Abstract—Time series classification is one of the very popular machine learning tasks. In this paper, we explore the application of Hidden Markov Model (HMM) for time series classification. We distinguish between two modes of HMM application. The first, in which a single model is built for each class. The second, in which one HMM is built for each time series. We then transfer both approaches for classifier construction to the domain of Fuzzy Cognitive Maps. The identified four models, HMM NN (HMM, one per series), HMM 1C (HMM, one per class), FCM NN, and FCM 1C are then studied in a series of experiments. We compare the performance of different models and investigate the impact of their hyperparameters on the time series classification accuracy. The empirical evaluation shows a clear advantage of the one-model-per-series approach. The results show that the choice between HMM and FCM should be dataset-dependent.

Index Terms—Time series, Classification, Hidden Markov Model, Fuzzy Cognitive Map

I. INTRODUCTION

The goal of time series classification is to assign correct class labels to time series based on information collected from a training set of samples. This task is related to standard pattern classification, but the difference is that the attributes are ordered and this ordering matters. There are many different real world domains in which we need to classify time series. Importantly, there is a huge qualitative difference between the different time series data sets that need to be classified. For example, in some domains we collect long time series, but the characteristic feature that is the basis for classification appears only once, at an unknown point in time. In other applications, there is a pattern whose frequency of occurrence determines class belongingness. Still in other domains, we can directly compare levels of phenomena at consecutive points in time. Undoubtedly, the wealth of diverse time series data sets that need to be processed in the real world requires new methods and exploration of existing approaches.

The literature of temporal data modelling offers a number of interesting models that can be described as state-based. Such models, whose roots can be seen in the automata theory, are represented by graphs whose vertices are responsible for information processing. This family of approaches includes not only overly popular neural models, but also less popular models, in particular Hidden Markov Model (HMM) and Fuzzy Cognitive Map (FCM). In this paper, we present a study on the application of HMMs and FCMs to time series classification.

We emphasize that there are already two modes of using HMMs for pattern classification. The first, in which one HMM is constructed for each class. The second, in which one HMM is built for each time series in the dataset to be classified. Both variants are present in the literature on standard pattern classification, and our contribution is to apply these two models to time series classification. However, no such methodology exists for Fuzzy Cognitive Maps. Therefore, we transfer the methodology of pattern classification using HMM to the area of time series classification using FCMs. That is, we propose two variants of time series classification using FCM. The first, in which one FCM is built for each class. The second, in which one FCM is built for each time series. These two variants of using FCMs to process data are new to the literature on time series and, in general, pattern classification.

In an empirical study using a set of 50 benchmark datasets, we analyze and compare the effectiveness of the proposed approaches. Experiments showed that the one-model-per-time-series variant outperforms the one-model-per-class variant in terms of classification accuracy. In the case of HMMs, this variant, also requires less training time. In the case of FCMs, it is more time consuming than the one-model-per-class scheme. The choice between HMM and FCM should depend on a dataset.

The paper is structured as follows. Section II presents the basic knowledge of time series classification. Sections III and IV present preliminary background knowledge and the methods investigated. Section V is devoted to the experimental evaluation of the proposed approaches. Section VI concludes the paper.
II. LITERATURE REVIEW ON TIME SERIES CLASSIFICATION

Time series classification is a thriving area of research. We can distinguish six types of approaches in this field.

The first group of approaches uses elastic measures of time series similarity, such as Dynamic Time Warping (DTW). Its purpose is to transform time series to facilitate their similarity assessment. DTW finds the so-called warping path, which ensures that the distance between two sequences is the smallest. There is an impressive amount of literature discussing different variants of DTW applied to time series classification. For instance, in [1] we find a description of DTW with performance enhancing corrections, while in [2] an algorithm called WDTW – Weighted DTW was introduced. A similar idea was conveyed under the name Flexible DTW (FDTW) in [3]. FDTW adds additional scoring to promote contiguously long one-to-one time series fragments.

The second group of methods uses the concept of time series shapelets. A shapelet is a subsequence of a given time series that represents well regularities in the time series. Methods based on shapelets are particularly suitable for datasets where there is a clear pattern in the values of the time series that uniquely identifies the class label, but the location of this pattern is not fixed. A simple algorithm that can be applied in such a case is the shapelet-based method presented in [4], which uses one shapelet per time series.

The third group of methods is based on time series segmentation. Such methods usually segment the time series into intervals and then extract numerical features that are the basis for building a classifier. An example method implementing segmentation is Time Series Forest presented in [5].

A significant volume of research has been put into the development of dictionary-based algorithms. Two very popular methods of this type are Bag of Patterns (BOP) [6] and Bag of Symbolic Fourier Approximation Symbols (BOSS) [7]. Large et al. [8] improved BOSS by introducing order-less feature histograms to represent the data.

The fifth group of methods uses deep neural networks to perform the task of time series classification. This group includes algorithms such as ROCKET [9], TS-CHIEF [10], and InceptionTime [11].

The group of methods most relevant to this paper are model-based approaches. They are less popular than distance-based or subsequence-based methods. In this group are classifiers based on FCM and HMM. They are addressed in a separate section of this paper.

To conclude the general literature review, it is worth mentioning that Hidden Markov Models or their extensions are used in the domain of time series classification typically not as main algorithms, but as supporting algorithms [12], [13]. Fuzzy Cognitive Maps, on the other hand, are already present in the literature of time series classification [14], but they are used in a different manner. In particular, trained FCM weight matrices are used to classify time series. In contrast, in this study we use FCM responses as a base for classification.

III. PRELIMINARIES

A. Introductory Notes on the Hidden Markov Model

Hidden Markov Model (HMM) is a statistical method for modeling systems. It is a Markov chain with hidden states. A Markov chain is a stochastic process with the assumption that change depends only on the current state. In other words, the value assumed by a random variable $S$ at time $t$ depends only on the value recorded at time $t - 1$. This assumption is called the Markov property. In the Hidden Markov Model, we deal with a compound Markov chain $(S_t, O_t)_{t=1}^{\infty}$, in which $(S_t)_{t=1}^{\infty}$ is a Markov chain and $(O_t)_{t=1}^{\infty}$ is a sequence of random variables. The values assumed by the random variable $S_t$, denoted as $s_t$, form the state space of the HMM.

Let us focus on the case, when $S_t$ is a discrete random variable. The values assumed by the random variable $O_t$, denoted as $o_t$, are called emissions or observations. They can be either discrete or continuous. If the observations are discrete, we usually generate them from a categorical distribution. If they are continuous, a Gaussian distribution can be used. In an HMM, we observe only the values of the variable $O_t$, while the underlying values of $S_t$ remain hidden – hence the name “hidden”.

Interestingly, there is an analogous computational model in the literature called probabilistic automaton, [15]. However, we will not pursue investigation in this direction since a probabilistic automaton generalizes the Markov chain model.

In order to learn the parameters of the HMM, a data-driven optimization procedure is necessary. Although there is no feasible exact algorithm to solve this problem, we have other methods available. Among several commonly used approaches is the Baum-Welch algorithm. It is based on the expectation-maximization (EM) algorithm, [16]. EM looks for the maximum likelihood estimate of the unknown parameters. It is a good choice when direct maximization of the log-likelihood function is difficult.

B. Introductory Notes on Fuzzy Cognitive Maps

In the focal point of this paper stand Fuzzy Cognitive Maps (FCMs), an information representation scheme designed to model temporal data. FCMs were developed by B. Kosko in 1986 [17] as a flexible extension of plain Cognitive Maps. FCMs represent temporal phenomena in the form of a weighted directed graph. A sketch of a generic FCM with three nodes is given in Fig. 2. The nodes in an FCM are called concepts.

FCMs process data according to the following formula:

$$x_i^{(t+1)} = f \left( \sum_{j=1}^{P} w_{ij} x_j^{(t)} \right)$$

$x_i^{(t+1)}$ is the output of the $i$th concept. It is computed for the moment in time $(t+1)$ based on input that was observed at the moment in time $t$. Input and output, that is $x$, belongs to the interval $[0, 1]$. $P$ is the number of concepts in the FCM. $w$
denote weights, $w_{ij} \in [-1, 1], i, j = 1, \ldots, P$. $f$ is a sigmoid function given in Eq. (2):

$$f(x) = \frac{1}{1 + e^{-\tau \cdot x}}$$  \hspace{1cm} (2)

$x$ is in the domain of real numbers from $(-\infty, \infty)$. $\tau$ is a parameter controlling the steepness of the sigmoid function, which resembles the S-shaped curve. Many papers on FCMs set $\tau$ to 2.5 or 5. $f$ squashes the output to the interval $[0, 1]$.

It becomes apparent that the FCM processing model, see Eq. (1), is suitable for describing the behavior of dynamical systems and time series in general. Of course, due to the finite nature of the model it is of particularly useful for data with seasonal and cyclic patterns.

FCM training boils down to the task of finding the values of weights between the concepts. This is usually accomplished through an iterative procedure that adjusts the weights to minimize the time series prediction one step forward. The process uses historical time series data and minimizes the Sum of Squared Errors (SSE) given in Eq. (3).

$$SSE = \sum_{i=1}^{N} \sum_{j=1}^{P} (x_{ji} - y_{ji})^2$$  \hspace{1cm} (3)

$y_{ji}$ is the predicted value of $x_{ji}$, $N$ is the number of observations in the set for which we calculate the SSE.

Minimization of Eq. (3) is usually performed using heuristic searches [18]. In this study, we use Differential Evolution. Thus, due to space limitations we restrict the discussion of the applied optimization method to the empirical study and skip theoretical explanation.

We use fuzzified time series as input data, which is used to create FCM model. The fuzzification step is implemented using the fuzzy c-means algorithm. We launch the clustering algorithm and obtain centroids. They are representing fuzzy sets and generalize the underlying time series values. We run the clustering procedure for a data set with a two-dimensional representation of the time series $((z_2, dz_2), (z_3, dz_3), \ldots, (z_N, dz_N))$, where $dz_i = z_i - z_{i-1}$ and $z_i$ is an $i$th element of the scalar time series.

We can link each original time series data point (a pair, $z_i = (z_i, dz_i)$) with each centroid using the following formula:

$$x_{ij} = \frac{1}{\sum_{k=1}^{P} \left( \frac{\|z_i - v_i\|}{\|z_i - v_k\|} \right)^{2/(M-1)}}$$  \hspace{1cm} (4)

where $v$ denotes a centroid and $M$ is a fuzzification coefficient. Centroids become FCM concepts. The membership formula given in Eq. (4) produces data that is ready to be used with an FCM that we will use to classify time series. Processing data on the level of fuzzy memberships to concepts
C1, C2, ... does not impose any limitations, because our ultimate goal is to construct a classifier.

IV. TIME SERIES CLASSIFICATION WITH FUZZY COGNITIVE MAPS AND HIDDEN MARKOV MODEL

A. Time Series Classification with Hidden Markov Model

The standard approach consists of training one Hidden Markov Model for each class (using all its time series) and classifying sequences to the class which model yields the highest probability of generating the sequence. This strategy will be denoted as HMM 1C. It is also possible to create one model for each training sequence. Then, we can construct a classifier of our choice using probabilities returned by all these models. We use Nearest Neighbour as the classification rule and refer to this method as HMM NN. Please note that the numbers of parameters in these two approaches are very different, as the number of trained models is much bigger when they correspond to individual sequences.

When continuous observations are concerned, emission probability of a hidden state is usually expressed in the form of Gaussian distribution or Gaussian Mixture distribution. Usage of other distributions (e.g. Poisson) is also possible, but less common. As we want to limit the number of trainable parameters to be able to learn on very short sequences, we use a single Gaussian distribution. The likelihood function maximized with the Baum-Welch algorithm will be optimized over three sets of parameters: probability of starting in each state, probabilities of transitioning to other states, and parameters governing the emission functions, in our case defined by means and covariance matrices. Since it is possible (and often advisable) to put constrains on the covariance matrices, we examine models with three types of matrices: spherical, diagonal and unconstrained. Baum-Welch algorithm is susceptible to getting stuck in local optima. To deal with this problem at least partially, we perform a few learning attempts from random starting points and choose the one that gives the highest value of the log-likelihood function.

B. The Contribution – a Novel Approach to Time Series Classification with Fuzzy Cognitive Maps

Our approach to time series modeling with Fuzzy Cognitive Maps is almost a mirror image of the two techniques presented in IV-A, but with Hidden Markov Models swapped for Fuzzy Cognitive Maps. Every series (or class) is modeled as Fuzzy Cognitive Map learned with Differential Evolution to minimize the Mean Squared Error between the map’s output and the real value for every pair of consecutive observations. When a new series is classified, the class of the model giving the lowest MSE is chosen. Just like with HMM, we examine both one-model-per-class (FCM 1C) and one-model-per-series (FCM NN) approaches, using Nearest Neighbour classification rule in the latter.

V. EXPERIMENTAL EVALUATION

A. Data Sets and Experimental Setup

In this section, we address with the conducted empirical experiments. These involved 50 datasets. All datasets come from publicly available repository http://www.timeseriesclassification.com. The experiments performed made the following common assumptions:

- The code was implemented in Python 3.7. We used the following external Python libraries: numpy, pandas, scipy, scikit-learn, hmmlearn, sktime, tqdm, patlib.
- The repository we used provides a ready division between training and test sets. The training sets were used for training purposes, but we split them into train and validation sets to perform 3-fold cross-validation.
- There were times when the Hidden Markov Models training procedure failed to create a valid model. This happened almost exclusively when unconstrained covariance matrices in one-model-per-sequence approach were used. When such a failure occurred, the accuracy of the method was set to zero for that cross-validation fold. This is an example of a rigorous approach – one could simply ignore the faulty model (especially when it corresponds to only one training sequence) and perform classification using all the remaining models.

The experiments were divided into stages. In the first stage, hyperparameters were tested for the FCM NN and FCM 1C models. Several combinations of DE hyperparameters used for FCM optimization were tested. We do not include the results here due to space limitations. One of universally optimal set of parameters was found to be as follows: maximum number of iterations 150, mutation 0.5, recombination 0.5, and population size 10. The only hyperparameter that needs to be tuned individually for each dataset is the number of concepts forming a map.

The hyperparameters for the HMM 1C and HMM NN optimization were tested similarly. The outcomes of these tests show that we can set the maximum number of iterations performed to 50 and random initializations to 10 for all experiments. The issue of how the algorithm behaves for different covariance matrices proved to be more challenging and we decided to make it a hyperparameter to be tuned individually for each dataset. Also, the number of hidden states was adjusted individually based on the accuracy of cross-validation.

B. Achieved Results

Fig. 3 shows the average classification accuracy on the whole cross-validated training data. We observe a superiority of the NN models. The only exception is HMM NN with unconstrained covariance matrices that was overall the worst of all tested methods.

Fig. 4 compares models in which either FCM or HMM was built separately for each time series (the NN models) with models where either FCM or HMM was built one in each class (the 1C models). We skipped HMM NN with unconstrained
covariance matrices which provided unfeasible results and, in addition, posed challenges at the optimization process. The plot shows clear advantage of the NN models.

The comparison of different models revealed that there is no one clear winner, the performance depends on the dataset. In Fig. 6, and Fig. 5, we show cases when different models provide better results.

It is possible to highlight groups of methods that produced highly correlated results (measured with Spearman’s Correlation). Results of HMM 1C with different covariance matrices were almost interchangeable (SC ≈ 0.97). The same was true for HMM NN spherical coupled with HMM NN diagonal. Similarities (FCM 1C ≈ FCM NN) and (HMM 1C ≈ HMM NN) were not that high (SC ≈ 0.85). Correlations among 1C methods and NN methods were even lower (SC ≈ 0.8), but not as low as between models that did not share any common trait (SC ≈ 0.72).

Despite similar accuracy results, the execution time of the methods differed significantly. As shown in Fig. 7, the execution time of Differential Evolution increased much faster than that for the Baum-Welch method even after the maximum number of iterations in DE was reached. Execution time per iteration in both DE and Baum-Welch depends linearly on the number of observations, regardless of whether learning is performed on all observations in the class or on each sequence separately. Thus, the only difference in computation time between NN and 1C methods stems from different behaviour of the optimizers. The average execution time of the HMM NN method was lower than for the HMM 1C, while the average execution time of the FCM NN method was higher than for the FCM 1C.

Subsequently, we present classification accuracy provided by the best model in each category (FCM 1C, FCM NN, HMM 1C, and HMM NN) trained for each dataset. Table I presents this comparison. It also contains information about winning model parameters. All accuracies concern test sets. All experiments were conducted with 3-fold cross-validation.
to allow establishing a relative quality of the results.

In about half of the studied datasets, FCM provided best models. In the other half, HMM did. What is interesting, the best results achieved using FCM are based on maps with less concepts than hidden states in a corresponding HMM. This is an important result speaking for the FCM model.

VI. CONCLUSION AND CRITICAL DISCUSSION

The paper presented an empirical study that aimed at the comparison of the effectiveness of Hidden Markov Model and Fuzzy Cognitive Map in the task of time series classification. Two schemes of data classification are compared for both models. The first one requires training of an FCM or HMM for each time series in a dataset. The second requires training one FCM or HMM per class. The study demonstrated that the first variant provides higher classification accuracy both for FCM and HMM. What is more, it turned out to be computationally less expensive. The second important development addressed in this paper was the transfer of pattern classification methodology from HMMs to FCMs. Experiments show that FCMs used in this manner achieve similar classification accuracy as HMMs for similar model set-ups. The downside of the FCM NN variant is its training time, which is higher than FCM 1C and that of HMMs.

Last but not least, we shall underline that the discussed methodology of time series classification using FCMs is not the only one present in the literature. There exist an FCM-based methodology introduced by Homenda and Jastrzebska [14], which, all in all, achieves higher classification accuracies than the method presented in this paper.

REFERENCES

[1] T. Rakthanmanon, B. Camba, A. Mueen, G. Batista, B. Westover, Q. Zhu, J. Zakaria, and E. Keogh, “Addressing big data time series: Mining trillions of time series subsequences under dynamic time warping,” ACM Transactions on Knowledge Discovery from Data, vol. 7, no. 3, pp. 10:1–10:31, 2013.

[2] Y.-S. Jeong, M. K. Jeong, and O. A. Omitaomu, “Weighted dynamic time warping for time series classification,” Pattern Recognition, vol. 44, no. 9, pp. 2231–2240, 2011.

[3] C.-J. Hsu, K.-S. Huang, C.-B. Yang, and Y.-P. Guo, “Flexible dynamic time warping for time series classification,” Procedia Computer Science, vol. 51, pp. 2838–2842, 2015, international Conference On Computational Science, ICCS 2015.

[4] L. Ye and E. Keogh, “Time series shapetets: a novel technique that allows accurate, interpretable and fast classification,” Data Mining and Knowledge Discovery, vol. 29, no. 6, pp. 1505–1530, 2015.

[5] H. Deng, G. Runger, E. Tuv, and M. Vladimir, “A time series forest for classification and feature extraction,” Information Sciences, vol. 239, pp. 142–153, 2013.

[6] J. Lin, R. Khade, and Y. Li, “Rotation-invariant similarity in time series using bag-of-patterns representation,” Journal of Intelligent Information Systems, vol. 39, no. 2, pp. 287–315, 2012.

[7] P. Schäfer, “The BOSS is concerned with time series classification in the presence of noise,” Data Mining and Knowledge Discovery, vol. 29, no. 6, pp. 1573–1599, 2015.

[8] J. Large, A. Bagnall, and R. Alimansz, Simon nad Tavenard, “On time series classification with dictionary-based classifiers,” Intelligent Data Analysis, vol. 23, no. 5, pp. 1073–1089, 2019.

[9] A. Dempster, P. Petitjean, and G. I. Webb, “ROCKET: exceptionally fast and accurate time series classification using random convolutional kernels,” Data Mining and Knowledge Discovery, vol. 34, no. 5, pp. 1454–1495, 2020.

[10] A. Shifaz, C. Pelletier, F. Petitjean, and G. Webb, “Ts-chief: a scalable and accurate forest algorithm for time series classification,” Data Mining and Knowledge Discovery, vol. 34, no. 5, 2020.

[11] H. Ismail Fawaz, B. Lucas, G. Forestier, C. Pelletier, D. F. Schmidt, J. Weber, G. I. Webb, L. Idoumghar, P.-A. Muller, and F. Petitjean, “Inceptiontime: Finding Alexnet for time series classification,” Data Mining and Knowledge Discovery, vol. 34, no. 6, pp. 1936–1962, 2020.

[12] A. Antonucci, R. De Rosa, A. Giusti, and F. Cuzzolin, “Robust classification of multivariate time series by imprecise hidden markov models,” International Journal of Approximate Reasoning, vol. 56, pp. 249–263, 2015.

[13] B. Esmael, A. Arnaout, R. K. Frühwirth, and G. Thonhauser, “Improving time series classification using hidden markov models,” in 2012 12th International Conference on Hybrid Intelligent Systems (HIS), 2012, pp. 502–507.

[14] W. Homenda and A. Jastrzebska, “Time-series classification using fuzzy cognitive maps,” IEEE Transactions on Fuzzy Systems, vol. 28, no. 7, pp. 1383–1394, 2020.

[15] M. O. Rabin, “Probabilistic automata,” Information and Control, vol. 6, no. 3, pp. 230–245, 1963.

[16] F. Jelinek, L. Bahl, and R. Mercer, “Design of a linguist statistical decoder for the recognition of continuous speech,” IEEE Transactions on Information Theory, vol. 21, no. 3, pp. 250–256, 1975.

[17] B. Kosko, “Fuzzy cognitive maps,” Int. J. Man-Mach. Stud., vol. 24, no. 1, pp. 65–75, Jan. 1986.

[18] J. L. Salmeron, T. Mansouri, M. R. Moghadam, and A. Mardani, “Learning fuzzy cognitive maps with modified asexual reproduction optimisation algorithm,” Knowledge-Based Systems, vol. 163, pp. 723–735, 2019.
| data set                         | # of classes | HMM IC | accuracy | hpar | HMM NN | accuracy | hpar | FCM IC | accuracy | hpar | FCM NN | accuracy | hpar |
|---------------------------------|--------------|--------|----------|------|--------|----------|------|--------|----------|------|--------|----------|------|
| Adiac                           | 37           | 58.82  | 60.61    | 8    | 66.50  | 6       | 71.10 | 6      |
| ArrowHead                       | 3            | 53.14  | 65.71    | 5    | 44.57  | 10      | 62.86 | 3      |
| Beef                            | 5            | 40.00  | 53.33    | 9    | 43.33  | 4       | 56.67 | 5      |
| BeetleFly                       | 2            | 85.00  | 75.00    | 3    | 55.00  | 4       | 75.00 | 5      |
| BirdChicken                     | 2            | 90.00  | 90.00    | 6    | 75.00  | 16      | 60.00 | 16     |
| Car                             | 4            | 70.00  | 58.33    | 5    | 53.33  | 12      | 58.33 | 9      |
| CBF                             | 3            | 93.89  | 97.67    | 4    | 62.33  | 6       | 66.22 | 3      |
| Computers                       | 2            | 62.40  | 74.00    | 3    | 68.00  | 9       | 67.60 | 5      |
| DistalPhalanxOut.AgeGroup       | 3            | 12.10  | 70.65    | 4    | 43.12  | 12      | 71.38 | 4      |
| DistalPhalanxTW                 | 6            | 63.31  | 61.15    | 4    | 64.03  | 8       | 56.83 | 5      |
| ECG200                          | 2            | 71.00  | 79.00    | 10   | 53.00  | 16      | 81.00 | 5      |
| ECG5000                         | 5            | 91.71  | 92.49    | 5    | 85.07  | 9       | 89.76 | 4      |
| ECGFiveDays                     | 2            | 55.17  | 82.23    | 10   | 75.73  | 9       | 67.83 | 8      |
| FaceAll                         | 14           | 63.85  | 78.28    | 16   | 45.74  | 8       | 48.52 | 8      |
| FaceFour                        | 4            | 69.32  | 62.50    | 9    | 68.18  | 10      | 55.68 | 4      |
| FacesUCR                       | 14           | 67.12  | 73.66    | 16   | 50.54  | 10      | 57.61 | 7      |
| Fish                            | 7            | 50.86  | 47.43    | 4    | 55.43  | 5       | 62.29 | 5      |
| GunPoint                        | 2            | 78.00  | 92.67    | 10   | 82.67  | 7       | 77.33 | 9      |
| Ham                             | 2            | 64.76  | 48.57    | 4    | 62.86  | 10      | 58.10 | 4      |
| Haptics                         | 5            | 28.90  | 26.62    | 16   | 35.06  | 6       | 25.97 | 10     |
| Herring                         | 2            | 67.19  | 56.25    | 16   | 53.12  | 3       | 53.12 | 8      |
| InlineSkate                     | 7            | 54.18  | 33.64    | 7    | 27.27  | 10      | 38.36 | 7      |
| InsectWingbeatSound             | 10           | 16.97  | 18.38    | 16   | 23.79  | 4       | 15.91 | 5      |
| ItalyPowerDemand                | 2            | 86.01  | 88.24    | 7    | 78.52  | 4       | 81.44 | 8      |
| Lightning2                      | 2            | 63.93  | 75.41    | 12   | 54.10  | 9       | 68.85 | 4      |
| Lightning7                      | 7            | 58.90  | 60.27    | 10   | 47.95  | 6       | 42.47 | 4      |
| Mallat                          | 8            | 79.91  | 74.58    | 16   | 88.02  | 9       | 80.51 | 8      |
| Meat                            | 3            | 80.00  | 88.33    | 9    | 93.33  | 4       | 68.33 | 3      |
| MiddlePhalanxOut.Correct        | 2            | 62.34  | 50.00    | 9    | 59.74  | 7       | 54.55 | 8      |
| Mid.PhalanxOut.AgeGroup         | 3            | 71.13  | 71.82    | 16   | 48.80  | 9       | 65.64 | 5      |
| MiddlePhalanxTW                 | 6            | 50.65  | 42.86    | 4    | 55.84  | 5       | 47.40 | 3      |
| MotoStrain                      | 2            | 83.31  | 79.63    | 10   | 81.39  | 6       | 80.35 | 6      |
| OliveOil                        | 4            | 40.00  | 40.00    | 6    | 80.00  | 7       | 76.67 | 7      |
| OSULeaf                         | 6            | 64.88  | 77.69    | 10   | 80.99  | 10      | 76.03 | 5      |
| PhalangeoOutlinesCorrect        | 2            | 63.75  | 70.05    | 10   | 56.53  | 12      | 71.91 | 5      |
| Plane                           | 7            | 95.24  | 100      | 3    | 100    | 7       | 100   | 7      |
| Prox.PhalanxOut.AgeGroup        | 3            | 82.93  | 82.93    | 4    | 83.90  | 7       | 79.02 | 7      |
| ProximalPhalanxTW               | 6            | 62.89  | 77.32    | 6    | 66.67  | 3       | 78.01 | 4      |
| ShapedetSms                     | 2            | 86.67  | 67.22    | 12   | 90.00  | 3       | 90.00 | 5      |
| SonyAIBORobotSurface1           | 2            | 95.51  | 92.01    | 8    | 86.19  | 7       | 82.70 | 3      |
| SonyAIBORobotSurface2           | 2            | 88.67  | 87.20    | 8    | 77.33  | 8       | 78.38 | 8      |
| Strawberry                      | 2            | 73.78  | 93.24    | 16   | 71.35  | 7       | 95.14 | 8      |
| SwedishLeaf                     | 15           | 84.00  | 85.92    | 6    | 73.76  | 9       | 78.88 | 9      |
| Symbols                         | 6            | 82.41  | 81.11    | 5    | 68.84  | 7       | 66.83 | 6      |
| SyntheticControl                | 6            | 94.33  | 94.67    | 9    | 66.33  | 9       | 66.67 | 5      |
| ToeSegmentation1                | 2            | 78.07  | 80.26    | 4    | 76.32  | 5       | 82.46 | 6      |
| ToeSegmentation2                | 2            | 70.00  | 76.15    | 10   | 69.23  | 7       | 71.54 | 7      |
| Trace                           | 4            | 87.00  | 99.00    | 5    | 93.00  | 3       | 97.00 | 3      |
| TwoLeadECG                      | 2            | 96.66  | 94.03    | 9    | 91.66  | 5       | 79.98 | 12     |
| Wafer                           | 2            | 96.90  | 96.51    | 12   | 83.40  | 12      | 98.26 | 6      |