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# Comparative Analysis of Time Series Classification Methods for Single and Multi Variate Data Classifiers with Different Similarities

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***Abstract :*** In recent times, time-series data is continuously growing in size, in addition to its variable statistical nature, which makes it a challenging problem in case of data mining algorithms to effectively predict, classify and index. At present, time-series classification is an active research topic in the field of data mining, since it finds applications in several domains. In general, there are several categories of classifiers existing in Time Series Classification (TSC), which defines the several way of including similarity measures in various domains like time, shape, frequency, etc., into more complex classifiers. TSC systems take part an imperative role in the applications data mining by means of classifying the available information in accordance with the time series.

The major objective of this study is to evaluate the relative performance of some familiar similarity measures based classification schemes on different domains. This study takes TSC schemes that completely depend on time series values of the data. Moreover, this study discussed more about that time series data characteristics considerably influence the performance of the TSC schemes. The results of the study can effectively support in the design of novel classification systems in which numerous classification schemes can be employed for the purpose of increasing the accuracy and efficiency of the TSC.

***Keywords :*** Time-series data, time series classification (TSC), accuracy, hybrid method.

## 1. INTRODUCTION

Time series, measurements of certain quantity taken on the basis of time, are measured and analyzed through the scientific disciplines, together with human heart beats in medicine, rates of inflation in economics, cosmic rays in astrophysics, sets of ordinary differential equations in mathematics and air temperatures in climate science. The major complication of obtaining valuable information from time series has correspondingly been treated in a large number of ways, comprising an analysis of the distribution, correlation structures, measures of entropy or complexity, stationary estimates, fits to several linear and nonlinear time-series models, and quantities obtained from the physical nonlinear time-series analysis literature. On the other hand, this wide-ranging of scientific techniques for understanding the properties and dynamics of time series has obtained less attention in the temporal data mining literature, which processes large databases of time series, typically with the objective of either clustering or classifying the data [1]–[3].

As an alternative, the complication of TSC has traditionally been addressed through the process of defining a distance metric between time series that comprises comparing the sequential values directly.

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Time Series Classification (TSC) complications, in which it considers time series as any ordered data set. On the whole, time-series data is repudiated as an order of values obtained at various time points, which is given in [4]. Typically, those values are evenly distributed across the time domain represented by [5]. It must be noted that time series values can be simply real numbers as in the case of univariate time-series, or they might be several observations received in each time point as in the scenario of Multivariate Time Series (MTS) [6]. This different variate time series have been used by scientists in an extensive range of fields comprising, data mining, machine learning, statistics, environmental sciences, signal processing, chemo-metrics, and computational biology.

**Two major tasks of TSC are normally**

(*i*) choosing a suitable representation of the time series, and (*ii*) choosing a correct measure of dissimilarity or distance between time series [7]. The works on representations and distance measures for TSC is wide-ranging [1], [7], [8]. Possibly the most straightforward representation of a time series is its time-domain form, and subsequently distances between time series deal with differences among the time-ordered measurements themselves. In case when short time series encode most significant patterns that require to be compared, new time series can be categorized by matching them to similar instances of time series with a known classification. This category of complication has traditionally been the concentration of the time series data mining community [1], [7], and states to this scheme as instance-based classification. An alternative scheme includes representing time series by means of a set of derived properties, or features, and thus transforming the temporal problem to a static one [9]. An extremely simple example involves representing a time series by means of just its mean and variance, in that way transforming time-series objects of any length into short vectors that encapsulate these two properties.

As a result, the increasing interest in TSC resulted in an excess of different scheme like [10]proposed a DTW based decision tree for the purpose of classifying time series, in [11]utilized a Multi-Layer Perception Neural Network, [12]presented a Super-Kernel Fusion approach, [13] used Static Minimization-Maximization scheme for the purpose of building Multiple Classifier Systems, [14] used Hidden Markov Models, [15]presented DTW distances to embed time series into a lower dimensional space by means of a LaplacianEigenmap. This process of embedding is designed to both increase accuracy and performance of TSC and there are much of different TSC schemes studied in the recent decades. As a result of increasing good performance of the classification results in time series data, here reviewed several TSC schemes and that have been discussed in depth with the aim of improving the proposed TSC hybrid method's accuracy and efficiency.

## 2. SURVEY OF TIME-SERIES CLASSIFICATION

### Time Series Classification

A time series is an order of data that is usually recorded in temporal order at regular intervals of time. Consider the problem of time series classification, a set of time series, $TS = \{TS_1, TS_2, ..., TS_n\}$, in which each time series has ordered real-valued observations $TS_i = < ts_{i1}, ts_{i2}, ts_{im} >$ and a class value. Here, the major objective is to discover a function that map from the space of possible time series to the space of possible class values. Incase of TSC, for the purpose of simplicity consider that the entire series are the same length, however this is not a requirement [16].

### Similarity Measures

TSC is a broadly explored problem in the field of machine learning and, to a certain extent; the entire classification problems depend on a measure of similarity among data. Similarity measures can be embedded into the classifier or introduced through the process of data transformation before classification. Discriminatory similarity features typically come under one of three categories: similarity in time (correlation-based), similarity in change (autocorrelation-based), and similarity in shape (shape-based).

## Similarity in Shape

This section completely focuses on representations that best capture similarity in shape. Similarity in shape describes the scenario where class membership is characterized through a common shape however the discriminatory shape is phase independent.

## Shapelets

Shapelets provide a mechanism for the purpose of detecting phase-independent shape-based similarity of subsequences, and therefore represent a better solution to a class of shape-based similarity complications than global elastic measures. A shapelet is a kind of subsequence of one time series in a dataset is represented through. Each subsequence of every series in is known as a candidate. Shapelets are found through an exhaustive search of each candidate between lengths and . Shapelets are independently normalized.

## Shapelet Assessment

Shapelet quality completely depends on the class values, which are separated through the set of distances. Four different quality measures are avail in assess the quality of shapelets, which are Information Gain (IG), Kruskal-Wallis, F-statistic and Mood's median. Altogether these quality measure schemes demonstrate and investigate quality measures for shapelets, and formulated a shapelet-transform algorithm in [17] detail representation in Table 1.

**Table 1**

**Hills, Et Al (2014) Proposed Shapelet Transformation Based Time Series Classification**

| *Title of the Paper* | *Journal Publications and Year* | *Keywords* | *Drawbacks-Existing System* | *Algorithm/ Method* | *Proposed Method* |
|---|---|---|---|---|---|
| Classification of time series by shapelet transformation | Springer, 2014 | Shapelet, Discriminatory feature, shapelet-based classifier, shapelet-discovery algorithm | •The primary demerits over the previous shapelet scheme is that the transformed data cannot be utilized in combination with any classifier<br>• There is recursive search for shapelets, this will surpassa classification time. | Shapelet-transform algorithm | The proposed standard shapelet quality IG shapelet-transform algorithm for time-series classification that extracts the best shapelets from a dataset in a single pass using a caching algorithm, and it allows the shapelets to be clustered to enhance interpretability. |

Shapelet transform utilized in this classification is effectively demonstrated in [18]. The significance of this transform using in the TSC is separating the transformation from the classification scheme with an ensemble approach, in which each member of the ensemble is built on a different transform of the original data. They demonstrate that, initially, on complications where the discriminatory features are not in the time domain, functioning in a different data space creates better performance improvement than designing a more complex classifier. Furthermore, an uncomplicated ensemble on transformed datasets can considerably improve simple classifiers. In case of TSC, apply this intuition to shapelets, and separate the transformation from the classifier. A shape-based similarity measure is introduced in [19], which is called the Angular Metric for Shape Similarity (AMSS), for the purpose of time series data. Distinct to most similarity or dissimilarity measures, AMSS not completely depends on individual data points of a time series however on vectors equivalently representing it. AMSS treats a time series as a vector sequence to concentrate on the shape of the data and relates data shapes by means of employing a variant of cosine similarity. Table 2 completely shows the detail of the shape similarity based Angular Metric TSC method[19].

**Table 2**

**Nakamura, Et Al (2013) Proposed A Shape-Based Similarity Measure For TSC With Ensemble Learning**

| *Title of the Paper* | *Journal Publications and Year* | *Keywords* | *Drawbacks- Existing System* | *Algorithm/ Method* | *Proposed Method* |
|---|---|---|---|---|---|
| A Shape-based Similarity Measure for Time Series Data with Ensemble Learning | IEEE, 2013 | Time series analysis, Similarity measures, Machine learning | • In previous works, there is no agreement with the potential drawback, *i.e.* ensemble learning is not adopted.<br>• Ensemble learning largely adopted to integrate data smoothing, when classification. Owing to this, the system needs increasing no. of time for transformation. | Angular Metric for Shape Similarity (AMSS) | • AMSS is, by design, expected to be robust to time and amplitude shifting and scaling, but sensitive to short-term oscillations.<br>• Experimental results reveal distinct properties of AMSS and its effectiveness when applied in the ensemble framework as compared with existing measures. |

In case of shape based TSC research has concentrated on several quality measures for different classifiers in different works in past years, in [20] discussed distance measure for nearest neighbor (NN) classifiers, in accordance with either the raw data, or on compressed or smoothed data. The experimental indication recommends that 1-NN with an elastic measure, for instance, Dynamic Time Warping (DTW),is the top scheme for smaller datasets; on the other hand, for instance the number of series increases "the accuracy of elastic measures converge with that of Euclidean distance"[20]. This concept has propagated through current research. In case of [21],it states that "there is a plethora of classification schemes that can be applied to time series; on the other hand, the entire current empirical evidence recommends that simple nearest neighbor classification is extremely difficult to beat". In recent times, there have been numerous alternative schemes, like weighted Dynamic Time Warping [22], Support Vector Machines (SVM) built on variable intervals [23], tree-based ensembles constructed on summary statistics [24], and a fusion of alternative distance measures [25].

The above mentioned schemes focused only on complications where the series from each class are observations of an underlying common curve in the time dimension. Variation nearby this underlying shape is rooted through noise in observation, and moreover by noise in indexing, which possibly will cause a slight phase shift. A typical model of this category of similarity is the cylinder-bell-funnel artificial dataset, in which there is noise around the underlying shape and in the index where the shape transitions. There is another set of complications involving cases in which similarity in shape defines class membership. Series inside a class might be differentiated through common sub-shapes that are phase independent; *i.e.*, the defining shape might begin at any point in the series.

When the underlying phase-independent shape that describes class membership is global, specifically, the shape is (roughly) the length of the series, and subsequently techniques in accordance with transformation into the frequency domain can be employed for the purpose of constructing classifiers [26].On the other hand, when the discriminatory shape is local, *i.e.*, significantly shorter than the series as a whole, at that point it is unlikely that the differences among classes will be detected by means of spectral schemes. In

[27] proposed shapelets for the purpose of addressing this category of problem. A shapelet is a time-series subsequence that can be utilized as a primitive for TSC based on local, phase-independent similarity in shape. Shapelet-based classification scheme includes measuring the similarity among a shapelet and each series, subsequently using this similarity as a discriminatory feature for the purpose of classification. The original shapelet-based classifier embeds the shapelet discovery algorithm in a decision tree, and makes use of information gain to assess the quality of candidates. A shapelet is found at each node of the tree through an enumerative search. Shapelets have been utilized in applications like early classification [28], gesture recognition [29], gait recognition [30], and clustering [31]. The comprehensive search for shapelets is extremely time consuming. As a result, the majority of shapelet research has completely focused on schemes to accelerate the search [32].This makes the search for shapelets extremely tractable, however does not address the vital issue of how best to utilize shapelets to solve TSC complications.

**Similarity in Change**

Similarity in change points out the situation where the appropriate discriminatory characteristics are associated with the autocorrelation function of each series. There are fundamentally two schemes for the purpose of modeling time series: models in accordance with Autocorrelation Function (ACF) and models in accordance with fitted curves. Auto Regressive Moving Average (ARMA) models and the multitude of variants that are obtained from the ACF have featured strongly in the statistical literature and have been revealed to exactly model several real world data sets.

The most common scheme in this condition is to fit an ARMA model, which forms a class of linear time series models which are extensively applicable and parsimonious in parameterization, subsequently base similarity on differences in model parameters. ARMA models and the multitude of variants that are obtained from the ACF have featured strongly in the statistical literature and have been shown to very accurately model several real world data sets. On the other hand, the huge majority of the statistical literature concentrates on either alternative model fitting schemes and structures, or forecasting with models fitted to reasonably short series. There has been extremely little consideration of how best to measure similarity among series in terms of time series objectives like query, clustering, classification or anomaly detection.

Some recent studies that do take discriminating between ARMA series into account, which tend to focus on substitute modeling schemes to account for factors like co-integration [33] or take alternative ways of comparing model parameters into consideration [34]. The foremost intention is to apply some of the modeling schemes developed in statistics to data mining complications, with the objective of rapid, well-organized discrimination. This similarity in change based time series classification completely concentrates on how best to categorize time series data, even though the schemes described here translate easily to other problem domains like clustering and query by content. In [18] it is argued that the easiest method to gain improvement on TSC complications is to transform into another data space where the discriminatory characteristics are more easily detected.

One transform taken in [35] extend this concept to show that the run length histogram also approximates the Advanced Custom Fields (ACF) and however can be computed in linear time and updated in constant time in the time series classification. In addition, this scheme show that classifiers constructed on the run length histogram, do not carry out considerably worse than those on the ACF. This scheme introduced a simple time series transformation for the purpose of detecting differences in series that can be accurately modeled as stationary Auto-Regressive (AR) processes. With the help of this AR model for the purpose of detecting a change of model based on a comparison of the entire historical data against recent observations it would necessitate fitting models to the complete data and the new data. When run lengths are employed the previous fitted model can be rapidly updated for the new data. Table 3 shows the detail of the method in [35].

**Table 3**
**Bagnall, et al (2013) proposed Auto Regressive Method for Tsc**

| *Title of the Paper* | *Journal Publications and Year* | *Keywords* | *Drawbacks-Existing System* | *Algorithm/Method* | *Proposed Method* |
|---|---|---|---|---|---|
| A Run Length ransformation for Discriminating Between Auto Regressive Time Series | Journal of lassification, Springer and 2014 | Time series classification, Run length distribution, Auto regressive model Approximation. | • In previous Run length based AR method representation cannot be updated online for new data. • Less time consuming. | Stationary autoregressive (AR) series model | • The transformation involves forming the histogram of above and below the mean run lengths. • The run length (RL) transformation has the benefits of being very fast, compact and updatable for new data in constant time. |

## Similarity in Time

Similarity in time is fundamentally described by the condition where the series from every class are observations of an underlying common curve in the time dimension. Variation all over the place in this underlying common shape is caused by means of noise in observation, and also by possible noise in indexing which possibly will cause a minor phase shift. Similarity in time can be quantified through measures like Euclidean distance or correlation ([36]; [37]). Similarity a classic example of this kind of similarity is the Cylinder-Bell-Funnel artificial data set, in which there is noise around the underlying shape, however also noise in the index of where the underlying shape transitions [38].

## Similarity in Ensembles

The correct similarity measure/transformation is evidently problem dependent. While considering [18] demonstrated that through ensembling transformations can considerably enhance the classification accuracy. Ensemble schemes have been shown to be extremely effective in combining single classifiers in a classification system, provide support for a higher accuracy than what's obtainable with a single classifier. To this point, the hybrid ensemble approaches have multiple systems trained with various settings, and an ensemble would bring certain improvement. An ensemble of classifiers of several categories complements one another in classification performance since they are varied from each other and make errors at various spaces. On the other hand, this ensemble approaches to be more to be effective in case of single variate time series data representations and it will increase the performance of classifiers.

There are several metrics for the purpose of assessing new different number of algorithms for TSC. On the other hand, accuracy is the most important. In case of [39] a new DTWCV algorithm for TSC is only of interest to the data mining community if it can considerably outperform and that to be of real interest it should outperform proportional ensemble with elastic distance measure. Table 4 shows the ensemble with elastic distance measure proposed in [39] and also shows the different literature work related in accordance with ensembles is as follows.

**Table 4**
**Lines & Bagnall (2014) Proposed Ensembles of Elastic Distance Measures for Time Series Classification**

| *Title of the Paper* | *Journal Publications and Year* | *Keywords* | *Drawbacks- Existing System* | *Algorithm/Method* | *Proposed Method* |
|---|---|---|---|---|---|
| Time series sification with nsembles of elastic Distance measures | Springer and 2014 | Time series lassification, Elastic distance measures, Ensembles | • Previously employed distance measures with ensemble methods do not provides considerably better accuracy.<br>• The individual classifiers does not provide out performance than an ensemble classifier. | DTWCV and Ensembling with elastic distance measure | • An ensemble classifier that effectively performs better than the individual classifiers.<br>• The ensemble is more perfect than schemes not based in the time domain. |

In recent times, a number of new elastic measures have been formulated which are variations of the time warp and edit distance schemes. A version of DTW that weights against large warping (WDTW) is given in [40]. The weighting approach can be utilized in conjunction with dynamic time warping and an alternate version based on first order differences (DDTW), as described in [41]. Variants on the edit distance scheme have also been introduced; including Edit Distance with Real Penalty (ERP) [13], Time Warp Edit (TWE) distance [42] and the Move–Split-Merge (MSM) distance metric [43].

## The different Parametric Methods for Classification

**Table 5**
**The Different Similarity Measures Based Proposed Classification Methods**

| *Title of the Paper* | *Journal Publications and Year* | *Keywords* | *Drawbacks- Existing System* | *Algorithm/ Method* | *Proposed Method* |
|---|---|---|---|---|---|
| A distance based time series ssification framework | Elsevier and 2015 | Time warping, lignment, Time series ssification | • Previously used schemes do not offer that the lassification accuracy completely depends on the structure of a time series dataset.<br>• Noise in a data set also controls the choice of the alignment technique. | A framework KNN and SVM classifiers designed for distance based time series classification | • The framework can be extended to execute new alignment and classification algorithms. |

| | | | | | |
|---|---|---|---|---|---|
| Model-based Time Series ssification | Springer and 2014 | | • Less lassification accuracy. • The efficiency of the classifier is more less when there is a present noise in the datasets. | • A filter-and-refine framework for time series Nearest Neighbor (NN) classification | • Model based Time Series Classification (MTSC) has better accuracy with use of an efficient way of modeling classes of time series using HMMs and proposed MTSC, a filter-and-refine framework for NN classification of time series. |
| Highly mparative feature-based time-series ssification | IEEE and 2014 | Time-series analysis, ssification, data mining | • The large no. of dataset reduces the performance efficiency of classifiers. | feature-based approach to time series classification | • Feature-based approach is most informative of the class structure are selected using greedy forward feature selection with a linear classifier. • The resulting feature-based classifiers automatically learn the differences between classes using a reduced number of time-series properties, and circumvent the need to calculate distances between time series. |

There are several wide-ranging models are available for the process of TSC. A generative model is an additional model in which the series is represented through the learned model parameters [44]. These schemes are indicated as “model-based kernels” [44]. While considering [45] for a comprehensive evaluation and comparison of the most prevalent time series similarity schemes.As a parameter-free approach, similarity based on Euclidean distance is extremely common and it was revealed to perform better for several applications [46]. Euclidean distance falls in the category of lock-step measures since it compares the ith value of one time series to the ith value of another [45]. This leads to Euclidean distance sensitive to the noise, scaling, translation and dilation of the patterns inside the time series. In contrast, it can execute well for certain applications as the training data size increases [45]. The elastic measures calculate the similarity invariant to definite nonlinear variations in the time dimension. This is accomplished through the comparison of one-to-many points as in Dynamic Time Warping (DTW) or one to-many/one-to-none points as in Longest Common Subsequence (LCSS). DTW distance is considered to be strong for numerous time series data mining complications. Moreover, Edit distance based schemes are shown to be competitive in this domain. ERP, TWE distance and the MSM are some of the effective schemes in this category. The following Table 5 shows the different parametric like distance based [47], model based [48] and feature based [49] approaches recently proposed for time series data.

The following section discusses regarding the different types of algorithm used in the above mentioned approaches.

**Time Series Classification Algorithms**

Similarity is detectable in phase independent and/or auto correlation related feature spaces more willingly than in the different domain. Although, complex classifiers might be capable of reconstructing this similarity through the internal non-linear mapping they employ to build the classifier, a far simpler and more intuitive scheme is to transform the data into an alternative space and make use of a basic classifier. In the same way, this work going to review the different classification schemes in the following order in Figure 1.

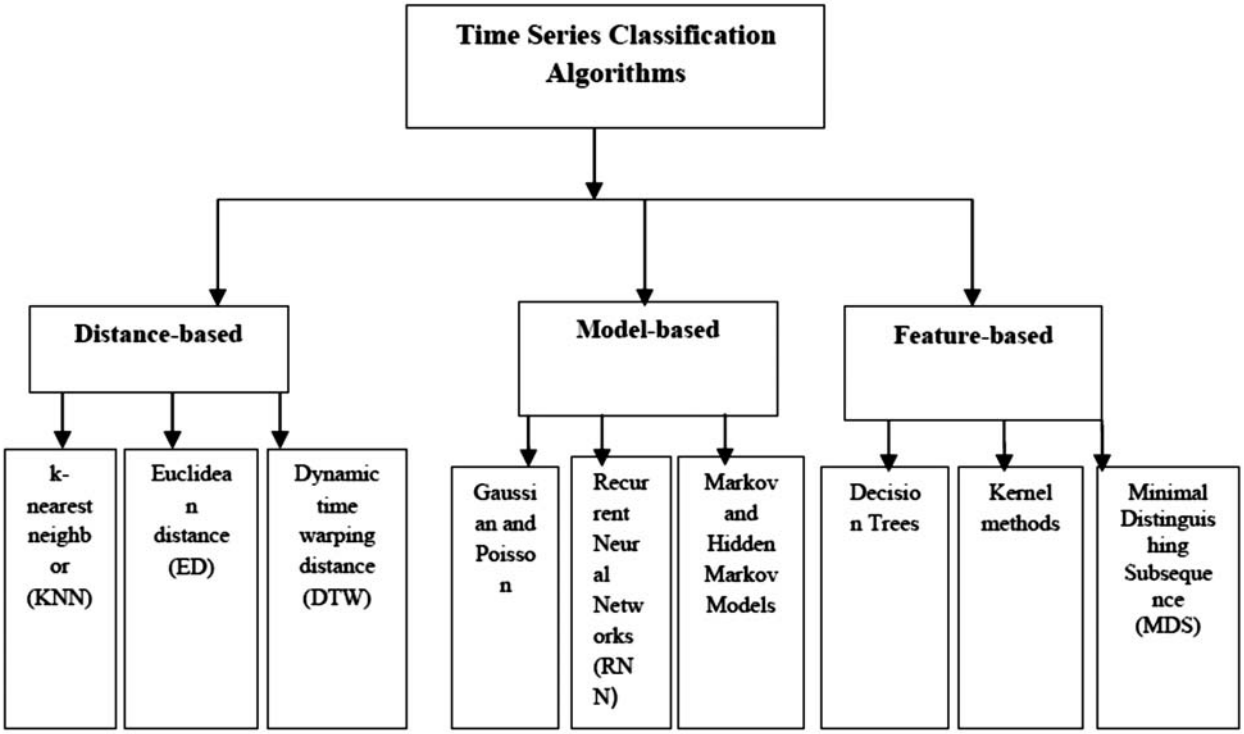


**Figure 1: Time series classification algorithms**

## Distance Based Classification

### K-Nearest Neighbour (KNN)

K-Nearest Neighbour (KNN) classification algorithm is completely based on the distance between series data. In case of conventional classification schemes to work with this series data, new dimensions have to be found for the purpose of determining the distance between two sequences. While considering [50],it describes that the choice of distance (similarity) measures play a substantial role in the quality of the classification scheme.

### Euclidean Distance (ED)

Euclidean Distance (ED) is an extensively adopted measurement, it needs the two series in comparison to be of equivalent length. It is one of the limitations of ED using in TSC, in case of [51], which emphasized on its sensitivity to distortion in time. Therefore, elastic similarity measures like DTW were needed to solve this complication.

### Dynamic Time Warping Distance (DTW)

DTW is a kind of non-linear mapping between two series where the distance between them is completely minimized. In [23] further explained the algorithm, in which $n \times m$ matrix is built, and each element in it represent a pair wise distance among points in the two sequences. A path in the matrix is subsequently searched where the total sum of distances is minimal, which is returned at that point as the distance between the two strings. DTW is computed by means of dynamic programming, therefore has a quadratic time complexity (O($n \times m$) or O($n$^2)). DTW also encounter the following local constraints, like 1. Boundary constraint, 2.Monotonicity constraint and 3.Continuity constraint.

In [52] defines Needleman-Wunsch global alignment scheme as given below: A similar matrix to the one described in DTW is built in which each axis represents one of the two sequences. The initial value of the entire cells is set to zero. Subsequently, fill the matrix applying the formula shown in equation 1, beginning from the bottom-right cell, by means of what is known as trace back procedure.

$$f(x), y = \begin{cases} f(x-1, y-1) + s(i_x, j_y), \\ f(x-1) - \mathrm{D} \\ f(x, y-1) - \mathrm{D} \end{cases} \tag{1}$$

Where($i$, $j$) indicates the log likelihood ratio of the pair occurring as an aligned pair as opposed to an unaligned pair, *i.e.* a way to the similarity of two characters in biological sequences. And is described as the gap-open penalty. The entire above DWT's are handled with single vitiate time series data, as discussed earlier, sequential data can be multivariate. In [27] found that breaking MTS into separate series and processing each one onits own result in overlooking the correlation among those variables. In [27] presented a newer distance-measurement scheme, Eros (Extended Frobenius norm), with the intention of dealing with MTS.

**Model Based Classification**

In accordance with [53], the model-based schemes build a model for the data inside a class and classify new data in relation to the model that best fits it. This work segmented the models utilized in classification into statistical and neural network ones. In accordance with [28], the statistical models like: Gaussian, Poisson, Markov and Hidden Markov Models, are built in order that they model the probability distribution of the data. In [29], in contrast, segmented models into predictive models that attempts to predict unavailable values of the data using the existing one, and descriptive models that attempts to discover patterns and associations in the data. This scheme will completely concentrate on the predictive models, because those are the ones utilized in classification, particularly Markov models which are utilized allot in sequence classification applications.

**Hidden Markov Model (HMM)**

In [29] defined regarding this scheme, and described as a collection of states S, an alphabet of symbols, a probability transition matrix T = ($t_{ij}$), and a probability emission matrix E = ($e_{ia}$). In case the system is in it has a probability of moving to state and aprobability $e_{ia}$ of emitting symbol. while considering [29],which explained the usage of HMM in classification as follows: For each class, a HMM is constructed with the assistance of training data from that class, subsequently new patterns are compared to the built models for the purpose of deciding which model (class) fits the new data the best. Compared against the distance and model based classifications, feature based classification deliver best result with utilization of the time series data, the feature based classification for time series data is described as follows.

In general, Artificial Neural Networks (ANN) is extremely close to statistical models [54]. In case of [55],which defines the Recurrent Neural Networks (RNN) as special category of ANN, in which there is a feedback connection in the network for the purpose of keeping track of its internal state when dealing with new inputs. RNN is extremely appropriate for sequential data since, as stated by [55], RNN has adequate potential of modeling the temporal nature of the sequence. Furthermore, [56] stated that in contradiction to HMM, RNN does not need knowledge of the data. This scheme is also claimed that RNN is protected against temporal noise. However, as seen earlier, they need fixed-length inputs.

**Feature Based Classification**

Classical classification schemes, like ANN and Decision Trees, carry out their classification in accordance with feature-set, hence feature-based TSC techniques work on transforming the series data into feature-set prior to the process of classification algorithms.

**Feature Vector Representation**

Feature-based representations of time series are built with the assistance of an extensive database of more number of time series analysis operations developed until that time [57]. The operations quantify an extensive range of time-series properties, together with basic statistics of the distribution of time-series values (*e.g.*, Gaussianity, location, outlier properties, spread,), linear correlations (*e.g.*, features of the power spectrum, autocorrelations), stationarity (*e.g.*, sliding window measures, StatAv, prediction errors), information theoretic and entropy/complexity measures (*e.g.*, Approximate Entropy, auto-mutual information, Lempel-Ziv complexity), methods from the physical nonlinear time series analysis literature (*e.g.*, Lyapunov exponent estimates, correlation dimension, surrogate data analysis), linear and nonlinear model fits [*e.g.*, goodness of fit estimates and parameter values from ARMA, Gaussian Process, and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models], and others (*e.g.*, wavelet methods, properties of networks derived from time series, etc.) [57]. All of these different categories of analysis schemes are encoded algorithmically as operations.

### Feature based Classification Algorithms

In order to introduce the highly comparative feature based classification scheme, these classification techniques have favored the interpretability of feature selection and classification schemes over their sophistication. Feature selection was accomplished by using greedy forward selection, and classification was done by means of linear discriminate classifiers. Moreover, sophisticated feature selection is a most significant process and classification [32] methods exist (*e.g.*, that permit for more robust and/or nonlinear classification boundaries) and must enhance the classification results.

### Decision Tree

This flexibility is to effectively incorporate a large and growing literature of sophisticated classifiers operating on feature vectors, together with decision trees in a feature space. The literature reviews regarding the decision tree algorithms are as follows. While considering [58], it noticed that algorithms that attempt to recognize tree-leaves based on their shapes are misled through the deformation in their shapes because of insects eating parts of them. Instead of depending on on the complete shape of the leaves (global features), they chose local features (patterns) that mostly discriminates the leaves from different trees. They transformed the shape data into a sequential one. The major intention is to discover sub-sequences or shapelets as they called them that are discriminating between classes. In order to determine which sub-sequences are to be selected, they ordered the entire sequences in accordance with their (Euclidean) distance from all possible shapelets. Subsequently, they started to search for a mid-point that completely divides member-sequences of each class.

### Minimal Distinguishing Subsequence

In the same way, [35] introduced a pattern-extraction scheme called Minimal Distinguishing Subsequence (MDS).

On the other hand, MDS permit for gaps inside the sub-sequences, which make it more appropriate to classifying biological sequences as mentioned earlier. Another feature-extraction scheme is to transform the time-series data into the frequency domain, in which data dimensionality can be considerably reduced. The modules with higher order coefficients replicate the global trends of the data, whereas the ones with lower order coefficients replicate the local trends in it [59].

Kernel Methods (KM) are also very decent in feature extraction, in addition; they can effectively handle symbol-sequences with various lengths. Even though [60] was dealing with text data as a collection of words more willingly than sequential data, it highlighted the capability of kernel schemes to manage textual data irrespective of its huge number of features. Differences among distance and feature based time series classifications, in the distance-based TSC, in which distances are computed between the ordered values of the time series, and feature-based TSC, which absorbs a classifier by means of a set of features obtained from the time series. Compare than the distance and model based classification, the resulting of feature-based classifiers automatically learn the differences among classes by means of a reduced number of time-series properties, and completely avoid the requirement to compute distances between time series.

## Ensemble Scheme for Classification

Ensemble schemes have found to be extremely effective in combining single classifiers in a classification system, providing a better accuracy than what's obtainable with a single classifier. To this point, the ensemble approaches have multiple systems trained with different settings, and an ensemble would bring certain improvement. An ensemble of classifiers of different categories complements one another in classification performance since they are completely different from each other and make errors at different area. On the other hand, this ensemble approaches to be more effective for single variate time series data representations and it will escalate the performance of classifiers.

The past works of TSC have formulated an ensemble scheme for TSC based on building classifiers on different data representations. This work primarily concentrated on the time and frequency domain based classification algorithm for TSC. Typically, the standard baseline schemes used in TSC research are 1-NN with Euclidean distance and/or dynamic time warping. These schemes do not increase the performance of classifiers in accordance with frequency counts, interval statistics, and complexity measures. In order to solve this complication, this research study finds the solution in accordance with the similarities in time and frequency domain using alternative transform based hybrid bio-inspired based classification schemes to considerably increase the efficiency of the classification accuracy in TSC.

## Hybrid Method

Based on the literature reviews, a deep studied is done regarding the different similarity measures and different categories of the TSC algorithm. Numerous similarity measures based classifiers implemented for TSC like the distance-based classifiers, including one Nearest Neighbor classifiers, Euclidean distance and Dynamic Time Warping and model based classifiers like Gaussian, poission, Markov Model and Hidden Markov Model and the features based classification schemes like Decision Tree, Minimal Distinguishing Subsequence with the extracted and meaningfully selected features with various similarity measures. These classification schemes performances are varied in accordance with the quality measures. With use of this review of several TSC scheme, it is observed that there are two ideas to effectively increase the classification accuracy, such as an alternative data space in discriminatory features of the data and ensemble schemes for single variate time series data analysis, those are examined with the several classification schemes with optimization process, specifically known as hybrid classification scheme, that will offer a better understanding of the properties of the time series dataset, and also increase the performance accuracy of classifier, moreover, that can guide further investigation.

## Proposing method for TSC: Transformation-Based Ensembles, Frequency Count using optimization based classifier for Time Series Classification

Earlier section of this literature discussed in detail about the collective classifiers constructed in the time, frequency, change, and shapelet transformation domains. Previously TSC work for the time domain utilized a collection of elastic distance measures. In case of other domains, there was a variety of standard classifiers were utilized.

In case of frequency domain, frequency counts are utilized for the purpose of classifying the time series data, which considerably increased the complexity level and the performance of the classifier is not increased at all. With the intention of solving these complications in frequency domain TSC, the Weighted Frequency Count (WFC) will be a best suggestion to resolve the TSC problem based on frequency domain and in case of time domain, Modified Auto Correlation measure will effectively increase the classification accuracy. The choice of classifiers in the heterogeneous ensemble is simply arbitrary, and the addition of more complex classifiers, the elimination of weaker classifiers, and the setting of parameters existing earlier. With the intention of improving the classification accuracy and to solve the aforementioned complications in TSC using optimization based schemes like hybrid particle swarm with firefly algorithm and hybrid cuckoo search and bee colony scheme is applied for the purpose of validating the classifier, remove the weak classifier. It also uses Independent Component Analysis (ICA) for the purpose of noise removal and in order to carry out time and frequency domain selection, Linear Discriminate analysis (LDA) is used. In case of other domains, a range of classifiers is used. Through wide-ranging experimentation with the help of UCR datasets by including all classifiers in one ensemble, which will be effectively prove that new proposal of the TSC method is considerably more precise than any of its components and any other previously released TSC algorithm.

This work assures that the Weighted Frequency Count (WFC) for frequency domain and Modified Auto Correlation for time domain, both of these schemes will significantly out-perform in TSC. This work also shows this scheme with Hybrid bio-inspired classification algorithm to be considerably better than the other competing schemes that have been examined in the literature.

## 3. RESULTS AND DISCUSSION

### Data Sets

The major contribution of this work is to focus, on certain TSC complications, various classifiers in the time domain will not perform well, and the simplest way to gain a substantial improvement is to convert the data into an alternative representation and construct classifiers based on frequency domain with Modified Frequency Count similarity measures and these frequency domains are combined with time domain classifiers will increase the time domain classifier performance considerably with Modified Auto Correlation similarity measure from there. In actual fact, for the majority of complications in the TSC using to resolve the UCR time series classification data sets [61], time domain classifiers work extremely well with frequency domain using similarity measures like weighted frequency count and modified auto correlation function based on hybrid classifiers. As a result, this review work include in experiments with 5 data sets from UCR repository, The origins of these data sets are described in Table6 as shown in below.

**Table 6**
**Time Series Classification Data Sets**

| *Data Set* | *Length* | *Classes* |
|---|---|---|
| Olive Oil | 570 | 4 |
| Coffee | 286 | 2 |
| Beef | 470 | 5 |
| Earthquakes | 512 | 2 |
| Electric Devices | 96 | 7 |

### Food Spectrograms

**Beef, Olive Oil and Coffee :** Food spectrographs are utilized in chemo metrics for the purpose of classifying food categories, a task that has obvious applications in food safety and quality assurance. The main objective is to construct classifiers with the intention that food type can be identified from the spectrum alone.

**Electrical Device Usage :** This data initiates from a trial of electricity smart metering devices, which includes measuring the power consumption of 187 households for various devices as identified by the participants. The data obtained on the 7 most commonly identified devices: kettle; washing machine; immersion heater; oven/cooker; cold group (fridge, freezer and fridge/freezer); dishwasher and screen group (computer and television). The classification problem is to predict device type given the daily measurements of the indicated device (96 attributes).

**Earthquakes :** The earthquake classification problem comprises predicting whether a main event is all set to occur in accordance with the most recent readings in the surrounding area. The data is obtained from Northern California Earthquake Data Center and each data is an averaged reading for one hour, with the initial reading taken on Dec 1st 1967, the last in 2003. This work completely converts this single time series into a classification problem by initially defining a major event as any reading of over 5 on the Rictor scale.

### Experimental Results Comparison

The primary objective is to make use of these data sets for the purpose of testing the hypothesis that ensembling across transformations considerably enhances accuracy. The secondary objective is to effectively explore alternative ways of combining classifiers and ensembles to attempt and effectively enhance the accuracy of the overall classifier and provide examining insights into a specific classification problem [62].

### Comparison of different TSC Algorithms

This study described different number of TSC algorithms that have been proposed recently. Here, these algorithms are not implemented, however this can compare the performance on the recently published UCR datasets. These comparison results are shown in Table 7. The complete results are rounded to three decimal places, for uniformity across all publications. Table7 completely describes the combination of different time series algorithm classification algorithm from several domain with ensembling scheme previously published results and new TSC scheme namely Hybrid method's [63] assumption results made on this literature survey, which provides the most accurate classification on different data sets. Many of the differences between classifiers are tiny, but however look at the data, it is clear that hybrid method will outperform the other classification algorithms.

**Table 7**
**Collected Published Results on the UCR Data Sets**

| *Classification Methods* / *Datasets* | *Existing Classifiers based on different domains* | | | | | | | | *Proposed Method* |
|---|---|---|---|---|---|---|---|---|---|
| | *KNN* | *ED* | *DTW* | *RNN* | *HMM* | *MDS* | *DT* | *KM* | *Hybrid classifiers* |
| Olive oil | 0.337 | 0.389 | 0.391 | 0.384 | 0.245 | 0.437 | 0.379 | 0.435 | 0.233 |
| Coffee | 0.278 | 0.25 | 0.179 | 0.236 | 0.004 | 0.036 | 0.179 | 0.123 | 0.064 |
| Beef | 0.478 | 0.467 | 0.467 | 0.5 | 0.287 | 0.24 | 0.433 | 0.167 | 0.133 |
| Earthquakes | 0.246 | 0.131 | 0.213 | 0.257 | 0.164 | 0.18 | 0.131 | 0.246 | 0.1 |
| Electric Devices | 0.187 | 0.305 | 0.305 | 0.046 | 0.211 | 0.379 | 0.287 | 0.267 | 0.112 |
| No. of Data sets | 34 | 45 | 19 | 44 | 42 | 38 | 23 | 34 | 45 |
| No.of Best | 2 | 1 | 1 | 6 | 5 | 3 | 4 | 6 | 27 |

Based on the comparative results of different classification algorithm in Table.7, it clearly proves that the new proposed Hybrid scheme is the most accurate on 26 of 45 data sets in TSC.

## 4. INFERENCE FROM EXISTING WORK

Several researchers were provided an effective investigation to manage classification issues by means of different domain classifiers. In this literature work completely concentrated on the TSC through a hybrid classifier based on Transformation-based ensembles, frequency count in frequency and time domain. This will effectively produce in the ensemble, and the insertion of more complex classifiers, the elimination of weaker classifiers, and the setting of parameters. Hybrid classifiers for TSC have been a preferred analysis topic for several years. On the other hand, these dominant classifiers ways have their inherent shortcomings and limitations. It must be observed that, fusion of the Hybrid classifiers schemes will normally provide better performances over using them one by one. Therefore, a hybrid classification schemes will be proposed to effectively deal with complex problems in TSC.

## 5. CONCLUSION AND FUTURE WORK

Based on the literature review, two ideas were formulated which effectively helps to improve the classification accuracy in accordance with the time series data. First idea is to transform into an alternative data space in which the discriminatory features are more easily detected. Second, TSC problems are revealed that with a single variate time series data representation, in which the simple ensemble schemes are employed for the purpose of achieving higher classification accuracy. Combination of these two ideas implemented in collective of ensembles of classifiers on different data transformations with frequency counts, regarded as hybrid method that enhances the accuracy of time-series classification.

In future, in accordance with this study, it will expose that the Hybrid classifiers in weighted frequency count similarity for frequency domain and Modified Auto correlation similarity measure for time domain with ensembling scheme are solving the TSC problems more effectively and the proposed work experimentally demonstrates the results of this new TSC scheme proves the hybrid classifiers given more classification accuracy result than the other standard classifiers. The weaker classifiers are also removes from the TSC system for efficient results.

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