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. To generate specific textual descriptions for each time series category, we employed a cross-validation grid search to obtain hard prompt templates tailored to each dataset.

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-Label [1]: 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 Ensembling [2]: 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.
- LPDeepSSL [3]: 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.
- MTL [4]: 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-TCC [5]: 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.
- SemiTime [6]: 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.
- SSSTC [7]: Xi et al. (2022) design a temporal relation prediction loss based on the spilt "past-anchor-future" seg-

[1]https://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/sstsc

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ments from labeled and unlabeled time series, thus contributing to time series semi-supervised classification.

- 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-frequencey 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 GitHub: https://github.com/qianlima-lab/DiffShape.

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.

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),

[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/benibaeumle/Learning-Shapelets
[12]https://github.com/benibaeumle/FSS-Algorithm
[13]https://github.com/qianlima-lab/ADSN

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: $Iter_{max}$;

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

Output: $w_f(\cdot)$, $g(\cdot)$, $w_s(\cdot)$, $h(\cdot)$ and $w_c(\cdot)$.

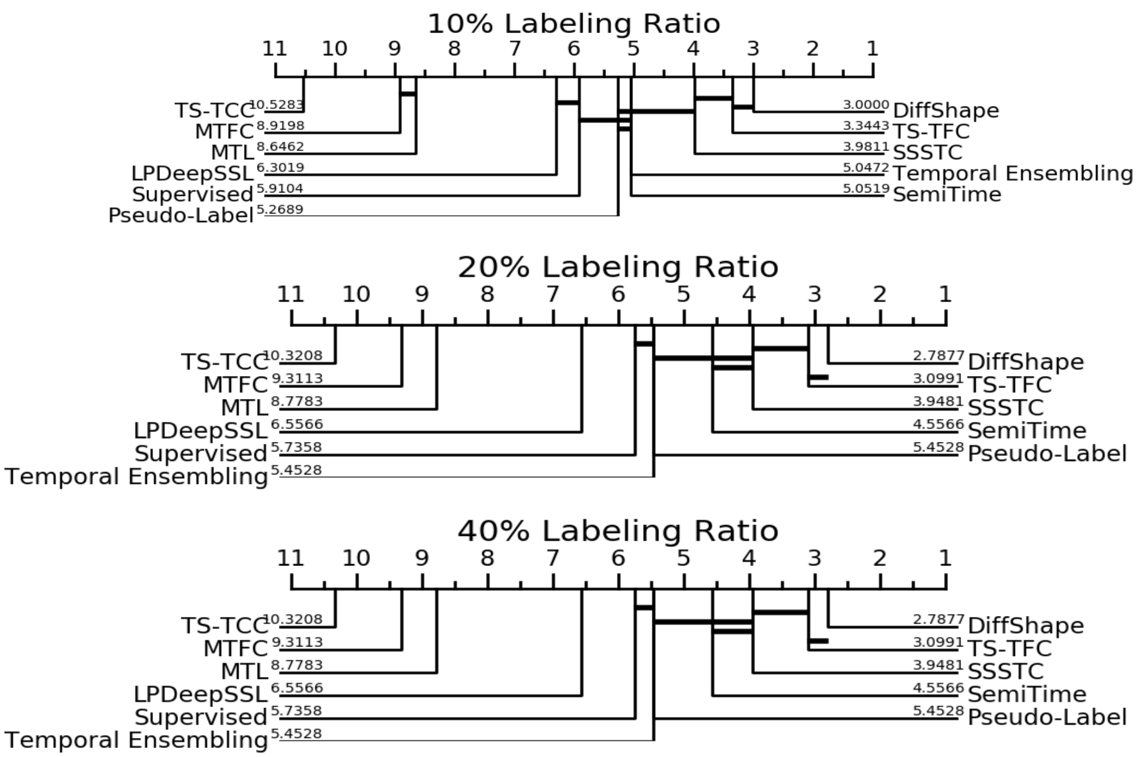
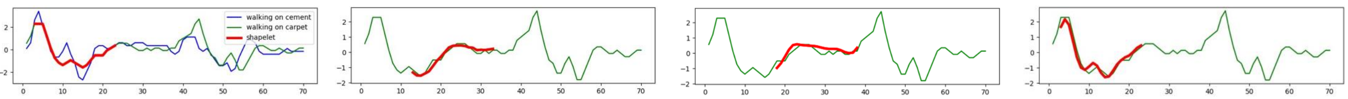
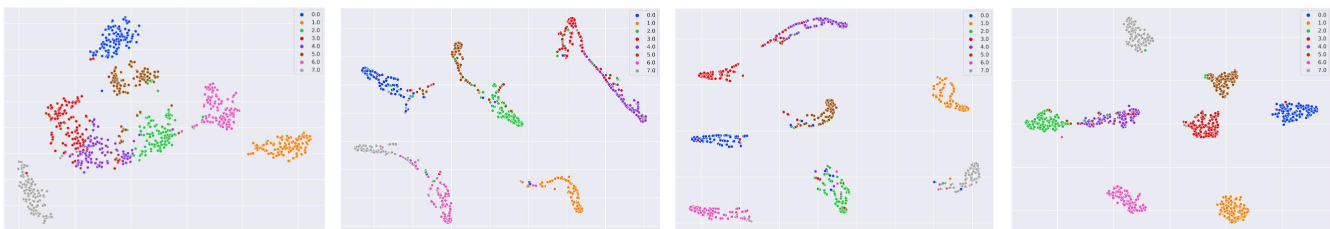


Figure 1: Critical Difference (CD) diagram (Demšar 2006) showing pairwise statistical difference comparison of 11 SSL methods on 106 UCR time series datasets. The CD diagram provides statistical insight into whether the differences are significant. By comparing the CD value of DiffShape with other 11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



(a) Raw shape (b) LTS (93.7%) (c) ADSN (92.4%) (d) DiffShape (98.7%)

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).



(a) Raw test set (b) SemiTime (79.0%) (c) TS-TFC (88.7%) (d) DiffShape (93.8%)

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.

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 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	**0.573**
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	**0.549**
4	ArrowHead	0.687	0.758	0.744	0.725	0.565	0.308	**0.765**	0.763	0.403	0.711	0.721
5	BME	0.633	0.672	0.694	0.661	0.667	0.550	0.678	0.672	0.517	0.694	**0.839**
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	**0.975**
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**	0.968
11	Computers	0.658	0.736	0.742	0.722	0.756	0.646	0.761	0.752	0.748	**0.764**	0.660
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**	0.589
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	**0.828**
18	DistalPhalanxOutlineCorrect	0.787	0.765	0.791	0.775	0.713	0.629	0.791	**0.814**	0.729	0.805	0.797
19	DistalPhalanxTW	0.746	0.732	0.741	0.699	0.731	0.691	**0.751**	0.750	0.655	0.742	0.749
20	DodgerLoopGame	0.651	0.676	0.708	0.632	0.576	0.481	0.683	0.708	0.620	0.842	**0.873**
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	0.798
23	ECG200	0.946	0.942	0.941	0.936	0.939	0.896	0.942	0.790	0.785	**0.950**	0.835
24	ECG5000	0.991	0.995	**0.997**	0.996	0.899	0.794	0.992	0.941	0.922	0.996	0.936
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	**0.688**
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**	0.496
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	0.763
33	FordA	0.891	0.900	0.906	0.899	0.890	0.800	0.905	0.914	0.629	0.907	**0.930**
34	FordB	0.881	0.877	0.884	0.882	0.872	0.805	0.892	**0.902**	0.774	0.873	0.901
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	**0.726**
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**	0.945
43	Ham	0.603	0.575	0.622	0.593	0.547	0.481	0.654	0.678	0.687	0.636	**0.702**
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	**0.386**
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	0.929
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	**0.559**
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	0.788
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	0.746
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**	0.702
68	PhalangesOutlinesCorrect	0.778	0.781	0.779	0.781	0.708	0.639	**0.806**	0.804	0.702	0.799	0.796
69	Phoneme	0.328	0.304	0.342	0.339	0.282	0.191	0.335	0.329	0.257	0.332	**0.343**
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	0.841
74	ProximalPhalanxOutlineCorrect	0.825	0.785	0.811	0.814	0.689	0.681	0.833	**0.845**	0.731	0.842	0.768
75	ProximalPhalanxTW	0.770	0.785	0.772	0.790	0.676	0.724	0.762	**0.797**	0.706	0.775	0.762
76	RefrigerationDevices	0.563	0.489	0.512	0.533	0.551	0.547	0.487	0.475	**0.567**	**0.567**	0.452
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	**0.440**
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	0.746
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	0.914
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	**0.763**
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	**0.702**
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	**0.479**
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**	0.794
	Avg. Rank	5.80	5.14	4.92	6.15	8.57	10.50	5.00	3.92	8.91	3.24	**2.92**
	Win	4	4	5	4	1	0	8	19	3	25	**51**

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	**0.972**
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**	0.994
11	Computers	0.794	**0.830**	0.792	0.776	0.798	0.650	0.802	0.816	0.808	0.796	0.674
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	0.811
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	0.774
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	**0.981**
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**	0.857
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	**0.911**
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	0.928
48	InlineSkate	0.366	0.412	0.408	0.441	0.299	0.163	0.346	0.369	0.277	**0.528**	0.365
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	0.829
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	0.787
68 PhalangesOutlinesCorrect	0.821	0.823	0.817	0.806	0.694	0.632	0.827	0.836	0.677	**0.838**	0.829
69 Phoneme	0.337	0.339	0.379	0.308	0.295	0.192	**0.388**	0.346	0.180	0.338	0.378
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	0.814
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	0.514
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**	0.749
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**	0.904
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	**0.812**
99 UWaveGestureLibraryY	0.664	0.654	0.659	0.650	0.523	0.420	0.666	0.670	0.536	0.680	**0.700**
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	**0.775**
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**	0.893
Avg. Rank	5.54	4.93	5.04	6.92	8.62	10.36	4.46	3.98	9.01	3.00	<u>2.86</u>
Win	3	6	6	3	3	0	10	17	2	27	<u>58</u>

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	**0.745**
2	AllGestureWiimoteY	0.766	0.677	0.743	0.685	0.587	0.272	0.763	0.787	0.468	0.786	**0.795**
3	AllGestureWiimoteZ	0.725	0.666	0.696	0.605	0.376	0.323	0.673	0.641	0.220	0.708	**0.737**
4	ArrowHead	0.886	0.891	0.853	0.867	0.801	0.589	0.896	0.929	0.503	0.914	**0.933**
5	BME	0.867	0.867	0.889	0.894	0.817	0.567	0.917	0.917	0.644	0.972	**0.989**
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	0.788
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	**0.936**
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	0.852
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	**0.875**
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	**0.991**
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	**0.926**
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**	0.980
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**	0.896
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**	0.694
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**	0.818
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	**0.983**
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	**0.908**
66	NonInvasiveFetalECGThorax2	0.351	0.440	0.460	0.179	0.109	0.048	0.632	0.396	0.082	0.520	**0.929**
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	0.852	0.858	0.846	0.847	0.661	0.640	**0.873**	0.860	0.685	0.853	0.865
69	Phoneme	0.420	0.445	0.457	0.437	0.330	0.219	0.443	0.384	0.254	**0.477**	0.459
70	PLAID	0.367	0.407	0.405	0.398	**0.449**	0.212	0.435	0.395	0.372	0.396	0.410
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	**0.942**
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**	0.810
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**	0.908
79	SemgHandMovementCh2	0.623	0.586	0.600	0.548	0.409	0.271	0.614	0.630	0.444	**0.662**	0.659
80	SemgHandSubjectCh2	0.828	0.798	0.799	0.732	0.582	0.537	0.846	0.861	0.700	0.858	**0.872**
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	**0.859**
99	UWaveGestureLibraryY	0.707	0.721	0.722	0.657	0.530	0.503	0.729	0.726	0.626	0.717	**0.795**
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	**0.740**
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**	0.938
	Avg. Rank	5.50	5.22	5.21	6.32	8.71	10.29	4.37	3.73	9.26	2.88	**2.62**
	Win	7	7	6	5	4	0	11	18	2	28	**64**

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**

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**

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	**0.980**
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**

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**

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**

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**

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

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)	<u>26.35</u>	<u>902.30</u>
	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	2855.10

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 <u>underlined</u>.

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