenarios like traffic, medicine, and human actions. Each UCR time series data contains a single training and testing set. However, most UCR time series datasets have a small number of samples in the training set and are even smaller than the test set. Furthermore, the original UCR dataset lacks a dedicated validation set for model training. In such a case, semi-supervised classification is performed directly on the training set of the original UCR dataset, which easily results in obtaining classification test results with a large bias. Following the suggestion given by (Dau et al. 2019; Liu et al. 2023), we initially merged the provided training and test sets for each UCR dataset. Subsequently, following (Liu et al. 2023), we restricted having an average of at least 30 samples per class within each dataset to ensure more stable classification test results. Therefore, we used 106 datasets from the original 128 UCR datasets for experimental analysis, and please refer to Table 1 for specific statistical information. Finally, we used a five-fold cross-validation method to obtain the training-validation-test set for each dataset according to the ratio of 60%-20%-20%. Notably, for UCR time series datasets containing missing values, we employed the mean imputation method for preprocessing.

Regarding the natural language descriptions associated with the 106 UCR time series datasets mentioned in Table 1, we formulated these descriptions by utilizing the original keyword information provided by the respective UCR dataset providers.

B Details of Baselines

In this study, we have chosen baselines that encompass two main aspects: (i) semi-supervised classification methods mainly for time series data; and (ii) shapelet-based time series classification methods. Concerning the existing SSL methods mainly for time series, we have selected 10 baselines as follows:

- Supervised: We solely employ the provided labeled data to train the model for supervised classification, utilizing the cross-entropy loss.
- Pseudo-Label¹: Lee et al. (2013) used soft labels predicted with high confidence by the classifier during training as pseudo-labels for unlabeled data for semi-supervised classification.
- Temporal Ensembling²: Laine and Aila (2016) form a consensus prediction of the unknown labels (or unlabeled data) using the outputs of the network-in-training on different epochs as a regularization strategy for semi-supervised classification.
- LPDeepSSL³: Iscen et al. (2019) employ a transductive label propagation method on the learned embeddings to obtain the pseudo-labels of unlabeled data for semi-supervised classification.
- MTL⁴: Jawed, Grabocka, and Schmidt-Thieme (2020) introduce a forecasting task to exploit the unlabeled time series data. Especially, they established multi-task learning approaches by using forecasting as an auxiliary task for time series semi-supervised classification.
- TS-TCC⁵: Eldele et al. (2021) design an unsupervised temporal and contextual contrastive learning loss for representation learning. Following (Liu et al. 2023), we use TS-TCC as a time series SSL baseline.
- SemiTime⁶: Fan et al. (2021) design a temporal relation prediction loss that operates on segments from labeled and unlabeled time series, specifically on past-future pairs. This mechanism is used to enhance time series semi-supervised classification.
- SSSTC⁷: Xi et al. (2022) design a temporal relation prediction loss based on the split “past-anchor-future” segments from labeled and unlabeled time series, thus contributing to time series semi-supervised classification.

¹https://github.com/iBelieveCJM/pseudo_label-pytorch

²<https://github.com/ferretj/temporal-ensembling>

³<https://github.com/ahmetius/LP-DeepSSL>

⁴<https://github.com/super-shayan/semi-super-ts-clf>

⁵<https://github.com/emadeldeen24/TS-TCC>

⁶<https://github.com/haoyfan/SemiTime>

⁷<https://github.com/mrxiliang/ssstsc>

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- MTFC ⁸: Wei et al. (2023) propose a time-frequency based multi-task learning method for time series semi-supervised classification. Specially, they use a forecasting task based on MTL for learning time-frequency features from unlabeled data.
- TS-TFC ⁹: Liu et al. (2023) propose a temporal-frequency co-training framework for time series semi-supervised classification. In particular, they employ complementary information from time-domain and frequency-domain views to select high-quality pseudo-labels for unlabeled data learning.

For the shapelet-based time series classification methods, we combined them with the pseudo-labeling strategy in DiffShape for time series semi-supervised classification. The specific information on the above baselines is as follows:

- ST ¹⁰: Lines et al. (2012) incorporate a shapelet transformation method to discover k best shapelets for time series classification.
- LTS ¹¹: Grabocka et al. (2014) first propose learning shapelets perspective based on a classification objective function via stochastic gradient learning for time series classification.
- FSS ¹²: Ji et al. (2019) introduce a fast shapelet selection method from original subsequences for time series classification.
- ADSN ¹³: Ma et al. (2020) propose adversarial dynamic shapelet networks to learn shapelets for time series classification.

For the above four methods, we first train them using labeled data. Then, we use the trained model to transform the training set (labeled and unlabeled data), validation set, and test set into the corresponding set of shapelets. Finally, we use the above set of shapelets to input into the same encoder and classifier as DiffShape for semi-supervised learning. The pseudo-code of our proposed DiffShape model is shown in Algorithm 1. For the reproduction source code of the above baselines and the source code of DiffShape, please refer to our anonymous GitHub: <https://anonymous.4open.science/r/diffshape-code>.

C Details of Main Results

For specific and detailed test classification results of DiffShape and the 10 SSL baselines on the 106 UCR time series datasets, kindly consult Table 2 (10% labeling ratio), Table 3 (20% labeling ratio), and Table 4 (40% labeling ratio). To facilitate the presentation and reading of the test classification accuracy results, we did not provide standard deviations of test classification accuracy for each baseline in Tables 2, 3 and 4. Also, we have included the critical difference diagram comparing DiffShape with the 10 SSL baselines in Figure 1.

⁸<https://github.com/Chixuan-Wei/SemiSuperTSC>

⁹<https://github.com/qianlima-lab/TS-TFC>

¹⁰<https://github.com/mlpotter/Shapelet.Transform/tree/main>

¹¹<https://github.com/benibaumle/Learning-Shapelets>

¹²<https://github.com/benibaumle/FSS-Algorithm>

¹³<https://github.com/qianlima-lab/ADSN>

D Details of Comparisons with Shapelet-based TSC Methods

For specific test classification results of DiffShape and four shapelet-based time series classification methods for semi-supervised classification on 12 UCR time series datasets, kindly refer to Table 5 (10% labeling ratio), Table 6 (20% labeling ratio), and Table 7 (40% labeling ratio). To enhance the clarity and readability of the results presentation, we have omitted reporting the standard deviation of the test classification results for each baseline in Tables 5, 6 and 7.

E Details of Results on a Few Labeled Time Series

For supervised classification test results of DiffShape and 2 shapelet-based time series classification methods, as well as 6 SSL methods with only a few labeled samples on 12 UCR time series datasets, kindly refer to Table 8 (2 labeled samples per class), Table 9 (5 labeled samples per class), and Table 10 (10 labeled samples per class). To enhance the clarity and readability of the results presentation, we have omitted reporting the standard deviation of the test classification results for each baseline in Tables 8, 9 and 10.

F Details of Ablation Study

For detailed results of the test classification accuracy from the DiffShape ablation experiments on the 12 UCR datasets with a labeling ratio of 10%, please consult Table 11. Additionally, for a comparative analysis of the shapelet visualization achieved by DiffShape and LTS (Grabocka et al. 2014), ADSN (Ma et al. 2020) on the *SonyAIBORobotSurface1* dataset with a labeling ratio of 10%, please refer to Figure 2. Moreover, for t-SNE (Van der Maaten and Hinton 2008) visualization results depicting the embeddings learned by DiffShape, SemiTime (Fan et al. 2021), and TS-TFC (Liu et al. 2023) on the *UWaveGestureLibraryAll* dataset with a labeling ratio of 10%, kindly refer to Figure 3.

G Runtime Analysis

We have chosen the *Trace* dataset (with a total of 200 samples and a sequence length of 275) and the *ChlorineConcentration* dataset (with a total of 4307 samples and a sequence length of 166) for the runtime analysis of various baselines, including seven SSL methods and four shapelet-based methods. To conduct this analysis, we computed the overall runtime for semi-supervised classification using five-fold cross-validation for all baselines, employing a 10% labeling ratio. For consistency, we utilized the same encoder and classifier for semi-supervised classification in each baseline, and all baselines were trained and tested on individual NVIDIA GeForce RTX 3090 GPUs. The runtime statistics for DiffShape and the mentioned baselines are provided in Table 12. Notably, we observed that DiffShape’s runtime is significantly lower compared to MTL (Jawed, Grabocka, and Schmidt-Thieme 2020), SemiTime (Fan et al. 2021), SSSTC (Xi et al. 2022), and MTFC (Wei et al. 2023). Additionally, DiffShape’s runtime is also lower than that of the shapelet-based approaches. Furthermore, our analysis

Algorithm 1: The pseudo-code of DiffShape model.

Input : Convolution layer $w_f(\cdot)$, 1-D U-Net $g(\cdot)$ for diffusion learning, Shapelets transformation encoder $w_s(\cdot)$, Frozen Pre-trained T5 language encoder $z(\cdot)$, Text projection head $h(\cdot)$, Classifier $w_c(\cdot)$, Number of Shapelets k , Length of a shapelet $L = \eta * N$, Sampling steps T , Batch size: B , Number of epochs: E_{max} , Number of iterations: $Iter_{max}$;

```
1 Obtain all real subsequences  $S_{train}$  from the labeled set  $\mathcal{D}^L$  and the unlabeled set  $\mathcal{D}^U$ ;  
2 for  $e \leftarrow 1$  to  $E_{max}$  do  
3   Shuffle training set  $S_{train}$ ;  
4   for  $iter \leftarrow 1$  to  $Iter_{max}$  do  
5     Fetch real subsequences  $S \in \mathbb{R}^{B \times L \times J}$  from shuffled  $S_{train}$ ;  
6     Obtain shapelets  $\mathbf{S}_0 = w_f(S)$ , where  $\mathbf{S}_0 \in \mathbb{R}^{B \times L \times k}$ ;  
7     Search similar real subsequences shapelets  $\mathbf{S}_r$  via  $\mathbf{S}_0$  from  $S$ , where  $\mathbf{S}_r \in \mathbb{R}^{B \times L \times k}$ ;  
8     Obtain shapelets  $\mathbf{S}_t$  via Eq. (2) added injected noise through a forward diffusion process;  
9     Training  $g(\cdot)$  via  $\mathcal{L}_{diff}$  through reverse diffusion process;  
10    Obtain sampling shapelets  $\hat{\mathbf{S}}_0$  via Eq. (8) and Eq. (9) by  $g(\cdot)$  of iteration  $T$  steps using only labeled shapelets;  
11    Obtain shapelets transformation embeddings  $r_s = w_s(\mathbf{S}_0, \hat{\mathbf{S}}_0)$ ;  
12    Obtain pseudo-labels of unlabeled data in  $\mathbf{S}_0$  via the predicted soft labels with high confidence of  $w_c(r_s)$ ;  
13    Construct natural language descriptions  $\mathbf{L}$  using the labels and pseudo-labels within  $\mathbf{S}_0$ ;  
14    Obtain language embeddings  $r_l = h(z(\mathbf{L}))$ ;  
15    Training  $r_s$  and  $r_l$  via  $\mathcal{L}_{lan}$  through contrastive language-shapelets learning;  
16    Update DiffShape ( $w_f(\cdot)$ ,  $g(\cdot)$ ,  $w_s(\cdot)$ ,  $h(\cdot)$  and  $w_c(\cdot)$ ) model via  $\mathcal{L}_{total}$ ;  
17  end  
18 end  
Output:  $w_f(\cdot)$ ,  $g(\cdot)$ ,  $w_s(\cdot)$ ,  $h(\cdot)$  and  $w_c(\cdot)$ .
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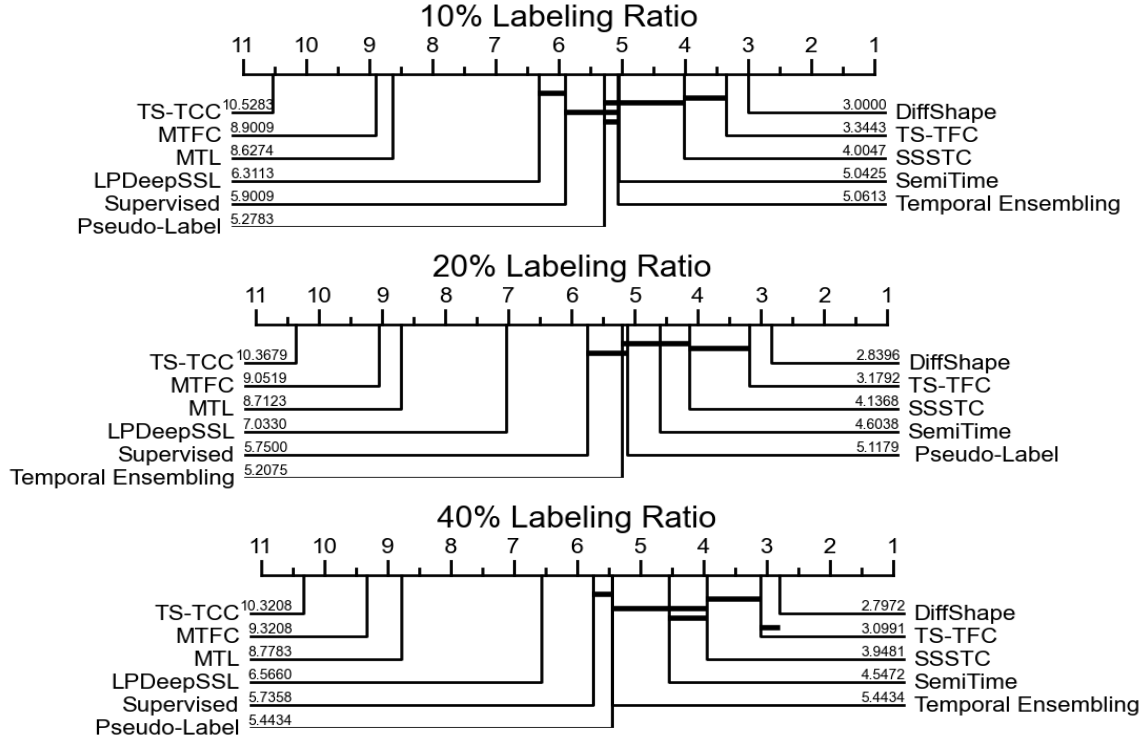


Figure 1: Critical Difference (CD) diagram (Demšar 2006) showing pairwise statistical difference comparison of 11 SSL methods on 106 UCR time series datasets. The CD diagram provides statistical insight into whether the differences are significant. By comparing the CD value of DiffShape with other 11 SSL methods, we find that the classification performance of DiffShape is significant compared to the other 11 methods.

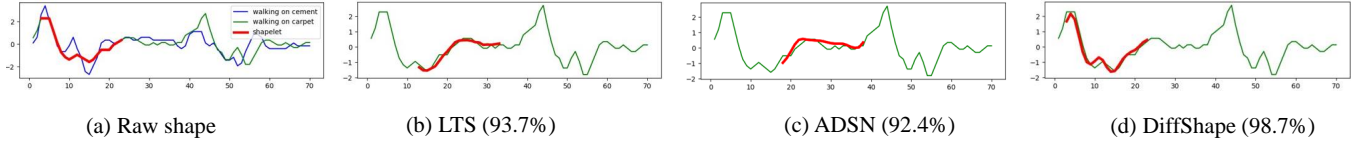


Figure 2: The visualization of shapelet on the *SonyAIBORobotSurface1* dataset with a 10% labeling ratio. The test accuracy is in parentheses. (a) represents a ground truth shapelet of *walking on carpet* class. The position of shapelet learned by (b) LTS and (c) ADSN is away from the ground truth in (a), while the position of shapelet obtained by (d) DiffShape is closer to the ground truth in (a).

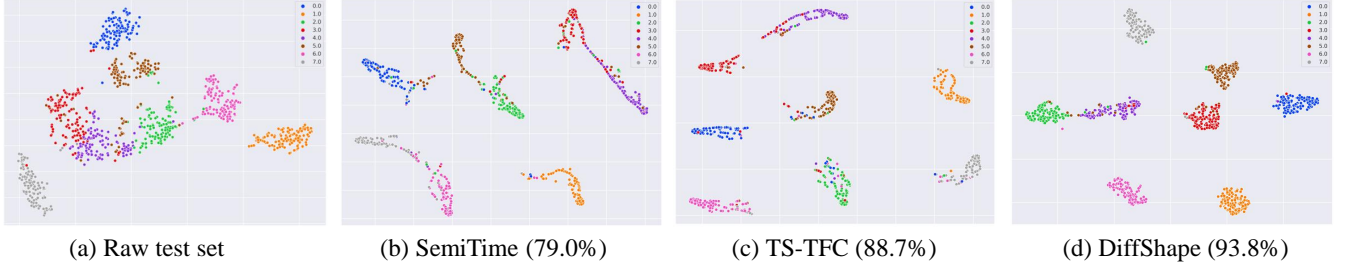


Figure 3: The t-SNE visualization on the *UWaveGestureLibraryAll* dataset with a 10% labeling ratio. The test accuracy is in parentheses. Comparing (a) Raw test set, (b) SemiTime and (c) TS-TFC, we find that the embeddings obtained by DiffShape are more discriminative between classes.

unveiled that Shapelet Transform (ST) (Lines et al. 2012), which is employed for time series classification via the identification of k best shapelets, displays a runtime that positively correlates with the sequence length of the samples. However, this correlation is not significantly observed with the total number of samples. On the contrary, the runtimes of other methods (LTS, ADSN, TS-TFC, and DiffShape) exhibit a positive correlation with the total number of samples.

ID	Name	# Total numbers	# Classes	# Length	ID	Name	# Total numbers	# Classes	# Length
1	AllGestureWiimoteX	1000	10	Vary	54	Lightning2	121	2	637
2	AllGestureWiimoteY	1000	10	Vary	55	Mallat	2400	8	1024
3	AllGestureWiimoteZ	1000	10	Vary	56	Meat	120	3	448
4	ArrowHead	211	3	251	57	MedicalImages	1141	10	99
5	BME	180	3	128	58	MelbournePedestrian	3633	10	24
6	Car	120	4	577	59	MiddlePhalanxOutlineAgeGroup	554	3	80
7	CBF	930	3	128	60	MiddlePhalanxOutlineCorrect	891	2	80
8	Chinatown	363	2	24	61	MiddlePhalanxTW	553	6	80
9	ChlorineConcentration	4307	3	166	62	MixedShapesRegularTrain	2925	5	1024
10	CinCECGTorso	1420	4	1639	63	MixedShapesSmallTrain	2525	5	1024
11	Computers	500	2	720	64	MoteStrain	1272	2	84
12	CricketX	780	12	300	65	NonInvasiveFetalECGThorax1	3765	42	750
13	CricketY	780	12	300	66	NonInvasiveFetalECGThorax2	3765	42	750
14	CricketZ	780	12	300	67	OSULeaf	442	6	427
15	Crop	24000	24	46	68	PhalangesOutlinesCorrect	2658	2	80
16	DiatomSizeReduction	322	4	345	69	Phoneme	2110	39	1024
17	DistalPhalanxOutlineAgeGroup	539	3	80	70	PLAID	1074	11	Vary
18	DistalPhalanxOutlineCorrect	876	2	80	71	Plane	210	7	144
19	DistalPhalanxTW	539	6	80	72	PowerCons	360	2	144
20	DodgerLoopGame	158	2	288	73	ProximalPhalanxOutlineAgeGroup	605	3	80
21	DodgerLoopWeekend	158	2	288	74	ProximalPhalanxOutlineCorrect	891	2	80
22	Earthquakes	461	2	512	75	ProximalPhalanxTW	605	6	80
23	ECG200	200	2	96	76	RefrigerationDevices	750	3	720
24	ECG5000	5000	5	140	77	ScreenType	750	3	720
25	ECGFiveDays	884	2	136	78	SemgHandGenderCh2	900	2	1500
26	ElectricDevices	16637	7	96	79	SemgHandMovementCh2	900	6	1500
27	EOGHorizontalSignal	724	12	1250	80	SemgHandSubjectCh2	900	5	1500
28	EOGVerticalSignal	724	12	1250	81	ShapeletSim	200	2	500
29	EthanolLevel	1004	4	1751	82	SmallKitchenAppliances	750	3	720
30	FaceAll	2250	14	131	83	SmoothSubspace	300	3	15
31	FacesUCR	2250	14	131	84	SonyAIBORobotSurface1	621	2	70
32	Fish	350	7	463	85	SonyAIBORobotSurface2	980	2	65
33	FordA	4921	2	500	86	StarLightCurves	9236	3	1024
34	FordB	4446	2	500	87	Strawberry	983	2	235
35	FreezerRegularTrain	3000	2	301	88	SwedishLeaf	1125	15	128
36	FreezerSmallTrain	2878	2	301	89	Symbols	1020	6	398
37	GesturePebbleZ1	304	6	Vary	90	SyntheticControl	600	6	60
38	GesturePebbleZ2	304	6	Vary	91	ToeSegmentation1	268	2	277
39	GunPoint	200	2	150	92	ToeSegmentation2	166	2	343
40	GunPointAgeSpan	451	2	150	93	Trace	200	4	275
41	GunPointMaleVersusFemale	451	2	150	94	TwoLeadECG	1162	2	82
42	GunPointOldVersusYoung	451	2	150	95	TwoPatterns	5000	4	128
43	Ham	214	2	431	96	UMD	180	3	150
44	HandOutlines	1370	2	2709	97	UWaveGestureLibraryAll	4478	8	945
45	Haptics	463	5	1092	98	UWaveGestureLibraryX	4478	8	315
46	Herring	128	2	512	99	UWaveGestureLibraryY	4478	8	315
47	HouseTwenty	159	2	2000	100	UWaveGestureLibraryZ	4478	8	315
48	InlineSkate	650	7	1882	101	Wafer	7164	2	152
49	InsectEPGRegularTrain	311	3	601	102	Wine	111	2	234
50	InsectEPGSmallTrain	266	3	601	103	WordSynonyms	905	25	270
51	InsectWingbeatSound	2200	11	256	104	Worms	258	5	900
52	ItalyPowerDemand	1096	2	24	105	WormsTwoClass	258	2	900
53	LargeKitchenAppliances	750	3	720	106	Yoga	3300	2	426

Table 1: The detailed information of the 106 UCR time series datasets. “Total numbers” represent the overall count of samples within the time series dataset. “Classes” indicates the number of classes present within each time series dataset. “Length” refers to the sequence length of individual time series within the corresponding dataset. The presence of “Vary” signifies that the dataset includes instances with missing values.

ID	Dataset	Supervised Pseudo-Label		TE	LPDeepSSL	MTL	TS-TCC	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	AllGestureWiimoteX	0.518	0.559	0.538	0.424	0.422	0.156	0.496	0.503	0.415	0.547	0.558
2	AllGestureWiimoteY	0.580	0.562	0.589	0.578	0.436	0.181	0.555	0.587	0.409	0.619	0.627
3	AllGestureWiimoteZ	0.537	0.537	0.540	0.375	0.346	0.209	0.503	0.541	0.227	0.543	0.552
4	ArrowHead	0.687	0.758	0.744	0.725	0.565	0.308	0.765	0.763	0.403	0.711	0.759
5	BME	0.633	0.672	0.694	0.661	0.667	0.550	0.678	0.672	0.517	0.694	0.872
6	Car	0.658	0.592	0.667	0.467	0.558	0.250	0.662	0.575	0.425	0.520	0.683
7	CBF	0.998	0.998	0.994	0.997	0.975	0.975	0.993	0.996	0.985	0.999	1.000
8	Chinatown	0.970	0.961	0.970	0.973	0.419	0.712	0.970	0.975	0.959	0.973	0.981
9	ChlorineConcentration	0.604	0.722	0.733	0.737	0.607	0.537	0.719	0.682	0.575	0.744	0.749
10	CinCECGTorso	0.911	0.940	0.925	0.927	0.881	0.702	0.915	0.934	0.613	0.998	0.982
11	Computers	0.658	0.736	0.742	0.722	0.756	0.646	0.761	0.752	0.748	0.764	0.742
12	CricketX	0.535	0.535	0.515	0.505	0.492	0.126	0.524	0.599	0.389	0.590	0.608
13	CricketY	0.527	0.541	0.531	0.451	0.367	0.146	0.524	0.564	0.430	0.540	0.594
14	CricketZ	0.537	0.567	0.560	0.550	0.459	0.156	0.563	0.609	0.460	0.619	0.639
15	Crop	0.674	0.667	0.667	0.656	0.624	0.410	0.628	0.685	0.595	0.685	0.701
16	DiatomSizeReduction	0.876	0.923	0.920	0.929	0.731	0.350	0.885	0.901	0.643	0.975	0.985
17	DistalPhalanxOutlineAgeGroup	0.822	0.821	0.824	0.820	0.764	0.753	0.790	0.776	0.764	0.826	0.838
18	DistalPhalanxOutlineCorrect	0.787	0.765	0.791	0.775	0.713	0.629	0.791	0.814	0.729	0.805	0.813
19	DistalPhalanxTW	0.746	0.732	0.741	0.699	0.731	0.691	0.751	0.750	0.655	0.742	0.742
20	DodgerLoopGame	0.651	0.676	0.708	0.632	0.576	0.481	0.683	0.708	0.620	0.842	0.880
21	DodgerLoopWeekend	0.810	0.778	0.760	0.815	0.703	0.797	0.852	0.924	0.873	0.849	0.918
22	Earthquakes	0.795	0.775	0.796	0.825	0.595	0.602	0.741	0.785	0.829	0.790	0.803
23	ECG200	0.946	0.942	0.941	0.936	0.939	0.896	0.942	0.790	0.785	0.950	0.875
24	ECG5000	0.991	0.995	0.997	0.996	0.899	0.794	0.992	0.941	0.922	0.996	0.945
25	ECGFiveDays	0.327	0.345	0.378	0.318	0.328	0.192	0.424	0.998	0.919	0.459	1.000
26	ElectricDevices	0.318	0.318	0.313	0.337	0.293	0.166	0.379	0.395	0.265	0.443	0.799
27	EOGHorizontalSignal	0.798	0.792	0.798	0.798	0.798	0.798	0.770	0.854	0.720	0.801	0.820
28	EOGVerticalSignal	0.852	0.838	0.838	0.832	0.809	0.663	0.844	0.372	0.296	0.857	0.579
29	EthanolLevel	0.547	0.389	0.427	0.292	0.263	0.249	0.554	0.570	0.269	0.580	0.589
30	FaceAll	0.864	0.942	0.942	0.919	0.806	0.246	0.921	0.912	0.802	0.933	0.943
31	FacesUCR	0.854	0.935	0.926	0.886	0.862	0.214	0.901	0.897	0.870	0.912	0.947
32	Fish	0.829	0.589	0.569	0.389	0.446	0.143	0.757	0.734	0.334	0.354	0.777
33	FordA	0.891	0.900	0.906	0.899	0.890	0.800	0.905	0.914	0.629	0.907	0.935
34	FordB	0.881	0.877	0.884	0.882	0.872	0.805	0.892	0.902	0.774	0.873	0.913
35	FreezerRegularTrain	0.998	0.994	0.997	0.998	0.638	0.761	0.992	0.998	0.607	0.997	0.998
36	FreezerSmallTrain	0.999	0.998	0.999	0.998	0.848	0.760	0.997	0.998	0.618	0.999	0.999
37	GesturePebbleZ1	0.651	0.586	0.593	0.563	0.591	0.187	0.677	0.714	0.622	0.434	0.671
38	GesturePebbleZ2	0.622	0.691	0.671	0.538	0.577	0.208	0.629	0.708	0.655	0.460	0.783
39	GunPoint	0.735	0.955	0.945	0.910	0.765	0.545	0.957	0.890	0.640	0.910	0.930
40	GunPointAgeSpan	0.858	0.949	0.920	0.942	0.882	0.774	0.969	0.982	0.879	0.982	0.956
41	GunPointMaleVersusFemale	0.967	0.992	0.993	0.991	0.989	0.956	0.991	0.996	0.971	0.998	0.989
42	GunPointOldVersusYoung	0.927	0.820	0.845	0.891	0.765	0.601	0.938	0.971	0.697	0.985	0.956
43	Ham	0.603	0.575	0.622	0.593	0.547	0.481	0.654	0.678	0.687	0.636	0.720
44	HandOutlines	0.800	0.811	0.832	0.777	0.643	0.639	0.805	0.812	0.736	0.875	0.880
45	Haptics	0.382	0.344	0.363	0.305	0.290	0.203	0.319	0.372	0.283	0.370	0.415
46	Herring	0.617	0.579	0.549	0.579	0.601	0.562	0.616	0.556	0.563	0.618	0.657
47	HouseTwenty	0.905	0.899	0.931	0.872	0.899	0.578	0.932	0.963	0.969	0.928	0.928
48	InlineSkate	0.239	0.294	0.362	0.360	0.257	0.161	0.215	0.251	0.162	0.428	0.315
49	InsectEPGRegularTrain	0.910	0.917	0.930	0.894	0.911	0.654	0.871	0.942	0.917	0.962	0.958
50	InsectEPGSmallTrain	0.922	0.888	0.888	0.888	0.853	0.631	0.884	0.922	0.861	0.944	0.899
51	InsectWingbeatSound	0.296	0.358	0.361	0.349	0.292	0.121	0.355	0.346	0.272	0.547	0.609
52	ItalyPowerDemand	0.947	0.964	0.955	0.971	0.875	0.886	0.960	0.939	0.951	0.965	0.972
53	LargeKitchenAppliances	0.857	0.857	0.832	0.835	0.756	0.603	0.868	0.819	0.597	0.843	0.792
54	Lightning2	0.637	0.744	0.654	0.627	0.628	0.612	0.666	0.695	0.662	0.746	0.754
55	Mallat	0.960	0.982	0.980	0.958	0.437	0.159	0.940	0.890	0.401	0.988	0.973
56	Meat	0.767	0.667	0.750	0.617	0.617	0.333	0.817	0.875	0.508	0.867	0.892
57	MedicalImages	0.619	0.674	0.653	0.639	0.562	0.521	0.608	0.640	0.536	0.637	0.637
58	MelbournePedestrian	0.854	0.842	0.846	0.847	0.525	0.501	0.847	0.854	0.589	0.864	0.867
59	MiddlePhalanxOutlineAgeGroup	0.753	0.744	0.737	0.728	0.608	0.582	0.725	0.758	0.708	0.731	0.756
60	MiddlePhalanxOutlineCorrect	0.772	0.764	0.744	0.741	0.654	0.622	0.764	0.789	0.682	0.817	0.818
61	MiddlePhalanxTW	0.595	0.590	0.585	0.579	0.528	0.551	0.586	0.593	0.570	0.579	0.590

62	MixedShapesRegularTrain	0.927	0.935	0.927	0.923	0.772	0.453	0.940	0.943	0.466	0.959	0.945
63	MixedShapesSmallTrain	0.914	0.921	0.926	0.913	0.795	0.454	0.924	0.917	0.414	0.962	0.933
64	MoteStrain	0.953	0.951	0.947	0.951	0.956	0.911	0.962	0.965	0.947	0.963	0.921
65	NonInvasiveFetalECGThorax1	0.247	0.342	0.316	0.255	0.082	0.028	0.316	0.281	0.079	0.327	0.670
66	NonInvasiveFetalECGThorax2	0.271	0.358	0.410	0.205	0.077	0.027	0.333	0.341	0.094	0.457	0.381
67	OSULeaf	0.862	0.766	0.808	0.815	0.769	0.347	0.849	0.885	0.571	0.899	0.719
68	PhalangesOutlinesCorrect	0.328	0.304	0.342	0.339	0.282	0.191	0.335	0.329	0.257	0.332	0.244
69	Phoneme	0.778	0.781	0.779	0.781	0.708	0.639	0.806	0.804	0.702	0.799	0.796
70	PLAID	0.289	0.292	0.294	0.291	0.298	0.168	0.303	0.307	0.148	0.290	0.340
71	Plane	0.852	0.886	0.886	0.886	0.781	0.248	0.892	0.905	0.471	0.817	0.886
72	PowerCons	0.811	0.822	0.828	0.764	0.786	0.778	0.832	0.789	0.814	0.811	0.903
73	ProximalPhalanxOutlineAgeGroup	0.822	0.848	0.828	0.845	0.668	0.783	0.817	0.835	0.655	0.826	0.833
74	ProximalPhalanxOutlineCorrect	0.825	0.785	0.811	0.814	0.689	0.681	0.833	0.845	0.731	0.842	0.824
75	ProximalPhalanxTW	0.770	0.785	0.772	0.790	0.676	0.724	0.762	0.797	0.706	0.775	0.780
76	RefrigerationDevices	0.563	0.489	0.512	0.533	0.551	0.547	0.487	0.475	0.567	0.567	0.507
77	ScreenType	0.532	0.551	0.581	0.545	0.552	0.395	0.505	0.575	0.573	0.521	0.563
78	SemgHandGenderCh2	0.701	0.742	0.772	0.728	0.646	0.659	0.777	0.781	0.721	0.804	0.809
79	SemgHandMovementCh2	0.390	0.414	0.417	0.389	0.303	0.211	0.400	0.416	0.329	0.423	0.466
80	SemgHandSubjectCh2	0.662	0.601	0.610	0.580	0.567	0.437	0.664	0.688	0.493	0.691	0.712
81	ShapeletSim	0.970	0.965	0.960	0.995	0.730	0.500	0.820	0.880	0.885	0.995	0.950
82	SmallKitchenAppliances	0.724	0.744	0.743	0.741	0.707	0.593	0.733	0.759	0.723	0.740	0.700
83	SmoothSubspace	0.840	0.827	0.843	0.873	0.637	0.543	0.870	0.893	0.679	0.897	0.877
84	SonyAIBORobotSurface1	0.990	0.994	0.992	0.994	0.973	0.971	0.992	0.989	0.968	0.994	0.987
85	SonyAIBORobotSurface2	0.986	0.989	0.984	0.984	0.971	0.964	0.989	0.994	0.932	0.991	0.985
86	StarLightCurves	0.951	0.976	0.976	0.976	0.516	0.847	0.977	0.950	0.868	0.978	0.897
87	Strawberry	0.698	0.927	0.932	0.930	0.755	0.643	0.928	0.938	0.750	0.939	0.940
88	SwedishLeaf	0.701	0.876	0.891	0.877	0.725	0.145	0.727	0.819	0.468	0.877	0.889
89	Symbols	0.989	0.988	0.990	0.992	0.766	0.759	0.993	0.995	0.747	0.989	0.981
90	SyntheticControl	0.955	0.950	0.942	0.930	0.947	0.917	0.965	0.982	0.948	0.980	0.995
91	ToeSegmentation1	0.888	0.855	0.870	0.840	0.866	0.713	0.892	0.914	0.852	0.896	0.899
92	ToeSegmentation2	0.855	0.856	0.830	0.855	0.759	0.752	0.850	0.825	0.856	0.777	0.898
93	Trace	0.875	0.830	0.805	0.885	0.830	0.485	0.860	0.965	0.780	0.935	1.000
94	TwoLeadECG	1.000	1.000	1.000	1.000	1.000	0.787	1.000	1.000	0.993	1.000	1.000
95	TwoPatterns	0.878	0.878	0.878	0.876	0.842	0.683	0.878	0.884	0.869	0.883	0.998
96	UMD	0.844	0.833	0.872	0.828	0.739	0.583	0.889	0.939	0.644	0.900	0.872
97	UWaveGestureLibraryAll	0.773	0.714	0.714	0.690	0.694	0.233	0.788	0.783	0.398	0.892	0.940
98	UWaveGestureLibraryX	0.727	0.728	0.723	0.710	0.552	0.310	0.733	0.746	0.388	0.757	0.793
99	UWaveGestureLibraryY	0.602	0.625	0.623	0.596	0.515	0.312	0.606	0.624	0.323	0.647	0.686
100	UWaveGestureLibraryZ	0.692	0.690	0.684	0.677	0.569	0.299	0.673	0.693	0.399	0.700	0.722
101	Wafer	0.977	0.933	0.952	0.972	0.909	0.894	0.913	0.913	0.894	0.998	0.996
102	Wine	0.583	0.576	0.540	0.667	0.578	0.504	0.667	0.738	0.487	0.583	0.676
103	WordSynonyms	0.348	0.319	0.296	0.274	0.306	0.214	0.371	0.364	0.243	0.372	0.539
104	Worms	0.550	0.535	0.570	0.504	0.523	0.437	0.579	0.542	0.446	0.574	0.549
105	WormsTwoClass	0.658	0.737	0.710	0.694	0.667	0.547	0.740	0.710	0.524	0.686	0.717
106	Yoga	0.848	0.856	0.859	0.839	0.701	0.529	0.880	0.851	0.587	0.899	0.830
Avg. Rank		5.79	5.15	4.93	6.17	8.55	10.50	4.99	3.94	8.89	3.23	2.92
Win		4	5	6	3	1	0	8	17	3	24	51
P-value		2.87E-07	1.24E-06	5.35E-06	5.66E-08	5.43E-19	1.88E-26	3.84E-06	1.63E-05	1.02E-21	4.08E-03	-

Table 2: The detailed test classification accuracy comparisons on 106 UCR time series datasets with a 10% labeling ratio. Win denotes the number of datasets in which the corresponding baseline achieved the best test accuracy. The best is in **bold**.

ID	Dataset	Supervised Pseudo-Label		TE	LPDeepSSL	MTL	TS-TCC	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	AllGestureWiimoteX	0.597	0.534	0.540	0.369	0.530	0.191	0.622	0.630	0.474	0.606	0.639
2	AllGestureWiimoteY	0.654	0.661	0.656	0.563	0.534	0.287	0.686	0.692	0.457	0.702	0.711
3	AllGestureWiimoteZ	0.608	0.534	0.575	0.504	0.346	0.250	0.633	0.638	0.129	0.649	0.672
4	ArrowHead	0.825	0.810	0.805	0.796	0.797	0.451	0.881	0.858	0.455	0.910	0.893
5	BME	0.683	0.794	0.739	0.722	0.633	0.556	0.728	0.706	0.556	0.806	0.978
6	Car	0.775	0.692	0.750	0.542	0.458	0.258	0.775	0.769	0.333	0.767	0.792
7	CBF	0.999	0.999	0.999	0.998	0.987	0.979	0.996	1.000	1.000	0.999	1.000
8	Chinatown	0.978	0.975	0.973	0.953	0.288	0.858	0.962	0.975	0.975	0.986	0.989
9	ChlorineConcentration	0.858	0.875	0.871	0.874	0.662	0.550	0.882	0.841	0.618	0.892	0.898
10	CinCECGTorso	0.976	0.988	0.985	0.955	0.854	0.675	0.989	0.971	0.655	1.000	0.997
11	Computers	0.794	0.830	0.792	0.776	0.798	0.650	0.802	0.816	0.808	0.796	0.796
12	CricketX	0.685	0.701	0.696	0.686	0.609	0.249	0.671	0.709	0.528	0.709	0.713
13	CricketY	0.635	0.683	0.687	0.654	0.541	0.191	0.667	0.694	0.481	0.714	0.719
14	CricketZ	0.639	0.691	0.672	0.671	0.581	0.185	0.621	0.713	0.545	0.700	0.701
15	Crop	0.716	0.710	0.716	0.711	0.664	0.462	0.716	0.728	0.566	0.726	0.746
16	DiatomSizeReduction	0.950	0.942	0.938	0.953	0.695	0.411	0.898	0.975	0.605	0.991	0.991
17	DistalPhalanxOutlineAgeGroup	0.827	0.818	0.831	0.831	0.764	0.772	0.818	0.815	0.666	0.800	0.813
18	DistalPhalanxOutlineCorrect	0.821	0.791	0.809	0.750	0.727	0.615	0.819	0.821	0.745	0.833	0.838
19	DistalPhalanxTW	0.777	0.754	0.787	0.767	0.733	0.698	0.753	0.800	0.605	0.774	0.765
20	DodgerLoopGame	0.723	0.793	0.820	0.765	0.581	0.519	0.786	0.741	0.634	0.863	0.924
21	DodgerLoopWeekend	0.937	0.943	0.906	0.912	0.673	0.759	0.881	0.912	0.874	0.949	0.987
22	Earthquakes	0.785	0.816	0.836	0.760	0.680	0.670	0.806	0.785	0.827	0.845	0.835
23	ECG200	0.947	0.944	0.943	0.940	0.942	0.899	0.952	0.820	0.800	0.946	0.907
24	ECG5000	0.999	0.997	0.998	0.993	0.983	0.840	0.998	0.947	0.930	1.000	0.969
25	ECGFiveDays	0.550	0.557	0.547	0.454	0.460	0.213	0.572	0.999	0.946	0.584	1.000
26	ElectricDevices	0.439	0.414	0.424	0.363	0.399	0.174	0.435	0.477	0.283	0.559	0.832
27	EOGHorizontalSignal	0.790	0.790	0.796	0.805	0.794	0.798	0.807	0.869	0.762	0.817	0.847
28	EOGVerticalSignal	0.860	0.863	0.862	0.858	0.836	0.769	0.862	0.463	0.324	0.865	0.596
29	EthanolLevel	0.663	0.636	0.625	0.539	0.244	0.253	0.640	0.611	0.254	0.686	0.689
30	FaceAll	0.952	0.966	0.963	0.937	0.856	0.425	0.958	0.967	0.893	0.972	0.982
31	FacesUCR	0.940	0.963	0.961	0.931	0.918	0.376	0.950	0.964	0.903	0.968	0.981
32	Fish	0.820	0.831	0.849	0.583	0.471	0.143	0.789	0.840	0.269	0.906	0.876
33	FordA	0.909	0.912	0.913	0.907	0.907	0.866	0.931	0.923	0.774	0.914	0.941
34	FordB	0.890	0.895	0.891	0.893	0.883	0.829	0.892	0.906	0.760	0.896	0.917
35	FreezerRegularTrain	0.997	0.997	0.997	0.898	0.681	0.758	0.995	0.998	0.820	0.998	0.999
36	FreezerSmallTrain	0.999	0.999	0.998	0.999	0.719	0.759	0.999	0.997	0.715	0.999	1.000
37	GesturePebbleZ1	0.829	0.751	0.760	0.711	0.760	0.250	0.793	0.849	0.793	0.796	0.905
38	GesturePebbleZ2	0.799	0.858	0.827	0.740	0.713	0.309	0.810	0.846	0.816	0.826	0.928
39	GunPoint	0.985	0.820	0.985	0.940	0.660	0.630	0.985	0.980	0.800	0.990	0.992
40	GunPointAgeSpan	0.987	0.991	0.978	0.989	0.767	0.857	0.996	0.991	0.872	0.987	0.988
41	GunPointMaleVersusFemale	0.987	0.993	0.991	0.892	0.993	0.982	0.996	1.000	0.682	0.998	0.999
42	GunPointOldVersusYoung	0.968	0.985	0.978	0.894	0.902	0.650	0.973	0.980	0.643	0.985	0.983
43	Ham	0.622	0.691	0.620	0.690	0.695	0.625	0.628	0.678	0.636	0.682	0.781
44	HandOutlines	0.868	0.868	0.848	0.834	0.682	0.639	0.833	0.843	0.708	0.897	0.900
45	Haptics	0.456	0.359	0.354	0.334	0.302	0.210	0.411	0.411	0.354	0.465	0.480
46	Herring	0.617	0.610	0.579	0.580	0.610	0.602	0.587	0.626	0.562	0.601	0.687
47	HouseTwenty	0.944	0.962	0.975	0.943	0.962	0.906	0.975	0.962	0.975	0.924	0.939
48	InlineSkate	0.366	0.412	0.408	0.441	0.299	0.163	0.346	0.369	0.277	0.528	0.395
49	InsectEPGRegularTrain	0.936	0.961	0.961	0.923	0.939	0.870	0.952	0.971	0.968	0.962	0.968
50	InsectEPGSmallTrain	0.959	0.981	0.981	0.785	0.970	0.830	0.989	0.981	0.936	0.963	0.949
51	InsectWingbeatSound	0.446	0.431	0.441	0.388	0.339	0.149	0.465	0.415	0.294	0.645	0.661
52	ItalyPowerDemand	0.961	0.967	0.964	0.973	0.830	0.929	0.962	0.964	0.908	0.970	0.975
53	LargeKitchenAppliances	0.912	0.915	0.901	0.883	0.892	0.620	0.883	0.923	0.615	0.913	0.897
54	Lightning2	0.612	0.669	0.678	0.686	0.627	0.636	0.712	0.629	0.645	0.712	0.786
55	Mallat	0.987	0.988	0.990	0.816	0.545	0.263	0.990	0.988	0.546	0.991	0.980
56	Meat	0.900	0.925	0.933	0.900	0.575	0.333	0.933	0.867	0.408	0.967	0.969
57	MedicalImages	0.664	0.708	0.708	0.704	0.557	0.521	0.615	0.692	0.563	0.696	0.701
58	MelbournePedestrian	0.893	0.869	0.872	0.869	0.664	0.629	0.893	0.900	0.577	0.899	0.902
59	MiddlePhalanxOutlineAgeGroup	0.756	0.757	0.762	0.751	0.497	0.724	0.734	0.746	0.592	0.764	0.766
60	MiddlePhalanxOutlineCorrect	0.797	0.759	0.774	0.773	0.660	0.622	0.802	0.800	0.660	0.821	0.829
61	MiddlePhalanxTW	0.591	0.612	0.622	0.612	0.420	0.540	0.613	0.598	0.539	0.629	0.635

62	MixedShapesRegularTrain	0.958	0.945	0.952	0.944	0.812	0.561	0.961	0.961	0.557	0.972	0.967
63	MixedShapesSmallTrain	0.949	0.947	0.953	0.942	0.716	0.583	0.960	0.955	0.521	0.972	0.959
64	MoteStrain	0.963	0.965	0.958	0.954	0.962	0.921	0.966	0.976	0.972	0.971	0.959
65	NonInvasiveFetalECGThorax1	0.460	0.426	0.454	0.382	0.084	0.033	0.523	0.448	0.118	0.386	0.802
66	NonInvasiveFetalECGThorax2	0.490	0.460	0.452	0.090	0.120	0.036	0.503	0.526	0.134	0.515	0.847
67	OSULeaf	0.930	0.923	0.928	0.886	0.840	0.410	0.942	0.937	0.516	0.935	0.858
68	PhalangesOutlinesCorrect	0.337	0.339	0.379	0.308	0.295	0.192	0.388	0.346	0.180	0.338	0.348
69	Phoneme	0.821	0.823	0.817	0.806	0.694	0.632	0.827	0.836	0.677	0.838	0.829
70	PLAID	0.357	0.337	0.347	0.312	0.365	0.194	0.342	0.382	0.288	0.317	0.378
71	Plane	1.000	1.000	1.000	1.000	0.929	0.486	1.000	1.000	0.405	1.000	0.986
72	PowerCons	0.814	0.844	0.831	0.822	0.786	0.761	0.851	0.856	0.814	0.814	0.903
73	ProximalPhalanxOutlineAgeGroup	0.825	0.840	0.831	0.848	0.783	0.783	0.850	0.858	0.461	0.856	0.859
74	ProximalPhalanxOutlineCorrect	0.861	0.850	0.864	0.870	0.469	0.703	0.871	0.865	0.744	0.859	0.834
75	ProximalPhalanxTW	0.769	0.789	0.789	0.786	0.693	0.727	0.790	0.787	0.450	0.793	0.807
76	RefrigerationDevices	0.576	0.639	0.627	0.572	0.583	0.564	0.596	0.543	0.565	0.655	0.576
77	ScreenType	0.601	0.648	0.656	0.640	0.601	0.409	0.591	0.629	0.551	0.639	0.619
78	SemgHandGenderCh2	0.856	0.788	0.804	0.793	0.724	0.662	0.836	0.828	0.822	0.879	0.862
79	SemgHandMovementCh2	0.501	0.449	0.493	0.431	0.331	0.258	0.477	0.524	0.439	0.516	0.522
80	SemgHandSubjectCh2	0.759	0.651	0.711	0.673	0.590	0.464	0.778	0.764	0.622	0.796	0.808
81	ShapeletSim	0.970	1.000	0.995	0.995	0.735	0.695	0.975	0.970	0.965	1.000	0.971
82	SmallKitchenAppliances	0.759	0.764	0.781	0.763	0.739	0.585	0.747	0.765	0.771	0.797	0.741
83	SmoothSubspace	0.893	0.927	0.903	0.933	0.790	0.867	0.937	0.897	0.792	0.883	0.888
84	SonyAIBORobotSurface1	0.997	0.990	0.989	0.990	0.990	0.974	0.992	0.997	0.987	0.997	0.991
85	SonyAIBORobotSurface2	0.990	0.995	0.996	0.987	0.981	0.979	0.989	0.994	0.985	0.996	0.992
86	StarLightCurves	0.977	0.978	0.977	0.837	0.613	0.849	0.979	0.980	0.898	0.980	0.924
87	Strawberry	0.894	0.947	0.952	0.942	0.646	0.643	0.949	0.958	0.666	0.949	0.960
88	SwedishLeaf	0.765	0.942	0.932	0.907	0.703	0.203	0.836	0.892	0.468	0.954	0.903
89	Symbols	0.994	0.991	0.989	0.990	0.835	0.896	0.991	0.996	0.669	0.996	0.991
90	SyntheticControl	0.985	0.988	0.985	0.983	0.978	0.885	0.988	0.982	0.965	0.995	0.995
91	ToeSegmentation1	0.953	0.955	0.963	0.952	0.955	0.899	0.963	0.974	0.930	0.963	0.957
92	ToeSegmentation2	0.795	0.886	0.880	0.848	0.807	0.789	0.875	0.934	0.843	0.530	0.934
93	Trace	0.995	0.995	0.995	0.990	0.975	0.590	1.000	1.000	0.955	1.000	1.000
94	TwoLeadECG	1.000	1.000	1.000	1.000	1.000	0.898	1.000	1.000	0.872	1.000	1.000
95	TwoPatterns	0.890	0.876	0.878	0.876	0.868	0.795	0.892	0.907	0.886	0.899	0.999
96	UMD	0.883	0.917	0.944	0.872	0.900	0.783	0.956	0.817	0.811	0.983	0.950
97	UWaveGestureLibraryAll	0.832	0.814	0.803	0.748	0.653	0.313	0.844	0.821	0.446	0.935	0.958
98	UWaveGestureLibraryX	0.768	0.743	0.737	0.730	0.520	0.446	0.761	0.779	0.619	0.779	0.827
99	UWaveGestureLibraryY	0.664	0.654	0.659	0.650	0.523	0.420	0.666	0.670	0.536	0.680	0.747
100	UWaveGestureLibraryZ	0.732	0.720	0.723	0.705	0.615	0.433	0.720	0.739	0.511	0.727	0.766
101	Wafer	0.998	0.914	0.997	0.996	0.913	0.894	0.998	0.999	0.894	1.000	1.000
102	Wine	0.738	0.673	0.699	0.638	0.450	0.487	0.749	0.666	0.541	0.738	0.865
103	WordSynonyms	0.411	0.393	0.400	0.366	0.350	0.230	0.456	0.432	0.242	0.448	0.617
104	Worms	0.531	0.512	0.492	0.567	0.602	0.481	0.575	0.566	0.492	0.469	0.568
105	WormsTwoClass	0.671	0.683	0.667	0.647	0.768	0.566	0.702	0.733	0.562	0.732	0.735
106	Yoga	0.888	0.901	0.899	0.893	0.763	0.562	0.910	0.892	0.661	0.927	0.899
Avg Rank		5.56	4.93	5.06	6.94	8.64	10.36	4.46	3.99	9.01	3.02	2.76
Win		3	6	6	3	3	0	10	17	2	27	58
P-value		2.01E-07	9.39E-07	3.45E-06	3.05E-09	4.79E-18	1.12E-24	3.44E-06	8.85E-07	1.81E-22	3.12E-03	-

Table 3: The detailed test classification accuracy comparisons on 106 UCR time series datasets with a 20% labeling ratio. Win denotes the number of datasets in which the corresponding baseline achieved the best test accuracy. The best is in **bold**.

ID	Dataset	Supervised Pseudo-Label		TE	LPDeepSSL	MTL	TS-TCC	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	AllGestureWiimoteX	0.676	0.674	0.702	0.557	0.556	0.195	0.670	0.653	0.514	0.685	0.760
2	AllGestureWiimoteY	0.766	0.677	0.743	0.685	0.587	0.272	0.763	0.787	0.468	0.786	0.805
3	AllGestureWiimoteZ	0.725	0.666	0.696	0.605	0.376	0.323	0.673	0.641	0.220	0.708	0.766
4	ArrowHead	0.886	0.891	0.853	0.867	0.801	0.589	0.896	0.929	0.503	0.914	0.943
5	BME	0.867	0.867	0.889	0.894	0.817	0.567	0.917	0.917	0.644	0.972	0.994
6	Car	0.817	0.815	0.833	0.783	0.633	0.250	0.758	0.894	0.483	0.892	0.897
7	CBF	1.000	1.000	0.999	0.999	0.984	0.985	0.999	1.000	1.000	1.000	1.000
8	Chinatown	0.984	0.986	0.982	0.986	0.288	0.910	0.982	0.989	0.987	0.986	0.992
9	ChlorineConcentration	0.961	0.972	0.975	0.962	0.658	0.555	0.964	0.949	0.703	0.976	0.978
10	CinCECGTorso	0.994	0.998	0.996	0.992	0.890	0.755	0.997	0.982	0.747	1.000	1.000
11	Computers	0.876	0.856	0.860	0.860	0.846	0.656	0.888	0.879	0.880	0.874	0.816
12	CricketX	0.819	0.813	0.814	0.780	0.722	0.301	0.790	0.810	0.514	0.824	0.828
13	CricketY	0.729	0.790	0.765	0.787	0.715	0.203	0.791	0.767	0.531	0.808	0.819
14	CricketZ	0.789	0.815	0.804	0.808	0.674	0.228	0.797	0.809	0.663	0.833	0.839
15	Crop	0.780	0.766	0.766	0.764	0.725	0.554	0.778	0.785	0.709	0.771	0.803
16	DiatomSizeReduction	0.994	0.978	0.967	0.988	0.833	0.351	0.957	0.998	0.456	0.997	0.999
17	DistalPhalanxOutlineAgeGroup	0.811	0.813	0.837	0.824	0.774	0.751	0.827	0.822	0.699	0.848	0.850
18	DistalPhalanxOutlineCorrect	0.822	0.837	0.832	0.816	0.708	0.615	0.842	0.838	0.743	0.834	0.845
19	DistalPhalanxTW	0.752	0.766	0.794	0.763	0.708	0.698	0.794	0.764	0.687	0.805	0.810
20	DodgerLoopGame	0.861	0.869	0.850	0.862	0.612	0.481	0.818	0.855	0.677	0.899	0.949
21	DodgerLoopWeekend	0.930	0.956	0.924	0.968	0.748	0.854	0.962	0.950	0.949	0.975	0.994
22	Earthquakes	0.885	0.891	0.890	0.910	0.773	0.670	0.915	0.807	0.859	0.885	0.866
23	ECG200	0.932	0.955	0.953	0.952	0.947	0.910	0.950	0.945	0.770	0.957	0.916
24	ECG5000	1.000	0.999	0.999	0.999	0.987	0.847	1.000	0.958	0.948	1.000	0.976
25	ECGFiveDays	0.645	0.631	0.633	0.577	0.603	0.231	0.650	1.000	0.865	0.724	1.000
26	ElectricDevices	0.577	0.563	0.510	0.425	0.462	0.276	0.460	0.706	0.313	0.695	0.883
27	EOGHorizontalSignal	0.798	0.781	0.787	0.798	0.814	0.798	0.796	0.626	0.313	0.827	0.849
28	EOGVerticalSignal	0.881	0.881	0.882	0.878	0.864	0.775	0.876	0.885	0.773	0.883	0.664
29	EthanolLevel	0.712	0.674	0.708	0.665	0.263	0.249	0.709	0.623	0.274	0.713	0.753
30	FaceAll	0.983	0.985	0.984	0.974	0.899	0.559	0.984	0.987	0.940	0.988	0.989
31	FacesUCR	0.987	0.978	0.978	0.973	0.942	0.550	0.978	0.990	0.920	0.986	0.989
32	Fish	0.923	0.919	0.917	0.880	0.477	0.143	0.943	0.960	0.340	0.951	0.923
33	FordA	0.928	0.927	0.928	0.922	0.918	0.898	0.936	0.942	0.767	0.927	0.949
34	FordB	0.903	0.900	0.898	0.895	0.887	0.878	0.900	0.917	0.751	0.905	0.934
35	FreezerRegularTrain	0.998	0.999	0.999	0.997	0.774	0.763	0.992	0.998	0.500	0.999	1.000
36	FreezerSmallTrain	0.992	0.998	0.998	0.998	0.710	0.762	0.998	0.999	0.501	0.999	1.000
37	GesturePebbleZ1	0.865	0.875	0.866	0.869	0.816	0.420	0.875	0.891	0.888	0.885	0.957
38	GesturePebbleZ2	0.872	0.905	0.878	0.852	0.844	0.475	0.876	0.911	0.915	0.908	0.954
39	GunPoint	0.995	1.000	1.000	0.990	0.940	0.775	1.000	0.990	0.900	1.000	0.998
40	GunPointAgeSpan	0.836	0.985	0.985	0.989	0.919	0.978	0.992	0.996	0.907	0.993	0.997
41	GunPointMaleVersusFemale	0.998	0.996	0.998	0.996	0.989	0.980	1.000	1.000	0.900	1.000	1.000
42	GunPointOldVersusYoung	0.972	0.927	0.907	0.922	0.842	0.758	0.983	0.993	0.628	0.987	0.989
43	Ham	0.678	0.701	0.794	0.743	0.678	0.519	0.682	0.776	0.730	0.725	0.855
44	HandOutlines	0.887	0.892	0.892	0.876	0.713	0.639	0.875	0.866	0.701	0.931	0.907
45	Haptics	0.467	0.465	0.475	0.437	0.322	0.214	0.504	0.460	0.337	0.531	0.560
46	Herring	0.540	0.650	0.656	0.625	0.563	0.602	0.691	0.624	0.562	0.587	0.705
47	HouseTwenty	0.956	0.994	0.994	0.994	0.956	0.906	0.988	0.969	0.944	0.963	0.948
48	InlineSkate	0.462	0.565	0.557	0.518	0.389	0.168	0.526	0.448	0.223	0.705	0.560
49	InsectEPGRegularTrain	0.974	0.994	0.994	0.997	0.997	0.961	0.990	0.997	0.974	0.987	0.981
50	InsectEPGSmallTrain	0.974	0.970	0.974	0.959	0.966	0.778	0.993	0.989	0.955	0.996	0.971
51	InsectWingbeatSound	0.546	0.544	0.491	0.439	0.355	0.272	0.574	0.523	0.271	0.746	0.717
52	ItalyPowerDemand	0.972	0.973	0.975	0.976	0.789	0.958	0.974	0.981	0.838	0.979	0.982
53	LargeKitchenAppliances	0.919	0.936	0.939	0.919	0.937	0.624	0.931	0.939	0.843	0.953	0.908
54	Lightning2	0.794	0.726	0.605	0.713	0.636	0.661	0.754	0.811	0.629	0.835	0.810
55	Mallat	0.991	0.990	0.992	0.990	0.340	0.321	0.993	0.991	0.579	0.995	0.992
56	Meat	0.967	0.658	0.975	0.858	0.617	0.333	0.965	0.908	0.333	0.975	0.992
57	MedicalImages	0.763	0.777	0.787	0.753	0.589	0.521	0.790	0.778	0.521	0.798	0.802
58	MelbournePedestrian	0.912	0.903	0.904	0.903	0.564	0.738	0.921	0.929	0.486	0.921	0.928
59	MiddlePhalanxOutlineAgeGroup	0.742	0.753	0.740	0.758	0.671	0.729	0.746	0.769	0.722	0.798	0.778
60	MiddlePhalanxOutlineCorrect	0.837	0.798	0.804	0.721	0.682	0.622	0.845	0.856	0.626	0.853	0.859
61	MiddlePhalanxTW	0.609	0.615	0.626	0.612	0.584	0.597	0.621	0.659	0.597	0.657	0.662

62	MixedShapesRegularTrain	0.969	0.968	0.962	0.966	0.744	0.683	0.972	0.977	0.378	0.974	0.978
63	MixedShapesSmallTrain	0.962	0.966	0.969	0.955	0.587	0.742	0.972	0.972	0.436	0.977	0.968
64	MoteStrain	0.969	0.973	0.971	0.969	0.967	0.943	0.970	0.976	0.977	0.970	0.975
65	NonInvasiveFetalECGThorax1	0.299	0.395	0.403	0.081	0.109	0.052	0.491	0.300	0.092	0.444	0.894
66	NonInvasiveFetalECGThorax2	0.351	0.440	0.460	0.179	0.109	0.048	0.632	0.396	0.082	0.520	0.926
67	OSULeaf	0.973	0.959	0.955	0.881	0.880	0.479	0.975	0.982	0.668	0.982	0.897
68	PhalangesOutlinesCorrect	0.420	0.445	0.457	0.437	0.330	0.219	0.443	0.384	0.254	0.477	0.459
69	Phoneme	0.852	0.858	0.846	0.847	0.661	0.640	0.873	0.860	0.685	0.853	0.865
70	PLAID	0.367	0.407	0.405	0.398	0.449	0.212	0.435	0.395	0.372	0.396	0.402
71	Plane	1.000	1.000	1.000	1.000	0.914	0.514	1.000	1.000	0.538	1.000	1.000
72	PowerCons	0.867	0.881	0.869	0.856	0.853	0.800	0.908	0.894	0.850	0.889	0.950
73	ProximalPhalanxOutlineAgeGroup	0.850	0.843	0.840	0.841	0.700	0.787	0.845	0.843	0.734	0.865	0.870
74	ProximalPhalanxOutlineCorrect	0.887	0.877	0.897	0.884	0.668	0.690	0.894	0.907	0.801	0.873	0.878
75	ProximalPhalanxTW	0.759	0.804	0.807	0.804	0.640	0.728	0.814	0.805	0.516	0.840	0.813
76	RefrigerationDevices	0.603	0.689	0.720	0.693	0.731	0.544	0.700	0.600	0.627	0.779	0.637
77	ScreenType	0.693	0.717	0.724	0.720	0.625	0.431	0.687	0.687	0.659	0.720	0.627
78	SemgHandGenderCh2	0.891	0.848	0.853	0.859	0.792	0.678	0.890	0.903	0.783	0.912	0.872
79	SemgHandMovementCh2	0.623	0.586	0.600	0.548	0.409	0.271	0.614	0.630	0.444	0.662	0.657
80	SemgHandSubjectCh2	0.828	0.798	0.799	0.732	0.582	0.537	0.846	0.861	0.700	0.858	0.892
81	ShapeletSim	0.995	0.985	0.995	0.995	0.975	0.800	0.990	1.000	0.995	1.000	0.989
82	SmallKitchenAppliances	0.779	0.797	0.789	0.800	0.728	0.589	0.805	0.801	0.753	0.827	0.767
83	SmoothSubspace	0.967	0.960	0.967	0.957	0.723	0.913	0.977	0.967	0.835	0.970	0.967
84	SonyAIBORobotSurface1	0.995	0.997	0.995	0.995	0.998	0.978	0.998	0.995	0.982	0.998	0.999
85	SonyAIBORobotSurface2	0.998	0.994	0.995	0.995	0.992	0.981	0.989	0.997	0.980	0.996	0.998
86	StarLightCurves	0.978	0.979	0.978	0.979	0.979	0.850	0.977	0.980	0.935	0.979	0.981
87	Strawberry	0.963	0.959	0.954	0.954	0.686	0.700	0.967	0.970	0.654	0.977	0.980
88	SwedishLeaf	0.968	0.956	0.948	0.941	0.814	0.553	0.953	0.978	0.473	0.979	0.926
89	Symbols	0.995	0.994	0.996	0.935	0.830	0.929	0.994	0.998	0.749	0.992	0.995
90	SyntheticControl	0.987	0.995	0.990	0.992	0.987	0.988	0.985	0.992	0.978	0.988	0.995
91	ToeSegmentation1	0.971	0.951	0.940	0.952	0.978	0.951	0.974	0.978	0.914	0.978	0.952
92	ToeSegmentation2	0.910	0.885	0.855	0.861	0.880	0.807	0.921	0.940	0.923	0.922	0.940
93	Trace	1.000	1.000	1.000	1.000	0.990	0.635	1.000	1.000	0.920	1.000	1.000
94	TwoLeadECG	1.000	1.000	1.000	1.000	1.000	0.995	1.000	1.000	0.990	1.000	1.000
95	TwoPatterns	0.905	0.906	0.901	0.909	0.886	0.833	0.915	0.918	0.903	0.918	1.000
96	UMD	0.983	0.983	0.983	0.972	0.911	0.750	0.978	0.996	0.833	0.994	0.999
97	UWaveGestureLibraryAll	0.874	0.880	0.874	0.860	0.668	0.478	0.879	0.876	0.535	0.923	0.977
98	UWaveGestureLibraryX	0.806	0.760	0.769	0.745	0.437	0.564	0.793	0.809	0.698	0.795	0.863
99	UWaveGestureLibraryY	0.707	0.721	0.722	0.657	0.530	0.503	0.729	0.726	0.626	0.717	0.808
100	UWaveGestureLibraryZ	0.788	0.784	0.781	0.765	0.480	0.534	0.784	0.800	0.631	0.794	0.812
101	Wafer	0.999	0.999	0.999	0.999	0.913	0.894	0.999	1.000	0.935	1.000	1.000
102	Wine	0.892	0.797	0.813	0.783	0.514	0.495	0.788	0.801	0.550	0.829	0.892
103	WordSynonyms	0.467	0.465	0.427	0.387	0.401	0.223	0.487	0.434	0.244	0.505	0.792
104	Worms	0.721	0.632	0.636	0.648	0.675	0.508	0.750	0.721	0.504	0.658	0.597
105	WormsTwoClass	0.760	0.761	0.768	0.760	0.756	0.670	0.783	0.771	0.562	0.728	0.802
106	Yoga	0.906	0.923	0.924	0.928	0.792	0.596	0.935	0.939	0.735	0.947	0.946
Avg. Rank		5.50	5.21	5.20	6.33	8.71	10.29	4.36	3.73	9.27	2.88	2.63
Win		7	7	6	5	4	0	11	18	2	28	64
P-value		1.44E-05	6.31E-06	1.59E-05	4.20E-06	1.52E-16	3.29E-24	1.84E-04	3.46E-04	9.40E-20	2.19E-02	-

Table 4: The detailed test classification accuracy comparisons on 106 UCR time series datasets with a 40% labeling ratio. Win denotes the number of datasets in which the corresponding baseline achieved the best test accuracy. The best is in **bold**.

ID	Dataset	ST	LTS	FFS	ADSN	DiffShape
1	ChlorineConcentration	0.510	0.445	0.536	0.232	0.749
2	DiatomSizeReduction	0.776	0.351	0.636	0.105	0.985
3	ECGFiveDays	0.925	0.727	0.778	0.916	1.000
4	GunPoint	0.725	0.720	0.694	0.760	0.930
5	ItalyPowerDemand	0.876	0.907	0.832	0.938	0.972
6	MedicalImages	0.507	0.521	0.521	0.520	0.637
7	MoteStrain	0.858	0.789	0.728	0.718	0.921
8	SonyAIBORobotSurface1	0.961	0.936	0.842	0.929	0.987
9	Symbols	0.613	0.463	0.433	0.549	0.981
10	SyntheticControl	0.558	0.695	0.475	0.523	0.995
11	Trace	0.320	0.350	0.500	0.455	1.000
12	TwoLeadECG	0.973	0.870	0.775	0.962	1.000
Avg. Rank		2.92	3.50	3.92	3.58	1.00
Win		0	0	0	0	12
P-value		1.60E-03	3.78E-04	2.86E-05	1.44E-03	-

Table 5: The detailed test classification accuracy comparisons on 12 UCR time series datasets with a 10% labeling ratio.

ID	Dataset	ST	LTS	FFS	ADSN	DiffShape
1	ChlorineConcentration	0.520	0.441	0.538	0.232	0.898
2	DiatomSizeReduction	0.752	0.416	0.646	0.106	0.991
3	ECGFiveDays	0.897	0.901	0.959	0.993	1.000
4	GunPoint	0.790	0.725	0.750	0.660	0.992
5	ItalyPowerDemand	0.901	0.932	0.818	0.938	0.975
6	MedicalImages	0.460	0.526	0.524	0.501	0.701
7	MoteStrain	0.899	0.832	0.839	0.883	0.959
8	SonyAIBORobotSurface1	0.966	0.939	0.824	0.916	0.991
9	Symbols	0.455	0.845	0.350	0.751	0.991
10	SyntheticControl	0.513	0.617	0.555	0.740	0.995
11	Trace	0.535	0.405	0.325	0.690	1.000
12	TwoLeadECG	0.983	0.945	0.829	0.971	1.000
Avg. Rank		3.25	3.50	3.92	3.33	1.00
Win		0	0	0	0	12
P-value		6.08E-04	7.37E-04	1.95E-04	3.37E-03	-

Table 6: The detailed test classification accuracy comparisons on 12 UCR time series datasets with a 20% labeling ratio.

ID	Dataset	ST	LTS	FFS	ADSN	DiffShape
1	ChlorineConcentration	0.625	0.462	0.541	0.232	0.978
2	DiatomSizeReduction	0.795	0.512	0.533	0.106	0.999
3	ECGFiveDays	0.991	0.940	0.998	0.921	1.000
4	GunPoint	0.880	0.810	0.690	0.905	0.998
5	ItalyPowerDemand	0.912	0.937	0.952	0.935	0.982
6	MedicalImages	0.511	0.522	0.530	0.528	0.802
7	MoteStrain	0.885	0.866	0.861	0.921	0.975
8	SonyAIBORobotSurface1	0.976	0.957	0.745	0.961	0.999
9	Symbols	0.629	0.444	0.573	0.645	0.995
10	SyntheticControl	0.495	0.753	0.575	0.620	0.995
11	Trace	0.580	0.550	0.569	0.735	1.000
12	TwoLeadECG	0.985	0.978	0.969	0.987	1.000
Avg. Rank		3.25	3.92	3.67	3.17	1.00
Win		0	0	0	0	12
P-value		9.24E-04	6.86E-04	1.56E-04	4.02E-03	-

Table 7: The detailed test classification accuracy comparisons on 12 UCR time series datasets with a 40% labeling ratio.

ID	Dataset	Supervised	LTS	ADSN	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	ChlorineConcentration	0.470	0.234	0.000	0.507	0.509	0.376	0.500	0.516
2	DiatomSizeReduction	0.879	0.304	0.000	0.832	0.838	0.709	0.873	0.966
3	ECGFiveDays	0.748	0.522	0.584	0.751	0.758	0.750	0.810	0.975
4	GunPoint	0.575	0.500	0.565	0.665	0.605	0.550	0.580	0.745
5	ItalyPowerDemand	0.845	0.501	0.791	0.874	0.882	0.834	0.875	0.955
6	MedicalImages	0.446	0.085	0.217	0.416	0.422	0.292	0.378	0.464
7	MoteStrain	0.853	0.462	0.660	0.858	0.859	0.866	0.874	0.868
8	SonyAIBORobotSurface1	0.919	0.438	0.704	0.944	0.936	0.870	0.950	0.879
9	Symbols	0.946	0.137	0.222	0.956	0.961	0.620	0.962	0.962
10	SyntheticControl	0.887	0.168	0.295	0.943	0.938	0.868	0.880	0.967
11	Trace	0.960	0.350	0.275	0.945	0.955	0.565	0.945	0.970
12	TwoLeadECG	0.871	0.508	0.547	0.919	0.927	0.501	0.886	0.930
Avg. Rank		4.25	7.67	7.08	3.50	2.92	5.92	3.08	1.42
Win		0	0	0	0	0	0	3	10
P-value		5.28E-03	8.07E-07	6.81E-05	2.14E-02	2.08E-02	2.18E-04	8.01E-03	-

Table 8: The detailed test classification accuracy comparisons on 12 UCR time series datasets with 2 label samples per class.

ID	Dataset	Supervised	LTS	ADSN	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	ChlorineConcentration	0.491	0.232	0.000	0.522	0.527	0.478	0.474	0.536
2	DiatomSizeReduction	0.981	0.304	0.000	0.969	0.978	0.608	0.985	0.988
3	ECGFiveDays	0.852	0.500	0.655	0.843	0.866	0.791	0.941	0.994
4	GunPoint	0.885	0.500	0.665	0.935	0.865	0.635	0.910	0.950
5	ItalyPowerDemand	0.910	0.501	0.792	0.942	0.931	0.854	0.922	0.966
6	MedicalImages	0.546	0.073	0.318	0.590	0.564	0.440	0.587	0.596
7	MoteStrain	0.862	0.462	0.622	0.868	0.874	0.872	0.887	0.882
8	SonyAIBORobotSurface1	0.952	0.438	0.578	0.952	0.952	0.886	0.961	0.931
9	Symbols	0.956	0.178	0.323	0.961	0.961	0.600	0.978	0.960
10	SyntheticControl	0.957	0.187	0.263	0.963	0.967	0.862	0.958	0.990
11	Trace	0.960	0.110	0.355	0.985	0.990	0.975	0.995	1.000
12	TwoLeadECG	0.950	0.471	0.548	0.966	0.972	0.501	0.978	0.985
Avg. Rank		4.50	7.83	7.00	3.25	3.00	5.83	2.58	1.67
Win		0	0	0	0	0	0	3	9
P-value		3.07E-03	1.37E-07	1.44E-05	3.96E-02	1.97E-02	8.12E-04	3.38E-02	-

Table 9: The detailed test classification accuracy comparisons on 12 UCR time series datasets with 5 label samples per class.

ID	Dataset	Supervised	LTS	ADSN	SemiTime	SSSTC	MTFC	TS-TFC	DiffShape
1	ChlorineConcentration	0.512	0.235	0.000	0.533	0.537	0.544	0.509	0.542
2	DiatomSizeReduction	0.982	0.304	0.000	0.988	0.988	0.528	0.985	0.991
3	ECGFiveDays	0.973	0.499	0.647	0.951	0.930	0.867	0.988	0.999
4	GunPoint	0.950	0.500	0.650	0.975	0.955	0.605	0.979	0.980
5	ItalyPowerDemand	0.954	0.501	0.553	0.965	0.956	0.935	0.957	0.971
6	MedicalImages	0.627	0.065	0.337	0.632	0.637	0.366	0.627	0.639
7	MoteStrain	0.880	0.462	0.596	0.889	0.896	0.893	0.892	0.892
8	SonyAIBORobotSurface1	0.968	0.438	0.752	0.977	0.973	0.921	0.979	0.974
9	Symbols	0.966	0.132	0.306	0.969	0.971	0.809	0.978	0.968
10	SyntheticControl	0.983	0.220	0.297	0.975	0.982	0.917	0.980	0.993
11	Trace	0.980	0.080	0.450	1.000	1.000	0.960	1.000	1.000
12	TwoLeadECG	0.969	0.500	0.565	0.976	0.983	0.682	0.990	0.993
Avg. Rank		4.58	7.83	7.08	3.17	2.83	5.33	2.75	1.75
Win		0	0	0	1	2	1	3	8
P-value		3.95E-05	1.28E-07	5.09E-06	1.94E-02	3.93E-02	2.51E-03	3.56E-02	-

Table 10: The detailed test classification accuracy comparisons on 12 UCR time series datasets with 10 label samples per class.

ID	Dataset	DiffShape	w/o Diff	real subsequence	random shape	w/o Language	w/o Diff & Language
1	ChlorineConcentration	0.749	0.614	0.613	0.577	0.581	0.571
2	DiatomSizeReduction	0.985	0.971	0.972	0.963	0.960	0.955
3	ECGFiveDays	1.000	1.000	1.000	1.000	1.000	0.981
4	GunPoint	0.930	0.920	0.920	0.925	0.925	0.915
5	ItalyPowerDemand	0.972	0.966	0.969	0.961	0.953	0.947
6	MedicalImages	0.637	0.615	0.618	0.616	0.589	0.543
7	MoteStrain	0.921	0.917	0.910	0.914	0.921	0.913
8	SonyAIBORobotSurface1	0.987	0.972	0.979	0.978	0.963	0.962
9	Symbols	0.981	0.979	0.978	0.971	0.977	0.961
10	SyntheticControl	0.995	0.992	0.992	0.992	0.992	0.992
11	Trace	1.000	0.950	0.970	0.953	0.975	0.975
12	TwoLeadECG	1.000	0.993	0.994	0.992	0.989	0.991
Avg. Rank		1.00	3.08	2.75	3.50	3.58	5.17
Win		12	1	1	1	1	0
P-value		-	3.35E-02	4.39E-02	4.14E-02	3.04E-02	1.22E-02

Table 11: The detailed test classification accuracy of ablation study on 12 UCR time series datasets with a 10% labeling ratio.

Method		Dataset	
		Trace	ChlorineConcentration
SSL baselines	Supervised (Cross entropy)	16.22	161.15
	Pseudo-Label (Lee et al. 2013)	26.35	902.30
	MTL (Jawed et al. 2020)	167.50	2671.55
	SemiTime (Fan et al. 2021)	898.40	3263.68
	SSSTC (Xi et al. 2022)	1030.06	4872.84
	MTFC (Wei et al. 2023)	217.27	4325.12
	TS-TFC (Liu et al. 2023)	30.19	986.95
Shapelet-based baselines	ST (Lines et al. 2012)	21487.61	11190.28
	LTS (Grabocka et al. 2014)	772.95	7343.92
	FSS (Ji et al. 2019),	129.70	4532.16
	ADSN (Ma et al. 2020)	1991.99	42826.91
DiffShape (Ours)		92.16	2355.10

Table 12: Analysis of runtime (in seconds) on the *Trace* and *ChlorineConcentration* time series datasets with a 10% labeling ratio for semi-supervised classification. The best is in **bold**, and the second best is in underlined.

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