

# Time-Series Clustering: A Comprehensive Study of Data Mining, Machine Learning, and Deep Learning Methods

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## ABSTRACT

Time-series clustering is a key task in time series analysis, enabling unsupervised data exploration and often serving as a subroutine for other tasks. Despite decades of active cross-disciplinary research, benchmarking of time-series clustering methods has received limited attention. Existing studies have (i) excluded popular methods and entire method classes; (ii) used a narrow range of distance measures; (iii) evaluated only a few datasets; (iv) lacked statistical validation; (v) had poor reproducibility; or (vi) relied on questionable evaluation setups. The rise of deep learning—especially foundation models claiming broad generalization—further emphasizes the need for comprehensive evaluation, as their role in time-series clustering remains largely untested. To address these gaps, we evaluate 84 time-series clustering methods across 10 method classes from data mining, machine learning, and deep learning. Our analysis spans 128 time-series datasets and uses rigorous statistical methods. Within a fair comparison framework, we (i) identify the top-performing method in each class; (ii) highlight previously overlooked, high-performing classes; (iii) challenge assumptions about elastic distance measures; (iv) refute the claimed superiority of deep learning methods, including foundation models; (v) expose reproducibility issues; (vi) analyze performance variation across dataset properties; and (vii) assess scalability. Our findings reveal an illusion of progress: no method significantly outperforms the decade-old  $k$ -Shape method. Still, we highlight a deep learning-based approach with notable promise. Our results provide a strong benchmark for advancing time-series clustering, and we have open-sourced our work to support future research.

## PVLDB Reference Format:

John Paparrizos and Sai Prasanna Teja Reddy Bogireddy. Time-Series Clustering: A Comprehensive Study of Data Mining, Machine Learning, and Deep Learning Methods. PVLDB, 18(11): 4380 - 4395, 2025.

doi:10.14778/3749646.3749700

## PVLDB Artifact Availability:

The source code, data, and/or other artifacts have been made available at [www.timeseries.org/tsclusteringeval](http://www.timeseries.org/tsclusteringeval).

## 1 INTRODUCTION

A time series is a temporal sequence of ordered, time-indexed measurements. Recent advances in data storage and processing allow

**Table 1: Summary of our experimental evaluation across 128 datasets. The last four columns show category cardinality and distance measures (in parentheses) evaluated in previous studies.**

Clustering Class	Category Cardinality	Distance Measures	[77]	[121]	[88]	[72]
Partitional	6	10	3(3)	5(3)	5(3)	2(9)
Kernel-Based	2	4	✗	1(3)	✗	✗
Hierarchical	2	10	1(1)	1(3)	✗	✗
Density-Based	3	10	1(2)	2(3)	✗	✗
Distribution-Based	2	10	✗	✗	✗	✗
Model-Based	5	-	✗	✗	✗	✗
Shapelet-Based	3	-	✗	1	1	✗
Semi-Supervised	2	-	✗	✗	✗	✗
Deep Learning	32	-	✗	✗	26	✗
Foundation	3	-	✗	✗	✗	✗

us to capture and analyze large data volumes, including time series [69, 78, 79, 86, 92, 93, 98, 124]. Availability of large volumes of time-series data has led to an enormous interest in their analysis [61, 108, 115, 129, 130] utilizing tasks such as clustering [10, 13, 47, 59, 81, 120, 121, 127, 128, 132], classification [9, 49, 67, 119], anomaly detection [18–23, 23–25, 38, 94–97, 116, 117, 143], and similarity search [15, 28, 32, 45, 50, 91, 118, 123, 125, 126, 131, 153]. Applications of time-series analysis are prevalent across various domains in everyday life, such as astronomy [75, 148], biology [11, 12], economics [27, 106], energy sciences [8, 107], engineering [110, 111], environmental sciences [63, 70], medicine [35, 133], and social sciences [27, 109]. The remarkable growth, along with the widespread availability of time series data, has stimulated considerable interest in deriving insights from time series.

Clustering has emerged as a valuable technique in large-scale data analysis, allowing for effective summarization of dataset characteristics and serving as a crucial preprocessing step for various time-series analytical tasks. The goal is to partition data into multiple homogeneous groups where each group represents a characteristic pattern or structure in the data. However, applying traditional clustering methods to time-series data is challenging due to the interdependence of values across different time steps in a sequence. Consequently, the right choice of distance measure is crucial in accurately distinguishing similar and dissimilar time-series sequences. In recent decades, time-series clustering has received significant attention [10, 39, 120, 134, 154, 156]. Despite the abundance of clustering techniques and distance measures, factors such as domain diversity of datasets, distortions in sequences, and high dimensionality introduce challenges in developing robust algorithms. All these characteristics make time-series clustering a hard problem to formalize and solve. Therefore, it is imperative to conduct a systematic evaluation to compare various time-series clustering algorithms and their distance measures to gather a deeper understanding of the components that impact the efficacy of diverse models.

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Proceedings of the VLDB Endowment, Vol. 18, No. 11 ISSN 2150-8097.  
doi:10.14778/3749646.3749700

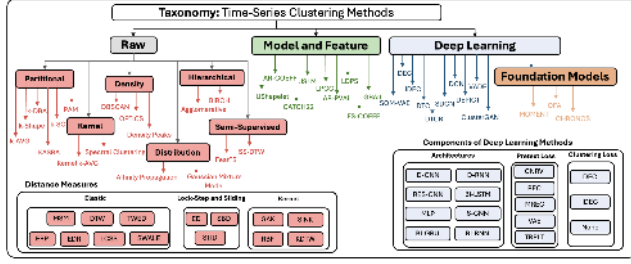


Figure 1: Taxonomy of time-series clustering methods.

Despite growing interest and numerous methods proposed, there has been a notable lack of thorough benchmarking analyses in the literature. Existing survey and benchmarking studies [2–4, 54, 77, 84, 88, 90, 121, 149] often suffer from limited scope regarding the diversity of clustering methods and categories. Furthermore, most clustering methods presented in these studies are evaluated on a limited number of datasets and arbitrary choice of assessment metrics. Reproducibility issues have emerged as a significant concern. The unavailability of original implementations for certain methods and the inadvertent introduction of potential bugs in popular third-party implementations hinder the ability to accurately replicate and validate previous findings. Table 1 compares and provides a quantitative summary of the existing benchmark studies and highlights the shortcomings in terms of missing classes and methods of time-series clustering algorithms and their distance measures. As a result, the conclusions from these studies are either incomplete or misleading and do not reflect actual progress in the field.

Given the gaps identified in previous research and the widespread interest in time-series clustering across various industries, conducting a thorough investigation is crucial. Our study is motivated by the need to address these shortcomings, aiming to provide research insights into time-series clustering. In addition, through our experimental evaluation of time-series clustering, we present several popular research questions (RQ) (see RQ1–RQ3 in Section 2) in the literature concerning (i) determining which time-series clustering methods, across the diverse classes of classical methods identified in the literature, demonstrate superior performance on a wide range of datasets; (ii) investigating the role of distance measures, including the effect of supervised tuning on parameter-dependent measures, in time-series clustering tasks; and (iii) exploring how deep learning and foundation models are leveraged in time-series clustering and assessing the impact they have on clustering performance. There are many misconceptions and biases in the answers to these questions, as they are derived from several popular prior studies on time-series clustering. Many of these studies employed buggy implementations, omitted methods, provided no or unclear parameter tuning instructions, omitted datasets, and arbitrarily selected metrics with little or no statistical testing. Therefore, it is imperative to address these enduring research questions.

In this study, we perform the most comprehensive analysis of time-series clustering to date, unveiling popular research questions in the current literature. In terms of **breadth** of this study, as depicted in Table 1, we incorporate 10 different clustering classes and consistently exceed the number of clustering techniques and appropriate distance measures implemented in each clustering class

compared to previous influential benchmarking studies. In addition, we present a taxonomy of time-series clustering methods in Figure 1, which summarizes the research efforts in this field. Regarding the **depth**, we compare all the clustering techniques presented in the study by evaluating them on the UCR time-series archive [34], comprising 128 datasets. This evaluation extends beyond the norm established by most individual time-series clustering studies [52, 101, 103] and benchmarking studies [72, 77, 88, 121], as we assess the performance of each clustering technique using three widely recognized clustering evaluation metrics. Additionally, two statistical tests are employed to demonstrate the statistical significance of the performance of clustering assessment metrics for a clustering technique relative to others, thereby contributing to a more comprehensive understanding of time-series clustering.

In summary, this study makes several key contributions: (i) it demonstrates that none of the time-series clustering methods proposed in the literature significantly outperform a decade-old method, namely,  $k$ -Shape; (ii) it offers a comprehensive evaluation of clustering categories and techniques often omitted from baseline comparisons in individual studies and benchmarking papers on time-series clustering; (iii) it critically assesses recent claims concerning parameter tuning and issues of reproducibility; (iv) it shows that deep learning-based time-series clustering models, including foundation models, do not statistically outperform leading classical models; (v) it introduces a novel distance-based deep contrastive time-series clustering model that exhibits promising potential; (vi) it includes a systematic evaluation of leading clustering algorithms, assessing performance variability across key dataset characteristics, analyzing their accuracy–runtime trade-offs, and performing a scalability analysis with respect to sequence length and dataset size; (vii) to facilitate future research and address the challenges identified, we are releasing a comprehensive, open-source library for time-series clustering at [1].

We start with the discussion on three popular research questions (Section 2). Then, we present our contributions:

- We provide an end-to-end and open-source benchmark containing 84 clustering methods spanning 10 different classes to ensure the reproducibility of our results (Section 3).
- We conduct a comprehensive evaluation of 8 well-known classes of classical time-series clustering methods (Section 4).
- We review and evaluate popular deep learning time-series clustering methods from the literature (Section 5.1).
- We further decompose the components of deep learning-based models into different design choices and analyze the impact of each component (Section 5.2 and 5.3).
- Finally, we present a comprehensive evaluation of clustering methods, assessing performance in terms of accuracy–runtime trade-offs, data distribution, and scalability (Section 6).

We conclude with the implications of our work and a discussion of new directions and challenges (Section 7).

## 2 THE THREE RESEARCH QUESTIONS

In this section, we outline three primary research questions arising from misconceptions and biases in time-series clustering. These questions reflect broader misunderstandings in the field that have, over time, been reinforced by subsequent research. Specifically, these questions address: (1) dataset selection, (2) evaluation metrics

and statistical tests, and (3) baseline comparisons and reproducibility. One major issue is the arbitrary selection of datasets for evaluation, as observed in [52, 77, 101, 103]. Often, researchers offer insufficient rationale for dataset choices, which may compromise claims of generalizability. Similarly, the choice of evaluation metrics and statistical tests can appear discretionary; applying these consistently would improve research objectivity and transparency. A further concern is the selection of baselines for comparisons. Some studies [52, 72, 77, 88, 101, 103] include a limited set of baselines, potentially omitting key methods that would provide a more comprehensive benchmark. Reproducibility also emerges as a significant challenge: the unavailability of original implementations complicates efforts to replicate and validate results in many published studies. Moreover, certain methods conceal critical evaluation parameters. For example, [72] evaluated popular parameter-dependent measures using default parameter values, thus obscuring their true potential. Similarly, [71] tested baseline models under parameter settings that appear suboptimal compared to those of the proposed approach. In particular, some baselines were restricted to 50 iterations, whereas the proposed model ran for 300 iterations; baseline centroids were initialized randomly, while the proposed model used *k*-Means++ initialization, a well-established enhancement that improves clustering quality. This reliance on additional iterations and *k*-Means++ initialization provided a performance advantage that baseline models did not leverage, raising concerns about fairness. Such disparities can mask the baseline methods' capabilities and complicate assessment of individual contributions in the proposed model. These issues continue to hinder the ability to draw definitive conclusions in the field, underscoring the persistent nature of these misconceptions across the literature.

Before framing our research questions, we must clarify that we do not suggest the discussed misconceptions were deliberately created or maliciously fabricated. Instead, we acknowledge they might arise from resource limitations, honest misinterpretations, or oversight. To address these misconceptions, we will use a question-and-answer format in our discussion to provide clarity and insight. **RQ 1: Which classical time-series clustering methods exhibit superior performance across datasets?**

**Discussion:** Literature lacks consensus on the most effective classical time-series clustering technique, as studies present conflicting results. For example, [77] evaluated nine partitional, hierarchical, and density-based methods, concluding that no method consistently outperforms others, since results depend on datasets and evaluation metrics. Similarly, [88] compared partitional methods and found no significant differences among *k*-AVG, *k*-Shape, and *k*-DBA. This ambiguity arises from two factors. First, many studies omit entire categories of methods, yielding incomplete evaluations. Second, methodological inconsistencies, such as variations in algorithm implementations (e.g., the *tslearn* implementation of *k*-Shape differs from the original authors) and differences in dataset selection or evaluation metrics, hinder reliable comparison. These limitations preclude definitive conclusions regarding the relative efficacy of classical clustering approaches.

**RQ 2: What is the role of distance measures in time-series clustering tasks, and how does supervised tuning of parameter-dependent measures affect their clustering performance?**

**Discussion:** Distance measures are pivotal in time-series clustering, as they quantify the degree of similarity or dissimilarity between sequences, influencing clustering outcomes and the algorithm's ability to discern patterns. Given the sequential nature of time-series data, often exhibiting variations in timing, amplitude, and shape, selecting an appropriate measure is essential. Traditionally, Euclidean Distance (ED) has been deemed inadequate for capturing shifts within sequences, leading to the belief in Dynamic Time Warping (DTW) as the superior approach due to its capacity to handle temporal distortions. However, Holder et al. [72] challenged this view by claiming ED's superiority in clustering tasks and reporting that parameter-free measures outperform many parameter-dependent measures. We contend that their study did not adequately explore parameter tuning for parameter-dependent measures, potentially overlooking their full capability, since the performance of parameter-dependent measures is highly sensitive to parameter settings. These conflicting findings underscore the need for a comprehensive evaluation of distance measures and the impact of supervised tuning. The lack of consensus on optimal distance measures and tuning procedures can lead practitioners to make suboptimal decisions.

**RQ 3: Do deep learning-based methods, including foundation models, outperform SOTA classical clustering methods?**

**Discussion:** While the prevailing consensus suggests that deep learning-based methods for time-series clustering surpass classical approaches, reflecting their success in domains such as computer vision [65, 147] and natural language processing [114, 155] the evidence supporting their superiority in time-series clustering is not definitive. Foundation models, such as large pre-trained neural networks and transformers, have introduced new possibilities for time-series clustering. Though successful in other domains, their application to time-series clustering is still largely unexplored and lacks comprehensive evaluation. Studies asserting that deep learning-based techniques surpass traditional algorithms often encounter several methodological challenges [88, 101, 103].

First, the choice of datasets, assessment metrics, and baselines can be arbitrary, lacking comprehensive evaluation and rendering the results difficult to generalize. Additionally, some studies [101] rely on baseline comparisons derived from previous research without actually re-running the original methods, which raises concerns about fairness in these settings. Others use highly tuned training parameters, such as learning rate and batch size, tailored to each dataset. Moreover, the absence of documentation for both the parameters and the tuning procedures impedes the generalizability of the approach and, in some instances, makes it impossible to reproduce the reported findings. This lack of transparency also calls into question the purportedly unsupervised nature of these methods, given the considerable degree of manual intervention involved. There is also a lack of surveys or benchmarks focusing on deep learning-based methods. Previous reviews [72, 77, 121] have predominantly excluded deep learning-based methods, leaving a gap in the comparative understanding of these approaches. The sole benchmark study on deep learning-based time-series clustering [88] reports significant performance improvements attributable to deep learning. However, despite its extensive evaluation, this study introduces too many variables to draw rigorous conclusions and overlooks a substantial portion of classical methods in its baseline comparisons. Moreover, among the classical methods selected

as baselines, we identified several implementation bugs. For instance, the tslearn implementation of  $k$ -Shape is inconsistent with the original author’s implementation and was erroneously applied to multivariate data by using only the first channel.

### 3 BACKGROUND

In this section, we review the relevant background necessary for our benchmarking study of time-series clustering methods.

**Datasets:** We conduct our evaluation using the UCR Time Series Archive [40], which is currently the largest publicly available collection of labeled time series datasets. The archive consists of 128 datasets collected from a diverse range of application domains, including biosignals, motion-capture data, image-based data, spectral and audio data, and device and power readings, among others. The datasets contain between 40 and 24,000 time series, with sequence lengths ranging from 15 to 2,844. All datasets are z-normalized, and each time series is associated with a single class label. A small subset of the datasets contains missing values and varying sequence lengths. Following the recommendations of the archive’s authors [34], we apply linear interpolation to impute missing values and resample shorter time series.

**Statistical Analysis:** We used the Wilcoxon signed-rank test [14, 43, 60, 150] with a 99% confidence level to perform analysis on pairwise comparison of results over multiple datasets. To control the family-wise error rate resulting from multiple pairwise comparisons, we adjusted the obtained p-values using the Holm–Bonferroni correction [73]. This reduces the likelihood of false positives while maintaining greater statistical power. We also apply the Friedman test [56] followed by the Nemenyi test [48] with a 90% confidence level to compare results across multiple methods and datasets as pairwise testing is not always adequate since null hypotheses are rejected because of random chance.

**Platform:** We conduct experiments on a cluster of 3 servers with identical configuration: Dual Intel(R) Xeon(R) Platinum 8168 (96-core with 2-way SMT), 2.70 GHz, 2TB RAM. Each server has an 8 NVIDIA Tesla V100-32GB with Ubuntu 18.04.3 LTS (64-bit) system.

**Implementation:** We have compiled a Python library containing state-of-the-art time-series clustering approaches evaluated in our study to ensure that all the comparisons are performed under the same framework for a consistent evaluation in terms of both performance and efficiency. For reproducibility purposes, we make all datasets, source codes, and results publicly available at [1].

**Experimental Settings:** To ensure the robustness of our findings, each algorithm evaluated in this study was executed independently 10 times. The resulting metrics were averaged prior to reporting and subsequent statistical analysis. To facilitate a fair comparison among clustering algorithms, common parameters were consistently set across all methods, unless explicitly stated otherwise. The number of clusters  $k$  was set equal to the true number of classes in each dataset; the number of iterations was fixed at 100; and the initialization strategy was specified as “random”.

**Evaluation Framework:** We evaluate the clustering performance using the following evaluation criteria: Rand Index (RI) [136], Adjusted Rand Index (ARI) [74] and Normalized Mutual Information (NMI) [157]. RI is a popular evaluation criterion in the literature [64, 101, 120, 151, 156, 159]. It ranges from 0 to 1, where 1 indicates perfect clustering and 0 indicates complete disagreement.

**Table 2: Pair-wise comparison of scalable partitional clustering algorithms with  $k$ -AVG + ED as the baseline.**

Clustering Algorithm	Distance Measure	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
$k$ -Shape	SBD	✓ (1.02e-6)	0.7335	0.2610	0.3444	86	4	38
KASBA	MSM	✗ (3.60e-3)	0.7223	0.2487	0.3345	81	0	47
$k$ -DBA	DTW	✗ (1.00e-0)	0.6791	0.2021	0.2776	47	0	81
$k$ -SC	STID	✗ (9.99e-1)	0.6282	0.1788	0.2492	38	0	90
$k$ -AVG	ED	-	<b>0.7160</b>	<b>0.2152</b>	<b>0.2994</b>	-	-	-

However, the expected RI of two random clustering results is not constant. ARI assumes a generalized hyper-geometric distribution where ground-truth and predicted clusters are randomly chosen, while the number of clusters and objects remains constant. NMI compares ground-truth to predicted clusters by quantifying mutual information. For the remainder of the evaluation, tabular results for all methods are presented in the following format. The “Better (Adj P Val)” column indicates whether an algorithm significantly outperforms the baseline based on the Wilcoxon test, with statistical significance determined using the Holm–Bonferroni-adjusted p-values. The symbol ✓ signifies that the algorithm exhibits statistically significant improvement relative to the baseline. Conversely, ✗ denotes statistically inferior performance compared to the baseline. The “RI,” “ARI,” and “NMI” columns display the mean values for the Rand Index, Adjusted Rand Index, and Normalized Mutual Information across 128 datasets. The last three columns show the number of datasets where an algorithm’s RI is better (“>”), equal (“=”), or worse (“<”) compared to the baseline. To assess the statistical differences in performance across multiple methods, we apply the Friedman–Nemenyi test to obtain the average rank of methods across all datasets, using the results to generate the critical difference (CD) diagrams. The solid line in the CD diagram indicates the group of methods that show no statistical significance.

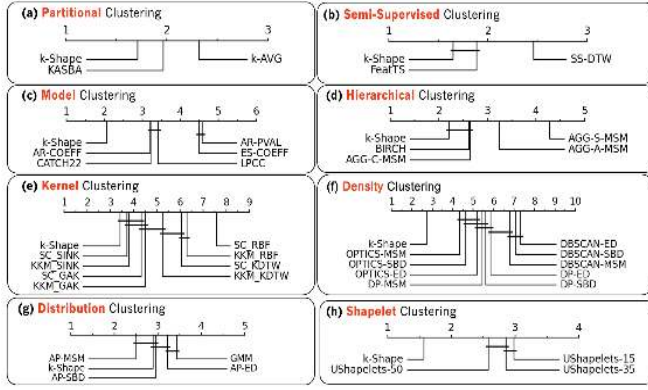
### 4 CLASSICAL TIME-SERIES CLUSTERING

In this section, we will discuss time-series clustering methods, categorized into two approaches by data utilization, as shown in Figure 1. The first includes methods that operate on raw data, adapting algorithms with novel distance measures or centroid computations. The second approach involves feature or model based methods that transform raw sequential data into representations suitable for Euclidean space, enabling conventional clustering algorithms. Our evaluation examines five categories within the raw-data based domain: partitional, kernel, density, hierarchical, and distribution-based techniques. Additionally, we investigate three categories within the model and feature based domain: shapelet-based, semi-supervised, and model-based techniques.

#### 4.1 Partitional Clustering

$k$ -AVG [102] and Partition Around Medoids (PAM) [82] are two popular partitional clustering methods.  $k$ -AVG minimizes intra-cluster distances by iteratively updating centroids, computed as the average of all points in a cluster, which may not correspond to actual samples. In contrast, PAM selects representative data points—medoids—as cluster centers, ensuring that all centers are real samples. Although PAM offers robustness against outliers and accommodates a variety of distance measures beyond Euclidean, its scalability is limited in comparison to  $k$ -AVG, which demonstrates linear scalability with dataset size. Shape-based clustering





**Figure 2: CD diagrams of (a) Partitional, (b) Semi-Supervised, (c) Model, (d) Hierarchical, (e) Kernel, (f) Density, (g) Distribution, and (h) Shapelet clustering algorithms based on their average ranks across datasets. The solid lines indicate groups of methods whose differences are not statistically significant.**

algorithms, which utilize distance measures invariant to scaling, translation, and shifting, represent another approach within partitional clustering. Among these, *k*-Shape [120] emerges as the leading *k*-AVG-like algorithm due to its scalability and accuracy in effective distance measure and centroid computation. Additionally, *k*-DBA [134] extends the *k*-AVG by incorporating DTW as the distance measure and employing DTW Barycenter Averaging (DBA) for centroid update, offering a more representative average of sequential data sets than simple averaging. Similarly, *k*-SC [154] adapts *k*-AVG to accommodate a scaling and translation invariant distance measure (STID), further refining the centroid update through the spectral norm of a matrix. KASBA [71] extends *k*-AVG with MSM distance measure and an alternative elastic *k*-Means++ centroids. The distance calculation can be pruned using the triangle inequality, and centroids are updated via stochastic subgradient descent for elastic barycenter averaging.

**Evaluation of Partitional Clustering:** For the first set of experiments, we performed an analysis of several widely recognized *scalable* partitional clustering algorithms. For these comparisons, we selected *k*-AVG as the baseline method due to its simplicity and widespread usage in clustering benchmarks. The results, presented in Table 2, demonstrate that *k*-Shape and KASBA surpass the baseline algorithm, *k*-AVG, in 86 and 81 out of 128 datasets, respectively, whereas, *k*-DBA and *k*-SC do so on only 47 and 38 datasets, respectively. Wilcoxon test (as presented in the “Better” column of Table 2) indicates that only *k*-Shape significantly outperforms *k*-AVG. Furthermore, the Friedman-Nemenyi test from Figure 2(a) reveals that *k*-Shape significantly outperforms both KASBA and *k*-AVG.

Consequently, we focus our subsequent analyses on *k*-Shape, as it is the only method that surpasses the baseline. We have identified that the widely used *k*-Shape implementation from *tslearn* contains critical bugs. To address these issues, we employed the original implementation provided by the *k*-Shape authors to generate our results, thereby resolving reproducibility concerns observed in recent literature. Given that *k*-Shape outperforms all scalable partitional methods, we will adopt *k*-Shape as the new baseline for subsequent analyses until a new method is found that statistically outperforms *k*-Shape. Subsequently, we evaluated the efficacy of

**Table 3: Pair-wise comparison of PAM across various popular distance measures using *k*-Shape as the baseline. For each parameter-dependent elastic measure, the first row in the “Parameters” column indicates the best parameters obtained with supervision [125], while the second row shows the unsupervised parameters.**

Similarity Measure	Parameters	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
MSM	LOOCV	✗ (1.00e-0)	0.7235	0.2335	0.3563	47	0	81
	$c = 0.5$	✗ (1.00e-0)	0.7209	0.2311	0.3532	46	0	82
TWED	LOOCV	✗ (1.00e-0)	0.7225	0.2335	0.3567	48	0	80
	$\lambda, v = 1, 0.0001$	✗ (1.00e-0)	0.7185	0.2195	0.3429	38	0	90
ERP	-	✗ (1.00e-0)	0.7222	0.2299	0.3541	43	0	85
SBD	-	✗ (1.00e-0)	0.7173	0.2180	0.3393	37	0	91
SWALE	LOOCV	✗ (1.00e-0)	0.7089	0.2072	0.3265	44	0	84
	$\epsilon = 0.2$	✗ (1.00e-0)	0.7060	0.1927	0.3101	41	0	87
DTW	LOOCV	✗ (1.00e-0)	0.7117	0.2076	0.3378	40	0	88
	$\delta = 0.1$	✗ (1.00e-0)	0.7087	0.2008	0.3284	44	0	84
EDR	LOOCV	✗ (1.00e-0)	0.7074	0.1919	0.3099	40	0	88
	$\epsilon = 0.1$	✗ (1.00e-0)	0.7034	0.1732	0.2898	36	0	92
LCSS	LOOCV	✗ (1.00e-0)	0.7060	0.1980	0.3156	41	0	87
	$\delta, \epsilon = 5, 0.2$	✗ (1.00e-0)	0.6998	0.1637	0.2855	33	0	95
ED	-	✗ (1.00e-0)	0.7012	0.1752	0.2988	31	0	97
<b>k-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

PAM, employing seven different elastic measures, namely, MSM [141], TWED [105], ERP [30], SWALE [112], DTW [16], EDR [31], and LCSS [5, 146] as well as the most effective lock-step and sliding measures from existing literature, Euclidean (ED) and SBD [120], respectively. We evaluated the performance of parameter-dependent elastic measures in both supervised and unsupervised settings, using parameter values drawn from [125]. Although utilizing supervised parameter selection may confer an inherent advantage, potentially bordering on bias, it was deemed necessary to fully ascertain the capabilities of these measures. From the ‘Better’ column in Table 3, it is evident that none of these measures, under both supervised and unsupervised settings, statistically outperform *k*-Shape according to the Wilcoxon test. The observed (1.00e-0) values in Table 3 can be attributed to the adjustment provided by the Holm–Bonferroni correction, which substantially reduces the likelihood of false positives while maintaining greater statistical power. Similarly, the upper portion of Figure 3(a) indicates that elastic measures employed with supervision on parameter tuning have no significant difference in performance compared to *k*-Shape, as indicated by the Friedman-Nemenyi test. In contrast, the lower section of Figure 3(a) provides compelling evidence of *k*-Shape’s superior performance over these measures in unsupervised settings.

## 4.2 Kernel-based Clustering

Kernel *k*-AVG (KKM) and Spectral Clustering (SC) offer distinct advantages for identifying clusters that are non-linearly separable within the original input space. KKM leverages a kernel function to project sequences into a higher-dimensional feature space, thereby facilitating the partitioning of data that becomes linearly separable in this new space [44]. In contrast, SC employs a different approach by computing eigenvectors from the affinity matrix and subsequently using these eigenvectors for clustering the data with *k*-AVG [113]. Our evaluation of these kernel-based methods incorporates four prominent kernel functions. Initially, we utilize the Radial Basis Function (RBF) [36], which effectively extends the Euclidean measure to a high-dimensional space, making sequences linearly separable. We also explore a sliding kernel, SINK [122], which assesses all possible alignments between two time-series

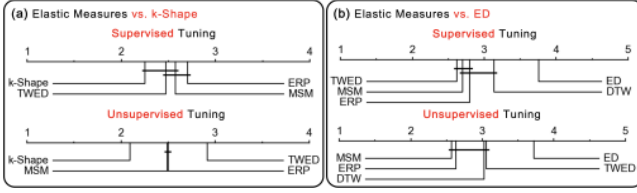


Figure 3: (a) CD diagrams of the top three Elastic measures with both supervised and unsupervised parameter settings [125], with *k*-Shape clustering (a strong baseline) across 128 datasets. (b) CD diagrams of the top three elastic measures with supervised and unsupervised parameter settings [125], along with DTW and ED, based on their average ranks across datasets. The solid lines indicate groups of methods whose differences are not statistically significant.

Table 4: Pair-wise comparison of Kernel-based clustering algorithms with *k*-Shape as the baseline.

Clustering Algorithm	Distance Measure	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
Kernel <i>k</i> -AVG	SINK	✗ (1.00e-0)	0.7287	0.2553	0.3461	56	0	72
	GAK	✗ (1.00e-0)	0.7119	0.2237	0.3499	42	0	86
	KDTW	✗ (1.00e-0)	0.6825	0.1020	0.2125	37	0	91
	RBF	✗ (1.00e-0)	0.6643	0.0241	0.1368	21	0	107
SC	SINK	✗ (1.00e-0)	0.7321	0.2661	0.3513	61	0	59
	GAK	✗ (1.00e-0)	0.6871	0.2421	0.3546	49	0	79
	KDTW	✗ (1.00e-0)	0.5681	0.1721	0.2896	30	0	98
	RBF	✗ (1.00e-0)	0.4863	0.0104	0.1182	14	0	114
<b><i>k</i>-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

sequences, thus providing a nuanced analysis of their similarities. Additionally, we investigate two kernels, GAK [37] and KDTW [105], designed to extend elastic measures, offering a sophisticated means of comparing the dissimilarity of time-series data.

**Evaluation of Kernel-based Clustering:** From the previous section, we adopted *k*-Shape as the new baseline for our subsequent analyses, given its strong performance, until we encounter a new method that statistically outperforms it. Now, we focus on evaluating the performance of KKM and SC, using four representative kernel measures: RBF, SINK, GAK, and KDTW. Our findings, presented in Table 4, juxtapose the clustering efficacy of these kernel measures against *k*-Shape. The comparative analysis reveals that, even under supervised conditions, none of the kernel measures statistically outperform *k*-Shape, as determined by the Wilcoxon test. Specifically, KKM’s performance with SINK, GAK, KDTW, and RBF kernels under supervised settings outperforms *k*-Shape in 56, 42, 37, and 21 instances, respectively. Similarly, SC’s efficacy with the same kernels outperforms *k*-Shape in 61, 49, 30, and 14 datasets, respectively. Poor performance of the RBF kernel underscores that Euclidean based measures underperform relative to elastic or alignment-based similarities in time-series clustering. As depicted in Figure 2(e), the Friedman-Nemenyi test suggests that none of the kernel-based methods outperform *k*-Shape.

### 4.3 Density-based Clustering

DBSCAN [51] is a leading density-based clustering algorithm that identifies densely packed, non-spherical clusters while isolating sparse outliers. It relies on the concept of reachability, wherein clusters are expanded by including neighboring data points within a specified radius. OPTICS [6] extends DBSCAN by producing an ordered traversal of points to detect clusters across regions of varying density; however, both methods require careful selection of parameters such as the neighborhood radius and minimum point

Table 5: Pair-wise comparison of Hierarchical clustering algorithms with *k*-Shape as the baseline.

Clustering Algorithm	Distance Measure	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
BIRCH	-	✗ (1.00e-0)	0.7123	0.2305	0.3483	47	0	81
AGG-C	MSM	✗ (1.00e-0)	0.7058	0.2415	0.3712	51	0	77
	SBD	✗ (1.00e-0)	0.6828	0.1962	0.3370	35	0	93
	ED	✗ (1.00e-0)	0.6820	0.1705	0.3006	32	0	96
AGG-A	MSM	✗ (1.00e-0)	0.6450	0.2152	0.3515	36	0	92
	SBD	✗ (1.00e-0)	0.6210	0.1577	0.2909	29	1	99
	ED	✗ (1.00e-0)	0.5959	0.1584	0.3010	30	0	98
AGG-S	MSM	✗ (1.00e-0)	0.4421	0.0841	0.1859	21	0	107
	SBD	✗ (1.00e-0)	0.4222	0.0660	0.1638	18	0	110
	ED	✗ (1.00e-0)	0.4222	0.0635	0.1600	18	0	110
<b><i>k</i>-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

count. In contrast, the Density Peaks algorithm [137] obviates explicit parameter specification by selecting cluster centers whose neighbors have lower local density and are maximally distant from points of higher density, then assigning remaining points to their nearest high-density neighbor.

**Evaluation of Density-based Clustering:** For this set of experiments, we evaluate the performance of various density-based clustering methods. For this evaluation, we incorporated the ED measure alongside two of the most effective sliding and elastic measures, SBD and MSM, identified as top performers in Section 4.1. To ensure a fair comparison: minPts was chosen via grid search over {5, 10, 15}; the  $\epsilon$  parameter in DBSCAN and the distance-cutoff parameter in Density Peaks were both determined using knee-point detection. Although density-based approaches are designed to robustly handle outliers, none of these methods consistently outperformed *k*-Shape on more than 30 datasets, thereby underscoring the superior performance of *k*-Shape. Moreover, as evidenced by the Friedman-Nemenyi test shown in Figure 2(f), *k*-Shape significantly outperforms density methods.

### 4.4 Hierarchical Clustering

In our evaluation study, we selected Agglomerative Clustering (AGG) [82] and BIRCH [160] as representative hierarchical clustering methods due to their widespread adoption. AGG employs a bottom-up strategy, initially treating each sequence within the dataset as a cluster. This approach progressively merges clusters based on their similarity, culminating in a unified cluster that encompasses all sequences. To ascertain the proximity between clusters, we employed recognized linkage criteria: single, average, and complete linkage. BIRCH is notable for its scalability and robustness in managing outliers. It constructs a cluster-feature tree that encapsulates the data’s essential cluster configurations while optimizing memory usage. Subsequent global clustering leverages summaries derived from the cluster-feature tree, employing agglomerative clustering techniques to ultimately achieve comprehensive clustering. **Evaluation of Hierarchical Clustering:** Akin to the evaluation from the previous section, we performed an assessment of AGG methods using the ED, SBD, and MSM measures. Our findings reveal a clear performance hierarchy among the agglomerative clustering strategies. Specifically, complete linkage consistently outperformed average linkage, which in turn showed significant superiority over single linkage across all evaluated distance measures. As summarized in Table 5, even the best-performing hierarchical methods, such as the agglomerative clustering with complete linkage, only

**Table 6: Pair-wise comparison of Distribution-based clustering algorithms with  $k$ -Shape as the baseline.**

Clustering Algorithm	Distance Measure	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
AP	MSM	✗ (6.85-e1)	0.7289	0.2204	0.4269	70	0	58
	SBD	✗ (1.00-e0)	0.7284	0.2180	0.4001	66	0	62
	ED	✗ (1.00-e0)	0.7137	0.1662	0.3731	57	0	71
GMM	-	✗ (1.00-e0)	0.7165	0.2193	0.3067	49	0	79
<b><math>k</math>-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

outperformed  $k$ -Shape in 51 out of the 128 datasets. The "Better" column in Table 5 and the corresponding Figure 2(d) provide further statistical evidence from Wilcoxon and Friedman-Nemenyi tests that none of the hierarchical methods outperform  $k$ -Shape.

#### 4.5 Distribution based Clustering

Affinity Propagation (AP) [55] identifies exemplars within datasets, around which clusters of data points are formed. Furthermore, this process entails treating all data points as potential exemplars and facilitating a message exchange among them until a consensus on the exemplars is reached. Gaussian Mixture Models (GMMs), as discussed in the works of [42, 142], offer a sophisticated framework for distribution-based clustering. Moreover, GMM posits that the data are generated from a finite mixture of Gaussian distributions, each corresponding to a cluster. These distributions, characterized by unknown parameters, are unraveled through the Expectation-Maximization algorithm, enabling the clustering of unlabeled data by estimating the parameters of the Gaussian mixture.

**Evaluation of Distribution based Clustering:** In line with our previous analysis, we selected the ED, SBD, and MSM measures. Our findings, detailed in Table 6, indicate that AP using MSM, SBD, and ED, as well as GMM, outperforms  $k$ -Shape clustering in 70, 66, 57, and 49 out of 128 datasets, respectively. However, despite the robust performance of the AP methods, statistical analysis using the Wilcoxon test and the Friedman-Nemenyi test indicates that none of the distribution-based methods decisively outperform  $k$ -Shape.

#### 4.6 Shapelet and Semi-Supervised Clustering

Unlike methods that use entire time-series sequences for clustering, U-Shapelets [156] utilize subsequences with pronounced patterns, shapelets, to identify outliers. However, this approach is confined to smaller datasets and does not scale with increasing data size. To mitigate this limitation, we employ a scalable U-Shapelets variant [145], which sustains clustering quality without significant compromise. Dynamic Time Warping (DTW) is renowned for its precision in quantifying similarity between time-series sequences, yet its application is hindered by the high computational cost associated with longer sequences. The Learning DTW Preserving Shapelets (LDPS) [99] framework approximates DTW distance using ED between shapelets, preserving the integrity of the original sequences. Additionally, the Unsupervised Shapelet Learning Model (USLM) [158] presents a shapelet-based clustering algorithm that employs an iterative learning process, leveraging pseudo-labels, spectral analysis, shapelet regularization, and regularized least-squares to derive shapelets and define decision boundaries effectively. In the semi-supervised category, FeatTS [144] leverages graph encoding and community detection to construct a co-occurrence matrix from extracted statistical features. SS-DTW [41]

**Table 7: Pair-wise comparison of Shapelet-based clustering algorithms with  $k$ -Shape as the baseline. An asterisk (\*) indicates that some methods are evaluated on a subset of datasets due to unfeasible runtimes.**

Clustering Algorithm	Shapelet Length	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
UShapelet	50%	✗ (1.00e-0)	0.5718	0.1510	0.2385	26	0	102
	35%	✗ (1.00e-0)	0.5227	0.1081	0.2014	24	0	104
	15%	✗ (1.00e-0)	0.4976	0.0885	0.1715	23	0	105
<b><math>k</math>-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-
LDPS*	-	-	0.6849	0.2835	0.3248	-	-	-
USLM*	-	-	0.5008	0.1213	0.1532	-	-	-
<b><math>k</math>-Shape*</b>	-	-	<b>0.6925</b>	<b>0.2943</b>	<b>0.3420</b>	-	-	-

**Table 8: Pair-wise comparison of Semi-Supervised clustering algorithms with  $k$ -Shape as the baseline.**

Clustering Algorithm	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
FeatTS	✗ (1.00-e0)	0.7203	0.2823	0.3229	59	0	69
SS-DTW	✗ (1.00-e0)	0.6307	0.1383	0.2427	28	1	99
<b><math>k</math>-Shape</b>	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

addresses the critical task of selecting an optimal DTW warping-window width, a parameter essential for clustering performance across diverse domains of datasets.

**Evaluation of Shapelet-based and Semi-Supervised Clustering:** We conducted an evaluation of the UShapelet model using three distinct shapelet lengths: 50%, 35%, and 15%. The results, summarized in Table 7, indicate that the U-Shapelet methods do not surpass the performance of the  $k$ -Shape algorithm in more than 26 of the 128 datasets. Other shapelet-based clustering techniques, such as USLM and LDPS, were evaluated on a smaller subset of 25 datasets due to prohibitive computational runtimes. Furthermore, both the "Better" column in Table 7 and Figure 2 (h) provide compelling evidence of  $k$ -Shape's superiority over shapelet-based clustering methods, as demonstrated by Wilcoxon and Friedman-Nemenyi statistical tests. Shapelet-based clustering, although conceptually promising, as it captures localized patterns, did not yield robust results. One possible explanation is that the unsupervised discovery of shapelets is inherently challenging and susceptible to overfitting noise or irrelevant patterns. Within the semi-supervised clustering category, as shown in Table 8, the FeatTS method emerged as the most effective, outperforming  $k$ -Shape in 59 of the 128 datasets. However, as illustrated in Figure 2(b), while FeatTS significantly outperforms SS-DTW, it demonstrates no substantial performance difference when compared with the  $k$ -Shape approach. For both categories, all parameters were set as in original implementations.

#### 4.7 Model and Feature based Clustering:

Model-based clustering assumes each sequence in a cluster is generated by a model following a probability distribution. Piccola [135] introduced complete linkage agglomerative clustering on autoregressive coefficients using Euclidean similarity. Kalpakis [81] applied  $k$ -Medoids clustering to Linear Predictive Coding Cepstra (LPCC), employing Euclidean similarity derived from autoregressive coefficients. This approach, emphasizing cepstral coefficients, distinguishes time series more effectively than coefficients from the Discrete Fourier Transform (DFT), Discrete Wavelet Transform (DWT), or Principal Component Analysis (PCA). The Chi-Square



**Table 9: Pair-wise comparison of Model-based clustering algorithms with  $k$ -Shape as the baseline.**

Clustering Algorithm	Parameters	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
$k$ -AVG	AR - COEFF	✗ (1.00e-0)	0.6885	0.1159	0.1881	32	0	96
	Catch22	✗ (1.00e-0)	0.6870	0.1409	0.2247	29	0	99
	LPCC	✗ (1.00e-0)	0.6851	0.1126	0.1820	33	0	95
	AR - P VAL	✗ (1.00e-0)	0.6502	0.0489	0.1135	17	0	111
	ES - COEFF	✗ (1.00e-0)	0.5839	0.0803	0.1557	26	0	102
$k$ -Shape	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

test assesses significant differences between stationary time series. Maharaj [104] proposed agglomerative hierarchical clustering based on Chi-Square p-values. A major limitation of model-based methods is their reliance on assumptions that may not hold, limiting applicability. catch22 [100] selects 22 features from the hctsa suite’s 4,791 features, capturing diverse time-series characteristics and providing a feasible solution for time-series signatures.

**Evaluation of Model and Feature based Clustering:** Techniques such as AR-COEFF, LPCC, AR - P VAL, and ES-COEFF utilize the coefficients from various time-series modeling methods for clustering, whereas Catch22 employs 22 meticulously selected time-series features for clustering purposes. Table 9 reveals that none of these methods outperform  $k$ -Shape in more than 33 out of 128 datasets. Similarly, "Better" column in Table 9 and Figure 2 (c) indicate that  $k$ -Shape statistically outperforms all model-based time-series clustering methods.

#### 4.8 Addressing $RQ1$ and $RQ2$

The results of our comprehensive evaluation of classical time-series clustering methods challenge several claims in the literature. For example, [72] report that  $k$ -Shape does not outperform  $k$ -AVG, yet Section 4.1 demonstrates this finding arises from unfair parameter settings (as discussed in Section 2). Similarly, [77, 88] reported underwhelming  $k$ -Shape performance in the literature, largely due to bugs in the tslearn implementation. However, using the original implementation shows that  $k$ -Shape, a decade-old approach, still outperforms all scalable partitional methods, establishing it as a robust baseline. Employing  $k$ -Shape as our benchmark, we evaluated other classical methods and found that none significantly surpassed it, thus providing critical insights into  $RQ1$ .

Addressing  $RQ2$ , our empirical results provide key insights that help resolve some ambiguities regarding distance measures in time-series clustering. Contrary to [72]’s assertion of the inefficacy of DTW compared to ED, our empirical evaluation (see Figure 3(b)) provides compelling evidence that DTW consistently outperforms ED with statistical significance across both supervised and unsupervised settings. This finding effectively addresses the first part of  $RQ2$ . The choice of parameters for parameter-dependent distance measures, such as MSM, TWED, SWALE, DTW, EDR, LCSS, SINK, GAK, KDTW, and RBF, is arbitrary in the literature. From Figure 3(a), we observe that, in the unsupervised setting,  $k$ -Shape outperforms the top elastic measure with statistical significance; in the supervised setting, there is no significant difference in performance. Likewise, TWED outranks all other elastic measures in the supervised context, whereas in the unsupervised setting it is outranked by parameter-free measures such as ERP. Similarly, kernel measures perform better in supervised than unsupervised settings. These results underscore the variability of distance-measure efficacy across contexts. It is notable that the right parameter choice significantly

**Table 10: Pair-wise comparison of Deep Learning-based clustering algorithms with  $k$ -Shape as the baseline.**

Clustering Algorithm	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
IDEC	✗ (1.00-e0)	0.7159	0.2150	0.2967	46	0	82
DEPICT	✗ (1.00-e0)	0.7111	0.1900	0.2743	42	0	86
SDCN	✗ (1.00-e0)	0.7104	0.2000	0.2884	45	0	83
DEC	✗ (1.00-e0)	0.7090	0.1935	0.2790	43	0	85
DTC	✗ (1.00-e0)	0.7085	0.2123	0.2985	43	1	85
ClusterGAN	✗ (1.00-e0)	0.7082	0.2100	0.2965	41	0	87
VADE	✗ (1.00-e0)	0.7027	0.1734	0.2605	33	0	95
DTCR	✗ (1.00-e0)	0.6832	0.1392	0.2184	28	0	100
SOM-VAE	✗ (1.00-e0)	0.6457	0.0976	0.1804	21	0	107
DCN	✗ (1.00-e0)	0.5716	0.0444	0.1097	15	0	113
$k$ -Shape	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

influences distance-measure performance. Hence, there is a serious need to explore methods that can determine accurate parameters in an unsupervised fashion. Therefore, there is clear evidence that parameter selection is crucial for parameter-dependent measures to reach fullest potential, thus addressing the second part of  $RQ2$ .

## 5 DEEP LEARNING BASED TIME-SERIES CLUSTERING

This section presents our investigation into deep learning-based clustering methods for time series, structured in two parts, as shown in Figure 1. First, we examine the efficacy of deep learning models, including foundation models, for time-series clustering in the literature. Then, we perform a comparative analysis to evaluate the impact of architectural elements and loss function choices on model performance. This approach offers a detailed understanding of how individual components affect overall clustering performance.

### 5.1 Existing Work

Most deep learning-based time-series clustering algorithms have predominantly adhered to a structured methodology, with minor variations in handling representation vectors. DCN [152] jointly optimizes representation learning via a deep autoencoder and  $k$ -Means clustering. DEC [151] iteratively optimizes a Kullback–Leibler divergence objective on an auxiliary target distribution to refine cluster assignments. IDEC [64] extends DEC by jointly optimizing clustering and autoencoder reconstruction losses, preserving local data structure. DTCR [101] integrates the  $k$ -Means objective with temporal reconstruction and an auxiliary classification task that distinguishes genuine and synthetic samples, enriching encoder representations with contextual depth. DTC [103] expanded on [64] by incorporating a more sophisticated autoencoder and various temporal similarity metrics to assess the Kullback-Leibler divergence between predicted and target distributions. SOM-VAE [52] introduced a framework employing a gradient-based self-organizing map alongside a Markov model, enabling discrete representation of time series sequences and probabilistic interpretation of temporal transitions. DEPICT [58] extends [64] by applying multi-reconstruction for pretext loss and cross-entropy for clustering loss, whereas SDCN [17] integrates a graph convolutional network to preserve local neighborhood structures within the latent space. VADE [80] extends variational autoencoders by learning distinct distributions for each cluster, and ClusterGAN [57] introduces a GAN-based framework that incorporates a clusterer network to





**Table 13: Pair-wise comparison of Deep Learning Architectures.**

Model Architecture	Architecture Type	Clustering Algorithm	RI	ARI	NMI
RES-CNN	Convolution	REC + None	0.7201	0.2359	0.3207
S-CNN	Convolution	REC + None	0.7122	0.2262	0.3164
MLP	Fully Connected	REC + None	0.7102	0.2234	0.3089
BI-RNN	Recurrent	REC + None	0.7060	0.1983	0.2877
BI-GRU	Recurrent	REC + None	0.6959	0.1818	0.2681
BI-GRU + ATTN	Recurrent	REC + None	0.6935	0.1916	0.2763
D-CNN	Convolution	REC + None	0.6845	0.2282	0.3115
D-RNN	Recurrent	REC + None	0.6823	0.1752	0.2526
BI-LSTM	Recurrent	REC + None	0.6687	0.1781	0.2831

encoder and decoder, and the mean squared error is computed between each layer in the decoder and the corresponding reflected layer in the encoder. **(c) Variational Autoencoder Loss (VAE)** [85]: Unlike regular autoencoder model, variational autoencoder maps input data to a multivariate latent distribution. Encoder and decoder are trained jointly to minimize reconstruction loss and converge expected and observed distributions. **(d) Triplet Loss (TRPLT)** [139]: It is a supervised method that pulls encoder representations from same class closer to the input while pushing away representations from other classes. Triplet loss in clustering utilizes a time-based sampling strategy to generate same and different classes samples in an unsupervised manner. **(e) Contrastive Loss (CNRV)** [33]: It learns representations by maximizing agreement between the input time-series and closest time-series to the input in the dataset by Euclidean (ED) metric.

• **Clustering Loss:** We employ seven popular clustering losses from the literature **(a) DEC** [151]: It improves object assignment confidence to its cluster using KL divergence between the soft assignment distribution and a target distribution from current cluster assignments. **(b) IDEC** [64]: An extension of DEC, combining reconstruction loss and KL divergence, with weight  $\gamma$  set to 0.1. **(c) DEPICT** [58]: It extends the IDEC with multi-reconstruction loss for pretext phase and standard cross-entropy loss for clustering phase. **(d) SDCN** [17]: It trains graph convolutional networks with the encoder to preserve local data relations using DTW distance based KNN-graph. **(e) VADE** [80]: It modifies variational autoencoder loss to better fit the clustering task by learning  $K$  (number of clusters) expected and observed distributions for each cluster. **(f) DTCR** [101]: It is a weighted combination of three training objectives where the first component is reconstruction loss, second component is  $K$ -Means loss and the final component is an auxiliary classification loss that can identify real and fake time-series data. **(g) ClusterGAN** [57]: It modifies regular GAN by adding an additional clusterer network  $C$  along with a discriminator network  $D$  and a generator network  $G$ . The clusterer network  $C : x \rightarrow \hat{z}$  generates the representation vectors from real input data and the generator network  $G : z \rightarrow \hat{x}$  generates the realistic input data from representation vectors. The discriminator network discriminates to identify if the joint distributions of samples and features ( $C(x), x$ ) and ( $z, G(z)$ ) belong to generator or clusterer.

**Evaluation of Comparative Study:** We conduct a comparative analysis to elucidate performance variances among components of deep learning models for time-series clustering. Our evaluation focuses on three elements: architectures, pretext losses, and clustering losses. First, we assess the performance of various architectures using reconstruction loss as the pretext loss without

**Table 14: Pair-wise comparison of Architectural, Pretext Loss, and Clustering Loss combinations, with  $k$ -Shape as the baseline.**

Clustering Algorithm	Model Architecture	Better (Adj. P Val)	RI	ARI	NMI	>	=	<
CNRV + NONE	RES-CNN	✗ (1.00e-0)	0.7393	0.2702	0.3832	64	0	64
CNRV + IDEC	RES-CNN	✗ (1.00e-0)	0.7337	0.2565	0.3709	55	0	73
MREC + IDEC	RES-CNN	✗ (1.00e-0)	0.7209	0.2480	0.3366	48	0	80
REC + IDEC	RES-CNN	✗ (1.00e-0)	0.7187	0.2331	0.3194	52	0	76
MREC + NONE	RES-CNN	✗ (1.00e-0)	0.7183	0.2474	0.3389	54	0	74
REC + NONE	RES-CNN	✗ (1.00e-0)	0.7181	0.2319	0.3184	53	0	75
CNRV + NONE	FCN	✗ (1.00e-0)	0.7201	0.1994	0.3191	56	0	72
CNRV + IDEC	FCN	✗ (1.00e-0)	0.7198	0.1932	0.3094	54	0	74
MREC + IDEC	FCN	✗ (1.00e-0)	0.7110	0.2227	0.3083	55	0	73
REC + IDEC	FCN	✗ (1.00e-0)	0.7098	0.2218	0.3075	52	0	76
MREC + NONE	FCN	✗ (1.00e-0)	0.7089	0.2205	0.3062	52	0	76
REC + NONE	FCN	✗ (1.00e-0)	0.7102	0.2215	0.3069	55	0	73
CNRV + NONE	BI-RNN	✗ (1.00e-0)	0.7187	0.2026	0.3182	51	0	77
CNRV + IDEC	BI-RNN	✗ (1.00e-0)	0.7147	0.1918	0.3080	46	0	82
MREC + IDEC	BI-RNN	✗ (1.00e-0)	0.6959	0.1830	0.2692	48	0	80
REC + IDEC	BI-RNN	✗ (1.00e-0)	0.6956	0.1825	0.2681	37	0	91
MREC + NONE	BI-RNN	✗ (1.00e-0)	0.6967	0.1846	0.2700	37	0	91
REC + NONE	BI-RNN	✗ (1.00e-0)	0.6951	0.1811	0.2667	39	0	89
<b><math>k</math>-Shape</b>	-	-	<b>0.7335</b>	<b>0.2610</b>	<b>0.3444</b>	-	-	-

any clustering loss. The findings, summarized in Table 13, indicate that convolution-based architectures, particularly the RES-CNN, surpass others in performance. Among fully-connected and recurrent architectures, the MLP and BI-RNN emerge as top performers, respectively. However, Friedman-Nemenyi test finds no statistically significant differences across architectures. In the subsequent phase, we investigate the effectiveness of various pretext losses in conjunction with IDEC and None clustering losses, employing the RES-CNN architecture. The findings, as detailed in Table 12, identify CNRV, MREC, and REC as the most effective pretext losses for both clustering frameworks. Using Friedman-Nemenyi tests, we gather compelling evidence that CNRV significantly outperforms the other pretext losses, while MREC and REC exhibit similar performance levels with no substantial differences. We select the best architectures, pretext losses, and clustering losses based on prior findings. The RES-CNN, MLP, and BI-RNN are designated as the premier models across convolutional, fully-connected, and recurrent architectural categories, respectively. Among pretext losses, CNRV, MREC, and REC are recognized for their superior performance. For clustering losses, both IDEC and None are identified as the most effective. An examination of these selected components, as depicted in Table 14, unveils intriguing observations. RES-CNN consistently outperforms other architectures across all pretext and clustering loss combinations. In the context of pretext losses, CNRV consistently outperforms alternatives, improving performance irrespective of architecture or clustering loss. Figure 4(b) shows that combining RES-CNN with CNRV and None clustering loss yields statistically significant improvements over other deep learning-based methods from literature. Finally, comparing IDEC and None clustering losses reveals no significant performance difference.

### 5.3 Addressing $RQ3$

The perceived advancements within the research community regarding the impact of deep learning on time-series clustering appear somewhat illusory. Many studies that introduce deep learning-based methods for time-series clustering typically adapt general-purpose deep clustering models or extend existing frameworks.

Additionally, there are significant issues with the evaluation frameworks used in these studies. For example, DTCR uses only 36 datasets. Additionally, DTCR uses only a few baselines and relies on baseline results borrowed from various studies, which carries the risk of adopting potential implementation flaws from those earlier works. Similarly, DTC’s evaluation is limited to only 13 datasets and relies on the ROC metric, which may not be the most suitable choice for clustering tasks. Additionally, DTC compares against just two baselines and lacks statistical testing, which considerably weakens the reliability of its results. SOM-VAE utilizes image data instead of time-series data. Similar to the other methods, it does not include statistical testing and overlooks several important techniques from the literature in its baseline comparisons. The absence of thorough statistical testing raises questions about whether the proposed advancements are statistically significant when compared against both classical state-of-the-art methods and earlier deep learning methods. Our analysis, as illustrated in Figure 4(a), demonstrates that the performance differences among deep learning-based clustering models are negligible, with none surpassing *k*-Shape.

A recent comparative study [88] exhaustively evaluates the core components of deep learning-based time-series clustering methods, but we identified several concerns. It introduces too many variables, making it difficult to draw rigorous conclusions, and fails to include foundational models or many classical methods in its baseline comparisons. We also discovered multiple implementation errors among the baselines; for example, the *tslearn* implementation of the *k*-Shape algorithm—deviating from the original author’s implementation—was incorrectly applied. In response, our study aims for a more streamlined evaluation, focusing on the architectural decisions, pretext loss, and clustering loss choices to provide clarity. Our findings, detailed in Figure 4(b), identify contrastive learning based models like RES-CNN architecture combined with CNRV pretext loss and NONE clustering loss as the sole configuration demonstrating superior performance over other deep learning-based methods documented in the literature. We attribute this to its ability to adeptly integrate time-series domain features to optimize contrastive loss. However, from Figure 4(c), we find that even this model does not exhibit a significant performance difference when compared to the *k*-Shape. Similarly, while foundation models have demonstrated exceptional performance in image and language tasks, they have failed to outperform classical methods in the time-series domain. This discrepancy prompts a critical reevaluation of the application of deep learning techniques to time-series data, suggesting the need for domain-specific adaptations rather than the uncritical replication of architectures designed for image and language domains. Therefore, the experiments demonstrate that deep learning-based time-series clustering methods, including foundation models, as described in existing literature, do not statistically surpass the performance of established classical methods. This insight critically addresses *RQ3*, shedding light on the actual impact of deep learning innovations in this field.

## 6 EXPERIMENTAL ANALYSIS

We present a detailed analysis of each clustering method’s performance under various conditions, including accuracy-to-runtime trade-offs (Section 6.1), sensitivity to data distribution characteristics (Section 6.2), and scalability on large-scale datasets (Section 6.3).

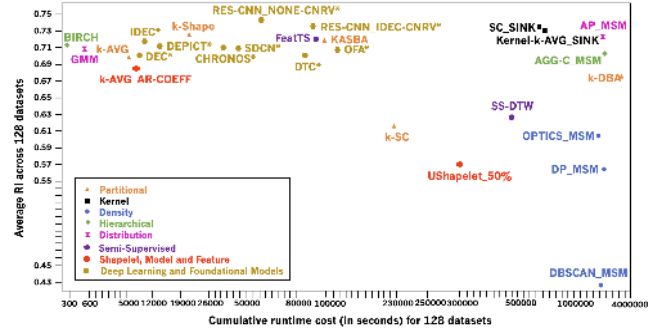


Figure 5: Performance-to-runtime comparison.

### 6.1 Accuracy-to-Runtime Analysis

We perform an in-depth analysis of the runtime expenses associated with various time-series clustering algorithms, juxtaposed with their performance metrics. Figure 5 presents the runtime costs of key algorithms explored in this study, as reported in the existing literature. We define runtime performance as the cumulative duration required by a method for fitting and inference. Our analysis reveals that BIRCH emerges as the fastest algorithm, demonstrating commendable efficiency while maintaining satisfactory clustering performance. BIRCH’s memory-efficient, online-learning optimization for large-scale datasets contrasts sharply with the substantially longer runtimes of other hierarchical methods. Furthermore, we identify *k*-Shape as the sole traditional algorithm that offers an advantageous balance between runtime efficiency and clustering efficacy. Deep learning based approaches also show potential by leveraging GPU acceleration to achieve speed and accuracy improvements unattainable by CPU only processing. For example, fitting models such as DEC and IDEC on a CPU requires up to five and eight times longer, respectively. Despite these gains, no deep learning method significantly surpasses classical strategies like *k*-Shape. However, contrastive methods like RES-CNN framework, using CNRV pretext loss and NONE clustering loss, show promising results, albeit with increased runtime. It is worth noting that runtime efficiencies for our contrastive method could be improved through strategic sampling of positive and negative samples.

### 6.2 Data Distribution Analysis

In our evaluation of the full UCR time-series archive (128 univariate datasets), we partitioned the data by several characteristics: cluster size (small:  $< 5$  vs. large:  $\geq 5$ ), number of samples (small:  $< 1,000$  vs. large:  $\geq 1,000$ ), sequence length (small:  $< 500$  vs. large:  $\geq 500$ ), stationarity, periodicity, and application domains. For each subset, we computed the rank for each algorithm. Periodicity, are assessed using periodogram analysis [83] and autocorrelation function tests [26], while stationarity is assessed using the augmented Dickey-Fuller test [46] and the KPSS test [87]. Figure 6 illustrates the resulting average-rank performance over 128 datasets. Overall, the *k*-Shape algorithm and the proposed contrastive learning method consistently achieved the best ranks across nearly all conditions, demonstrating robust performance. However, the analysis also revealed notable deviations: the feature-driven method FeatTS attained the best rank on datasets with fewer than five clusters (reflecting its graph-based encoding of cluster structure).



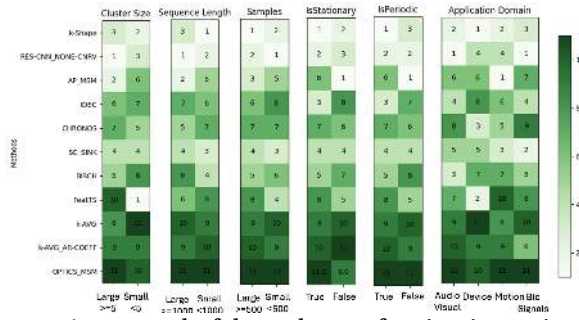


Figure 6: Average rank of the ten best-performing time-series clustering methods (along with  $k$ -AVG baseline), one for each category, evaluated across varying dataset characteristics: cluster size, number of samples, sequence length, stationarity, periodicity, and application domain. A lighter color indicates a superior performance.

### 6.3 Scalability Analysis

A comprehensive scalability evaluation of the clustering methods was conducted, with results summarized in Figure 7. Experiments systematically varied both the length of individual time series and the number of samples, measuring runtime (in seconds) for each method. Both axes in the figures are plotted on a logarithmic scale to illustrate performance trends across diverse data sizes. Synthetic data generated in the style of the UCR Cylinder-Bell-Funnel (CBF) dataset enabled controlled variation of sequence length and sample count while preserving benchmark characteristics. All experiments were performed on a single CPU core to ensure a consistent, hardware-independent comparison—isolating differences attributable solely to algorithmic complexity and implementation.

This study evaluates the computational scalability of various time-series clustering algorithms as functions of the number of series ( $N$ ) and sequence length ( $T$ ). Standard  $k$ -AVG and its autoregressive (AR)-enhanced variant both exhibit linear complexity in  $N$  and  $T$  ( $O(NT)$ ), whereas  $k$ -Shape scales near-linearly in  $N$  but incurs cubic growth in  $T$  ( $O(NT^3)$ ). The hierarchical method BIRCH achieves near  $O(N \log N)$  behaviour in  $N$  and linear scaling in  $T$  through its  $O(NT)$  incremental summary updates. In contrast, algorithms relying on pairwise distance measure (MSM) distances, such as AP-MSM and OPTICS-MSM, must compute an  $N \times N$  distance matrix with each distance costing  $O(T^2)$  via dynamic programming, resulting in an overall  $O(N^2T^2)$  distance-computation cost. The spectral clustering variant SC-SINK similarly builds an  $N \times N$  affinity matrix at  $O(N^2T^2)$  and then solves an  $O(N^3)$  eigenproblem, rendering it impractical for moderate to large datasets without algorithmic acceleration. Deep learning based clustering methods incur significantly higher runtimes due to iterative gradient-descent optimization and complex architectures, making them prohibitively slow for large  $N$  or long  $T$  absent hardware acceleration. However, when GPUs are available, models such as CNRV can leverage parallel batch training and vectorized computations to achieve scalability comparable to classical approaches.

Empirical results indicate that  $k$ -Shape offers the best balance between clustering accuracy and computational efficiency: although it is slower than  $k$ -AVG,  $k$ -AVG AR, and BIRCH, our evaluation above shows that  $k$ -Shape nonetheless attains superior clustering performance. It occupies a “sweet spot” between fast/low-performance

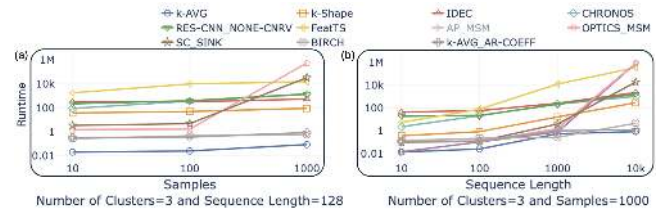


Figure 7: Scalability analysis of the ten best-performing time-series clustering methods ( $k$ -AVG as the baseline) for each category. Clustering runtime (seconds) is presented as (a) a function of number of time-series samples  $N$  and (b) as a function of sequence length  $T$ .

and slow/high-performance methods. This renders  $k$ -Shape particularly well suited for large-scale applications with constrained computational resources. Similarly, it is important to note that deep learning-based models can significantly benefit from GPU acceleration due to parallel batch training and vectorized processing. Specifically, CNRV not only demonstrated top-tier clustering performance among deep learning-based methods but also shows strong potential for scalability in large-scale settings.

## 7 CONCLUSIONS AND DISCUSSION

Time-series clustering is a prominent task in time series analysis, yet the literature reveals a substantial gap in systematic, comprehensive evaluations and benchmarking. Despite decades of research, existing benchmarks have significant limitations. We identify these shortcomings and present the most comprehensive analysis to date, evaluating 84 clustering methods across ten distinct classes in data mining, machine learning, and deep learning. Our study yields insights that challenge prevailing assumptions. Although many methods have been proposed, no algorithm consistently outperforms the decade-old baseline  $k$ -Shape, suggesting perceived progress may be illusory due to limited evaluation practices. Comprehensive assessments across diverse datasets with rigorous significance testing are imperative to confirm observed improvements genuine rather than artifacts of selective benchmarking. Moreover, reproducibility issues further obscure true performance. Notably, parameter-dependent distance measures, when optimally tuned, demonstrate significant performance gains over untuned counterparts, highlighting the importance of parameter optimization.

Deep learning-based approaches, despite their popularity, have yet to surpass classical methods, often achieving comparable results at substantially higher computational cost. Emerging foundation models offer promise through large-scale pretraining; however, reliance on data overlapping standard evaluation sets introduces contamination and in-distribution bias, so reported gains may not generalize to truly unseen data. Rigorous out-of-distribution testing and strict dataset separation are required to validate genuine advances. In this context, we propose a new time-series distance measure based contrastive learning approach that shows promise and may benefit from refined sampling strategies. By addressing three persistent research questions, our analysis provides insights into design choices that advance time-series clustering and enhances understanding of current techniques. Ultimately, our findings underscore the critical importance and ongoing demand for refined time-series clustering methodologies, calling for further research.



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