

# Scalable Classifier-Agnostic Channel Selection for Multivariate Time Series Classification

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**Abstract** Accuracy is a key focus of current work in time series classification. However, speed and data reduction are equally important in many applications, especially when the data scale and storage requirements rapidly increase. Current multivariate time series classification (MTSC) algorithms need hundreds of compute hours to complete training and prediction. This is due to the nature of multivariate time series data which grows with the number of time series, their length and the number of channels. In many applications, not all the channels are useful for the classification task, hence we require methods that can efficiently select useful channels and thus save computational resources. We propose and evaluate two methods for channel selection. Our techniques work by representing each class by a prototype time series and performing channel selection based on the prototype distance between classes. The main hypothesis is that useful channels enable better separation between classes; hence, channels with a longer distance between class prototypes are more useful. On the UEA MTSC benchmark, we show that these techniques achieve significant data reduction and classifier speedup for similar levels of classification accuracy. Channel selection is applied as a pre-processing step before training state-of-the-art MTSC algorithms and saves about 70% of computation time and data storage with preserved accuracy. Furthermore, our methods enable efficient classifiers, such as ROCKET, to achieve better accuracy than using no selection or greedy forward channel selection. To further study the impact of our techniques, we present experiments on classifying synthetic multivariate time series datasets with more than 100 channels, as well as a real-world case study on a dataset with 50 channels. In both cases, our channel selection methods result in significant data reduction with preserved or improved accuracy.

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## 1 Introduction

Time-series data are ordered sequences of numeric values recorded over time, collected in vast quantities and used in many application domains. Low-cost sensors coupled with rapid advances in IoT devices and cloud infrastructure has fuelled time series data collection in agriculture (Riaboff et al., 2022), equipment monitoring (Kanawaday and Sane, 2017), health (Fabietti et al., 2021), sports<sup>1</sup> and fitness (Singh et al., 2021).

The ease of collecting time-series data comes up with its own set of computational challenges. The scale of data collected increases rapidly, and so do the computational resources required to store and analyse this data. For example, in equipment monitoring in the cloud, there can be thousands of samples collected per minute, millions of time series to be monitored, and the number of monitored services is growing rapidly (Adams et al., 2020). Most time-series data are recorded in multivariate form where the temporal sequences come from multiple channels. For example, the Heartbeat dataset from the UEA MTSC benchmark has 61 channels. Each channel is the heartbeat’s sound recorded at different locations in the body. In our real-world case study, the time series have 50 channels. In this setting, an exercise named Military Press (MP) is performed, where a person lifts a barbell above their head from shoulder level, and the tracked motion data is collected from different body parts. Each body part tracked along an XY-axis acts as a channel and the primary objective is to classify the multivariate temporal sequences into normal and aberrant subtypes (see Figure 1 for an illustrative example). For this problem, only a subset of the body parts (e.g., channels corresponding to the upper body) is useful for the classification task. In our experiments we show that by selecting a useful subset using our channel selection methods, we benefit from data reduction and also significantly gain in accuracy, as the noisy channels that can confuse the classifier are removed before training the classifier.

To evaluate the impact of channel selection, we work with recent multivariate time series classifiers, ROCKET (Dempster et al., 2020), Weasel-Muse (Schäfer and Leser, 2018) and MrSEQL-SAX (Le Nguyen et al., 2019b). These approaches were shown to have state-of-the-art accuracy and can complete training and prediction on the full UEA MTSC benchmark in less than 7 days (Dhariyal et al., 2020; Ruiz et al., 2020). One important aspect of the classifiers mentioned above is that they use data from all the channels during training, and it is evident from our experiments that this is not the best strategy. The data from only a few channels could be more than sufficient to achieve the same or higher accuracy, thus reducing the time and memory required by the classifiers. For example, the DuckDuckGees dataset has 1,345 channels, but using

<sup>1</sup> <https://www.outputsports.com/>

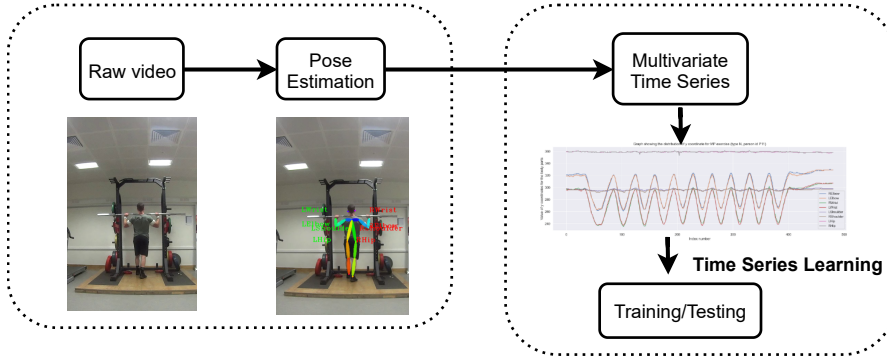


Fig. 1: From video to multivariate time series using OpenPose (figure reproduced from (Singh et al., 2021) with the permission of the authors).

only 30% of those channels (as selected by our methods) actually improve the accuracy of the classifier while reducing the data significantly. Similar impacts of our methods can be observed in many of the other UEA MTSC datasets.

This work extends the preliminary study (Dhariyal et al., 2021) on fast channel selection for multivariate time series classification. Although the primary focus of previous and current studies remains the same, i.e., improving classifier scalability while preserving accuracy, in this study we aim to achieve this along with maintaining robustness to noise. We achieve this goal by extending the previous channel selection methodology by studying different types of prototypes for representing classes, refining our channel selection and ranking methods and studying robustness to common data challenges, e.g., noise, minority classes and concept drift.

We evaluate our methods on the popular UEA MTSC benchmark and on synthetic time series, which simulate different types of signals, e.g. gaussian, pseudo-periodic, autoregressive and diverse data generation processes, where the relevant points are static or are moving, to simulate concept drift. These simulated datasets help us to analyse the behaviour of channel selection across different domains. For example, EEG waveforms are generally pseudo-periodic (Sainio et al., 1983), finance data usually follows auto-regressive patterns (Chou, 2005), while vibration mechanics involves a lot of Gaussian processes (Avendaño-Valencia et al., 2017). We also include a real-world case study on a human motion dataset collected as multivariate time series with 50 channels. We encounter challenges such as input noise due to the data collection process, minority classes, and relevant patterns that can shift for different time series due to the different motion characteristics of different people.

The primary objective of this study is to perform fast channel selection leading to data reduction without compromising on accuracy. We aim to achieve this by removing unnecessary channels, so that existing MTSC algorithms can perform classification efficiently and accurately.

**The main contributions of this work are:**

- We present new channel selection techniques, which are fast, scalable, robust to different types of noise in the input data and classifier-agnostic.
- We conduct extensive experiments on the UEA MTSC benchmark and report 75% reduction in computation time and a data reduction of 60% using our approaches, while preserving accuracy.
- We demonstrate a significant improvement in the accuracy (more than 20%) of the state-of-the-art classifier ROCKETS on synthetic datasets with varying levels of difficulty in identifying important channels.
- We show significant accuracy improvement for ROCKETS (more than 5%) on a real-world case study of our methods on a human motion MTSC dataset with 50 channels, recorded for classifying the Military Press strength and conditioning exercise.

## 2 Related Work

In this section we give a brief overview of state-of-the-art MTSC methods, and discuss existing approaches for channel selection.

### 2.1 Multivariate Time Series Classification

The recent empirical surveys (Ruiz et al., 2020; Dhariyal et al., 2020) provide a detailed overview of progress in MTSC. This section describes a subset of the classifiers discussed in these surveys that were used in this work to evaluate the impact of channel selection methods. We select these classifiers based on their accuracy on established benchmarks, availability of open source code and the computation time required to complete training and prediction on the UEA MTSC benchmark (less than 7 days).

#### 2.1.1 ROCKETS

ROCKETS (Dempster et al., 2020) is one of the most accurate time-series classifiers, initially proposed for univariate time series classification and later extended to MTSC. ROCKETS relies on convolutional kernels to extract time-series features. The kernels in ROCKETS are generated randomly; however, unlike in Convolutional Neural Networks, they are static throughout the classification process. The kernel properties like length, dilation, stride, bias and zero-padding are sampled randomly. The MTSC version of ROCKETS also performs channel selection randomly, selecting a maximum of 12 channels for any MTSC dataset. Therefore, the runtime is not significantly affected by the number of channels, especially for datasets with more than 12 channels.

The kernels are a linear transformation of the input time series. A linear classifier, ridge regression, trains on the feature vector formed by global max pooling and the proportion of positive values (PPV) features extracted from the convolution time series from every channel. ROCKETS has become very

popular due to its high accuracy and speed, yet the impact of channel selection on this classifier in the MTSC task has not been examined extensively.

### 2.1.2 *MrSEQL-SAX*

The linear classifier MrSEQL (Le Nguyen et al., 2019a) extracts symbolic features from the time series. The method transforms time-series data to multiple symbolic representations of different domains (e.g., SFA (Schäfer and Höggqvist, 2012) in the frequency domain and SAX (Lin et al., 2007) in the time domain) and into different resolutions using various window sizes. The classifier extracts discriminative subsequences from the symbolic representations, and these subsequences are later combined to form a single feature vector used to train a classification model. The method was initially developed for univariate time series classification but later adapted to MTSC; the adapted version views each channel as an independent time series. The symbolic transformations are computationally expensive. Furthermore, the transformation over multiple windows iterating over full-time series incurs a high cost for the scalability of the classifier. Therefore, reducing the number of channels can significantly improve the classifier’s scalability. This study focuses on MrSEQL-SAX (MrSEQL using only SAX features) as it is more efficient than the variant combining SAX and SFA transformations.

### 2.1.3 *WEASEL-MUSE*

WEASEL-MUSE (Schäfer and Leser, 2018) is an extension of the WEASEL algorithm (Schäfer and Leser, 2017) to MTSC data. The classifier builds a bag-of-patterns (BOP) model using the SFA transform for every channel. It captures the patterns by rolling multiple windows of varying sizes on raw and derivative time series, and transforming those segments into unigram and bigram words. The classifier links these words to their respective channel and creates a histogram for each channel separately. To deal with the large number of features from every channel, the Chi-square feature selection method removes the irrelevant features. The selected features are concatenated into a single feature vector which is the input to a logistic regression algorithm. Like MrSEQL, the WEASEL-MUSE classifier also iterates over the entire time series for every channel and performs the SFA transform for every window. This iteration and transformation increases the overall computation cost. Also, storing many unigrams and bigrams in memory is quite expensive. Therefore, we expect that channel selection would positively impact this classifier.

## 2.2 Channel Selection for Multivariate Time Series Classification

Channel selection for multivariate time series is a recurring topic in the MTSC literature. However, the focus of most work has been on accuracy rather than scalability.

The most recent work on channel selection (Kathirgamanathan and Cunningham, 2020) aims to identify the best subset of channels. The proposed method calculates a merit score based on correlation patterns of the outputs from the classifiers. The algorithm iterates through every possible subset to calculate the merit score, followed by a wrapper search on the subset with the top 5% merit score. 1NN-DTW is employed as the wrapper to perform the classification. The computational bottleneck of this work is using DTW over every possible subset to identify the useful channels.

Another notable study is CleVer (Yoon et al., 2005) where the author proposed three unsupervised feature subset selection techniques employing Common Principal Component Analysis (CPCA) (Krzanowski, 1979) to measure the importance of each sensor. The authors build a correlation coefficient matrix among different channels for each MTS. The principal components of each coefficient matrix are calculated, all the principal components are aggregated together, and descriptive component principal components are calculated. The  $l_2$ -norm of the resulting vector generates the rank of each channel.

Hu et al. (2013) proposed a framework for channel selection using a voting-based method. The two criteria used were distance-based classification and confidence-based classification. These methods were proposed for streaming data, which is outside the scope of the current study.

A recent study (Han and Niculescu-Mizil, 2020) presents an algorithm for channel ranking and channel selection. The channel ranking algorithm assigns a relevance score for each channel. The relevance scores are constructed on a similarity graph among the channels. The authors find the largest eigenvector of the normalized adjacency matrix of the similarity graph, which reflects its cluster structure. Apart from channel ranking, the authors also propose channel subset selection. From the adjacency matrix above, the algorithm finds the linear combination of matrices that approximates the labels' similarity matrix and uses the minimum number of redundant channels. Although the proposed channel ranking and selection approach performs well regarding the accuracy, it is slow. The authors mention that they face computation issues while building the graph representation for each feature.

The works mentioned above perform channel selection at the cost of computation time, sometimes leading to significantly increased time as compared to the default classifiers without channel selection. We note that none of the methods described above have open-source code available to perform comparative analysis. In order to compare our methods to a strong baseline, we adapt the feature selection methods from scikit-learn<sup>2</sup> to work with multivariate time series, by considering each channel as a single feature. We also investigate another baseline that uses the  $l_2$ -norm of each channel as a criteria for ranking and selecting channels. We provide all the data and code for reproducing our results<sup>3</sup>.

<sup>2</sup> [https://scikit-learn.org/stable/modules/generated/sklearn.feature\\_selection.SequentialFeatureSelector.html](https://scikit-learn.org/stable/modules/generated/sklearn.feature_selection.SequentialFeatureSelector.html)

<sup>3</sup> <https://github.com/mlgig/ChannelSelectionMTSC>

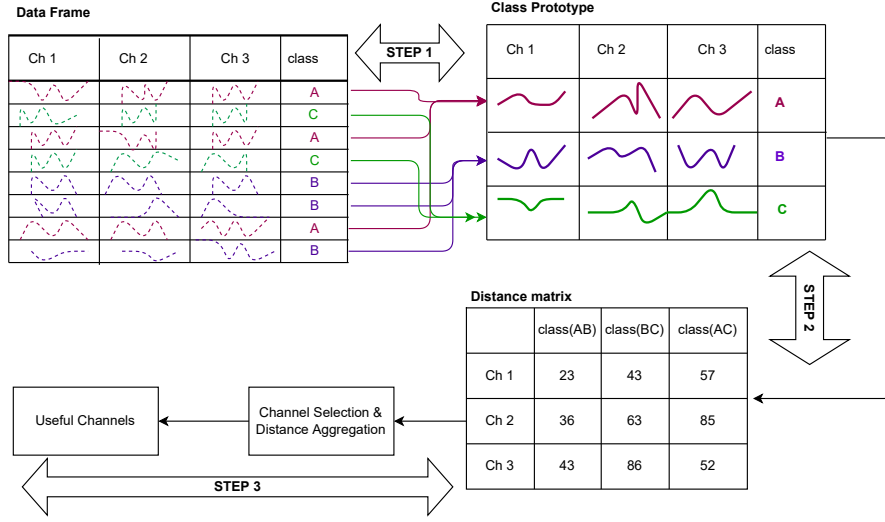


Fig. 2: Channel Selection Pipeline: 1. Compute class prototypes for each class and each channel. 2. For each channel, compute distance between prototype pairs. 3. Select the channel subset with the highest distance between prototypes. Hypothesis: Channels with higher distance are more useful for separating the classes in the subsequent classification task.

### 3 Methods

In this section we present our methodology for channel selection and discuss the key components by means of an example from our case study.

The proposed channel selection techniques depend on three components: *class prototype*, *distance matrix* and *distance aggregation* (Figure 2). Class prototypes are basically representations of each class in the dataset. The class prototype is also a multivariate time series. The key idea of this approach is that by comparing class prototypes for each channel, we can get an indication of which channel is more useful. The channels that increase the distance between class prototypes are more likely to be useful for the classification task, since they add in class discrimination. In the next step we compute a distance matrix between prototypes (pairwise distances between class prototypes) and use distance aggregation to rank and select channels. Next we discuss different choices of class prototypes and how to employ the distance matrix to select useful channels.

#### 3.1 Class Prototypes

A representative prototype of a class is necessary for the proposed techniques. In our approach, it is also important that the class prototypes are inexpensive

to compute. Extending our previous work (Dhariyal et al., 2021) on channel selection, here we investigate other choices for the class prototypes, with a specific focus on robustness to noise. We focus on three prototypes: mean, median and MAD (data trimmed using median absolute deviation (Leys et al., 2013)). Next, we formally define the class prototypes.

Let  $X \in R^{n \times d \times l}$  be an MTS dataset and  $y$  the labels of the time series in the dataset;  $n$  represents the number of time series in the dataset,  $d$  represents the number of channels in the multivariate time series, and  $l$  is the length of the time series.

**Mean Prototype:** Let  $X_A = \{s \in X \mid y(s) = A\}$  be the subset of  $X$  that contains only samples from class A. The mean prototype of class A is computed as the *mean* of all the time series in that class, i.e., the centroid:

$$C_A[i, j] = \frac{\sum_{k=1}^{k=m} X_A[k, i, j]}{m} \quad (1)$$

where  $m$  is the number of samples in class A. The multi-channel mean prototype  $C_A$  is a  $d \times l$  matrix in which each row  $C_{A,i}$  is the centroid of class A for channel  $i$ .

**Median Prototype:** Mean estimation is known to be susceptible to outliers. Median is an alternative to remedy this issue. For class A, the median prototype is computed as:

$$M_A[i, j] = \text{calculate\_median}(X_A[k, i, j]_{k=1}^{k=m}) \quad (2)$$

where  $m$  is the number of samples in class A. The multi-channel median prototype  $M_A$  is a  $d \times l$  matrix in which each row  $M_{A,i}$  is the median-center of class A for channel  $i$ . From hereon, we refer to the median prototype as the median for simplicity.

**MAD prototype:** Another method to handle outliers is clamping, i.e., replacing outliers with predetermined threshold values. We propose the MAD prototype for multivariate time series, which clamps the outliers using Median Absolute Deviation (Leys et al. (2013)). The MAD of class A is computed as follows:

$$\text{mad}_A[i, j] = \text{median}(|X_A[k, i, j] - M_A[i, j]|_{k=1}^{k=m}) \quad (3)$$

The upper and lower thresholds for clamping are then defined as

$$\text{upper\_limit} = M_A + 0.5 * \text{mad}_A$$

$$\text{lower\_limit} = M_A - 0.5 * \text{mad}_A$$

For a channel  $i$ , the MAD prototype for class A is calculated as the mean of the clamped dataset  $\bar{X}$  (values outside of the  $[\text{lower\_limit}, \text{upper\_limit}]$  range are replaced with the respective boundary values).

$$\text{MAD}_A[i, j] = \frac{\sum_{k=1}^{k=m} \bar{X}_A[k, i, j]}{m} \quad (4)$$

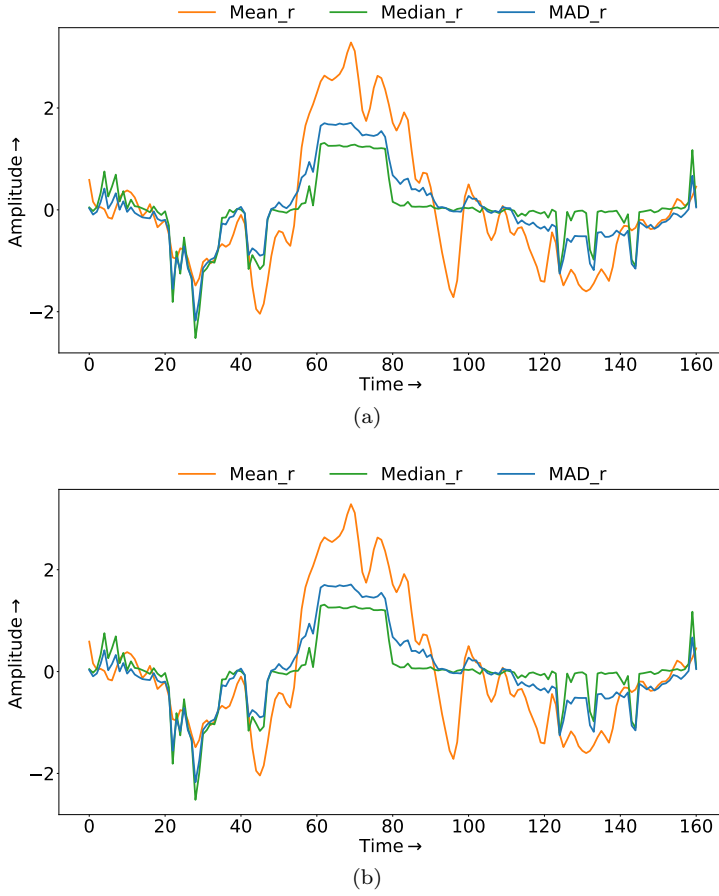


Fig. 3: Class prototypes for the classes normal (n) and reduced (r) for the left wrist channel along the X-axis (details of this dataset are given in the case study Section 7).

The multi-channel MAD prototype  $MAD_A$  is a  $d \times l$  matrix in which each row  $MAD_{A,i}$  is the (clamped) centroid of class  $A$  for channel  $i$ . For the purpose of simplicity we refer to this prototype as MAD.

Figure 3 illustrates the prototypes for two classes in the Military Press dataset. We notice that the mean prototype is more volatile than the other two, which can be explained by the outliers in the data. For this task, the time series data is obtained using body pose estimation libraries, and when the body is not fully visible or the estimation is not accurate, there can be outliers in the data. On the other hand, median and MAD prototypes follow each other closely. However, the MAD prototype seems to be more reflective of changes in the data.

### 3.2 Distance Matrix

We compare the class prototypes by measuring their Euclidean distance for each channel and for each pair of classes. The result is a distance matrix, which is a two-dimensional array of channels and class pairs. In Figure 2, the distance matrix tells us that the (Euclidean) distances between class A and class B prototypes in channel 1, 2, and 3 are 23, 36, and 43, respectively. This implies that channel 3 might be more useful than channel 1 and 2 in separating class A and class B. Table 18 illustrates a real distance matrix for the Military Press dataset. It is important to note that we also tested DTW as an alternative distance measure, which is usually preferred in time series analysis. Nevertheless, DTW is more expensive, hyperparameter sensitive, and its benefit when compared to Euclidean distance was unnoticeable in our experiments (see Appendix for details results in Tables 45 and 47).

### 3.3 Distance Aggregation and Channel Selection

#### 3.3.1 The ECS and ECP Channel Selection Algorithms

The preliminary study Dhariyal et al. (2021) proposed three techniques to perform channel selection using a simple class centroid as prototype, namely, KMeans, ECS (Elbow Class Sum), and ECP (Elbow Class Pairwise). Since KMeans performed poorly in comparison with ECS and ECP, we did not include it in this study. Here, we present the pseudo-code for our two algorithms ECS and ECP and present new extensions of our methodology in order to be more robust to data noise. In particular, we investigate new class prototypes, different ways to compute and aggregate the distance matrix and expand the channel selection and ranking strategy.

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**Algorithm 1:** ECS Channel Selection for an MTSC dataset.

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**Input:** Training dataset:  $X, y$

**Output:** Selected channels, ranking of channels

- 1 Initialization;
  - 2 For each channel in  $X$  and each class, compute class prototype;
  - 3 Compute distance matrix;
  - 4 Sum the distance matrix across rows;
  - 5 Sort channels by sum in decreasing order;
  - 6 Find the elbow on the sorted channels;
  - 7 Selected channels = channels with sum  $>$  elbow point ;
  - 8 Rank channels by total distance summed over class pairs;
  - 9 Return Selected channels and their ranks;
- 

Algorithms 1 and 2 describe the distance aggregation and channel selection steps for the ECS and ECP methods respectively. ECS evaluates each channel by the total sum of pairwise distances between class prototypes for that channel. However, for some tasks, there are classes that are more distinguishable

**Algorithm 2:** ECP Channel Selection for an MTSC dataset.

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**Input:** Training dataset:  $X, y$   
**Output:** Selected channels, ranking of channels

- 1 Initialization;
- 2 For each channel in  $X$  and each class, compute class prototype;
- 3 Compute distance matrix;
- 4 For each column in the distance matrix;
- 5     Rank the channels in decreasing order of the distance in the corresponding column of the distance matrix;
- 6     Find the elbow on the ranked channels;
- 7     Selected channels = Selected channels  $\cup$  channels with distance  $>$  elbow point;
- 8 Rank channels by total distance summed over class pairs;
- 9 Return Selected channels and ranks;

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than the others, hence the distance-sum can be dominated by the distances between these classes. As a result, channels that are specifically more useful for the less distinguishable classes might be ignored. To address this issue, ECP iterates through every class pair and selects the best channels for each pair. The final set of selected channels is a union over the selection for each pair. In this way, ECP ensures that the channels that might be ignored in ECS, also have a good chance to be selected.

In addition, we have evaluated a simpler baseline technique to rank channels using their  $l_2$ -norm. The basic idea of using the  $l_2$ -norm is that channels with higher magnitude might be more useful for discriminating between classes

### 3.3.2 Elbow Cut on Ranked Channels

Both the ECS and ECP algorithms employ an heuristic for automatically selecting a set of channels from a given ranked list of channels. This heuristic is commonly known as the elbow cut. The elbow cut is used to select channels from the distance matrix (ECP) or the distance sums (ECS). It identifies an inflection point on a ranked list of distances (Figure 4) and returns the channels based on this point (commonly known as the elbow point).

The elbow point (see Figure 4) is the point at the highest distance  $d$  from the line  $b$  joining the initial and ending point in a ranked list. The distance  $d$  to any point on the distance curve is calculated by using a vector projection of  $p$  on the line  $b$  as shown in Equation 5.

$$d = |p - (p \cdot \hat{b})\hat{b}| \quad (5)$$

where  $\hat{b} (= \frac{b}{\|b\|})$  is the unit vector in the direction of line  $b$ . The  $p \cdot \hat{b}$  is the scalar projection of  $p$  onto  $\hat{b}$  (Perwass et al. (2009)) and Equation 5 is obtained by the triangle formula. Thus, the elbow-point is

$$\text{elbow} = \text{argmax}(d) \quad (6)$$

The channels before the *elbow* are selected as useful channels (highlighted in green) for classification, and the smaller dataset with this subset of channels

is used for the classification step. It is clear from Figure 4 that the elbow point can be relaxed, thus allowing a trade-off between data storage and the accuracy of classification.

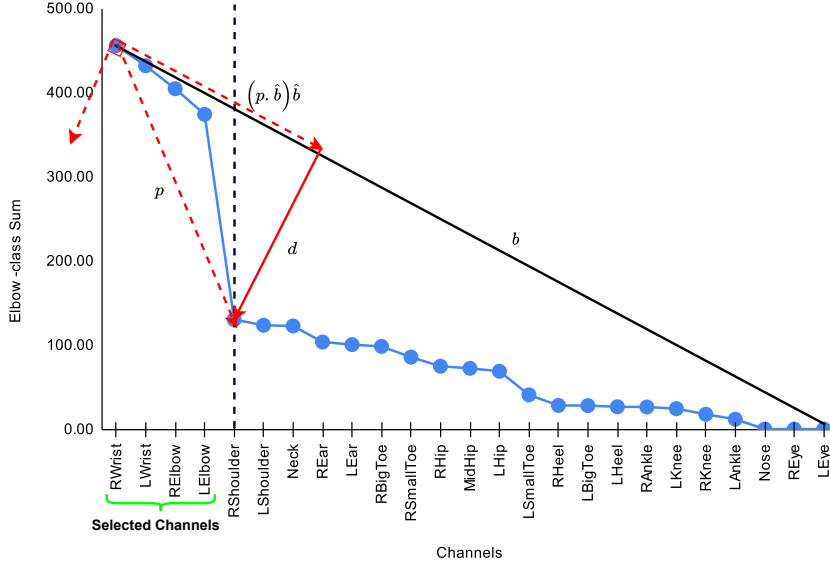


Fig. 4: Elbow-cut example for channel selection on the Military Press dataset using the *MAD* class prototype.

### 3.3.3 Channel Ranking

Although the proposed channel selection reduces the system’s computation requirements, it is not always possible to allocate a clear meaning to selected channels without domain experts. This work presents a method to rank channels according to their discriminative power (where distance between classes is used as a proxy for discrimination). ECS directly works on the sorted distances; therefore, it is easier to rank channels according to the distances. In the case of ECP, the channels selected by ECP are finally ranked based on the sum of distances across classes, similar to the first step in ECS.

### 3.4 Computational Complexity

As mentioned in Section 3.1 the dataset is defined with  $n$ ,  $d$  and  $l$  as parameters for the number of time series, number of channels, and length of time series. Let  $c$  be the number of the classes. To analyze the time complexity for our

proposed algorithms, we break the techniques into three steps, as illustrated in Figure 2, namely: 1. computation of class prototypes, 2. distance matrix formulation, and 3. channel selection.

The time complexity to create the class prototypes is  $\sim \mathcal{O}(n \times l \times d)$ . The distance matrix stores the distance for each channel for every class pair; therefore, the complexity of computing the distances for each class combination drives the time complexity. Theoretically the time complexity to create a distance matrix with  $d$  channels is  $\sim \mathcal{O}(c^2 \times l \times d)$ . In the final step, the elbow cut takes  $\sim \mathcal{O}(d \times \log(d))$  to sort and perform elbow cut in ECS and  $\sim \mathcal{O}(c^2 \times d \times \log(d))$  in ECP.

The total time complexity for channel selection is then the sum of the three steps: compute prototypes + compute class pairwise distances for each channel + sort distances and compute elbow point, which is  $\sim \mathcal{O}(n \times l \times d) + \mathcal{O}(c^2 \times l \times d) + \mathcal{O}(c^2 \times d \times \log(d))$ . In practice,  $d$  and  $c$  are typically small numbers in comparison to  $n$  and  $l$ . It is very rare for a multivariate time series dataset to have more than tens of classes or hundreds of channels. Therefore it is acceptable to assume that  $\log(d) \ll l$  and  $c^2 < n$ . As a result, the final complexity is  $\sim \mathcal{O}(n \times l \times d)$ . Table 7 show the empirical time and memory results for ECS and ECP and reflects the theoretical complexity derived here.

Regarding space complexity, the only additional information stored is the distance matrix, which grows  $\sim \mathcal{O}(c^2 \times d)$ . This is insignificant given that the values of  $d$  and  $c$  are typically small.

## 4 Evaluation on Benchmark Datasets

The approaches designed in this study are evaluated using state-of-the-art multivariate time series classification algorithms from the popular Python library `sktime` (Löning et al. (2019)). It should be noted that the algorithms are not tuned, but are used with the default parameters recommended in the original papers. However, our objective in designing experiments is to understand the relative gain or loss in computational aspects of MTSC algorithms using the proposed channel selection techniques instead of benchmarking MTSC algorithms. All the experiments were run on a Intel(R) Xeon(R) Gold 6140 CPU server with 256GB RAM. We release all our data and code in our Github repository<sup>4</sup>.

### 4.1 Datasets

The UEA/UCR Time Series Classification archive (Bagnall et al., 2017) is a collection of univariate and multivariate time series data. The repository contains 30 multivariate datasets from various application domains, e.g. ECG, motion classification, spectra classification. These heterogeneous datasets vary regarding the number of channels (from 2 to 1,345), the number of time series

<sup>4</sup> <https://github.com/mlgig/ChannelSelectionMTSC>

(12 to 30,000) and time series length (8 to 17,894). Here we work with the subset of 26 datasets with equal-length time series. The datasets have pre-defined splits into train and test sets and we use these splits for our evaluation. We call this archive the UEA MTSC benchmark.

#### 4.2 State-of-the-art MTSC Algorithms

Before analyzing the performance of channel selection, we benchmark existing state-of-the-art algorithms on our system. Table 1 shows the performance of classifiers on the 26 datasets. For ease of comparison we first show the average accuracy over the 26 datasets, as well as the total runtime to complete training and prediction over all datasets. In order to test for the statistical significance of these results, we follow the recommendations (Demšar, 2006; Garcia and Herrera, 2008; Benavoli et al., 2016). The accuracy gain is evaluated using a Wilcoxon signed-rank test with Holm correction and visualised with the critical difference (CD) diagram. The CD shows the ranking of methods with respect to their average accuracy rank computed across multiple datasets. Methods that do not have a statistically significant difference in rank, are connected with a thick horizontal line. For computing the CD we use the R library *scmamp*<sup>5</sup> (Calvo and Santafé, 2016). ROCKET is the best method for scalability and accuracy, closely followed by WeaselMuse and MrSEQL-SAX. However, WeaselMuse and MrSEQL-SAX are slow in comparison to ROCKET. For comparison, in Table 2 we show the performance of these classifiers after channel selection with our methods. We also see in Figure 5 that there is no significant difference between classifier accuracy before and after channel selection, i.e., with fewer channels and less computation time. We describe next a comparison of our methods to a strong greedy feature selection baseline, as well as a sensitivity analysis for the main components in our methods.

Classifiers	Avg. Accuracy	Time (minutes)
Rocket	71.58	36.93
WeaselMuse	70.28	3774.47
MrSEQL-SAX	66.99	7314.05
Total Memory (data size)	1.2 GB	

Table 1: Performance of state-of-the-art multivariate time series classifiers on 26 UEA datasets before channel selection.

<sup>5</sup> <https://github.com/b0rxa/scmamp>

Classifiers	Accuracy	Time (minutes)
Rocket	73.01	29.26
WeaselMuse	71.26	1104.10
MrSEQL-SAX	68.30	2818.70
Total Memory (data size)	0.38 GB	

Table 2: Performance of state-of-the-art multivariate time series classifiers on 26 UEA datasets after channel selection. The best combination of prototype and channel selection approach is used for computing these values. For more details on best performance for each dataset please see Table 19.

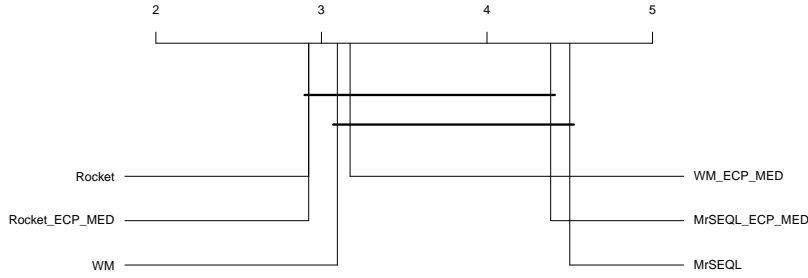


Fig. 5: Performance of MTSC classifiers with and without channel selection.

## 5 Baseline Comparison: Forward Channel Selection

Filter and Wrapper methods (John et al., 1994) are the methods of choice for performing feature selection in tabular data (Guyon and Elisseeff, 2003). The difference between the two methods is that the wrapper methods are exposed to classifier performance while the filter methods are agnostic of any classification evaluation metrics. A wrapper method was proposed in (Kathirgamanathan and Cunningham, 2020) but no code was made available to facilitate comparison, and it is apparent from that work that the method would be computationally expensive. We modify the forward feature selection in scikit-learn to a forward channel selection (FCS) method, where a channel of multivariate time series replaces a feature. There are two types of wrapper methods, namely, forward selection and backward elimination. This study uses tweaked forward selection as a baseline method. We deliberately leave the backward elimination method out as it is slow and requires a lot more memory when compared with forward selection. In default forward selection, the method greedily evaluates channels using a classifier and cross-validation, and provides a ranked list as output. The default setting selects the top 50% channels. As an alternative, domain knowledge can be used to decide the number of channels to be selected. To make the baseline stronger (than the default 50% selection), we tweak this method to select channels starting from the best channel and adding channels until there is no more gain in accuracy (the accuracy tends to increase when

starting from the best channel and adding new channels, and then tends to decrease once less informative channels are added). This is similar in nature to using the elbow cut to cut the ranked list of channels.

Classifier	Avg. Accuracy	Time (minutes)
ROCKET	71.58	36.93
FCS-ROCKET	70.96	3685.13

Table 3: Forward Channel Selection using ROCKET as estimator on 26 datasets.

Table 3 shows the performance of the forward channel selection with ROCKET. We find enough evidence of the performance of FCS as it clearly shows that the default classifier, ROCKET, is much faster and more accurate than the baseline, FCS-ROCKET. Therefore it contradicts the primary argument of this work, which is enabling the existing classifier to scale better. It is not feasible to perform forward channel selection for other MTSC methods for computational reasons.

### 5.1 Proposed Channel Selection Methods

In this section we focus on analysing the impact of different class prototypes and channel selection algorithms on the accuracy and runtime of the MTS classifiers. Table 4 shows the performance of the Median class prototype along with the Mean class prototype. The column  $\Delta\text{Acc}$  shows the difference in accuracy between the default classifier and the one with channel selection. The %Time column shows the amount of time saved due to channel selection. The Median class prototype, and ECP perform better than the Mean class prototype. The ECP-Median channel selection achieves better performance than the default version of ROCKET and MrSEQL-SAX, additionally, saving computation time and memory.

Prototype→	Mean				Median			
Channel Selection→	ECS		ECP		ECS		ECP	
Classifier↓	$\Delta\text{Acc}$	%Time	$\Delta\text{Acc}$	%Time	$\Delta\text{Acc}$	%Time	$\Delta\text{Acc}$	%Time
Rocket	-4.41	36.74	0.00	14.19	-5.02	28.51	+0.11	18.30
WeaselMuse	-3.80	76.90	-1.57	67.97	-6.18	77.64	-1.32	68.02
MrSEQL-SAX	-3.85	71.74	+0.45	59.65	-3.67	71.05	+0.36	59.66

Table 4: Performance of channel selection on 26 equal-length UEA datasets.

Although ECP-Median improved the performance, both the class prototypes have their virtues, as described in Section 3. The MAD centroid combines both the Mean class prototype and Median class prototype properties. Table

Prototype→	MAD			
Channel Selection→	ECS		ECP	
Classifier↓	ΔAcc	%Time	ΔAcc	%Time
ROCKET	-4.53	27.59	+0.28	17.67
WeaselMuse	-5.77	83.19	-1.34	74.39
MrSEQL-SAX	-3.31	83.39	+0.38	77.11

Table 5: Performance of channel selection with the MAD prototype on the 26 UEA datasets. ECP-MAD outperforms the other selection strategies.

5 shows the results when using MAD as the class prototype. The computation time also reduces significantly in the case of Weasel-Muse and MrSEQL-SAX.

To further understand the impact of different selection strategies, we have tested another approach for ranking and selecting channels. We first calculate the  $l_2$ -norm of class prototypes for each class instead of the euclidean distance between a class pair. Table 6 illustrates the performance of the  $l_2$ -norm on two class-prototypes namely, Mean and Median. Here we examine if channel selection can be performed directly based on the channels' magnitude, rather than the distance between class prototypes. Table 6 illustrates the performance of using the  $l_2$ -norm on two-class prototypes namely, Mean and Median.

Prototype→	Mean				Median			
Channel Selection→	ECS		ECP		ECS		ECP	
Classifier↓	ΔAcc	%Time	ΔAcc	%Time	ΔAcc	%Time	ΔAcc	%Time
ROCKET	-6.03	40.49	-0.21	19.36	-4.58	30.10	+0.30	21.30
WeaselMuse	-4.80	80.31	-0.66	69.07	-6.07	78.06	-2.14	72.04
MrSEQL-SAX	-5.14	79.60	-0.74	71.14	-5.61	78.95	-0.04	71.49

Table 6: Channel selection using the  $l_2$ -norm instead of distance between class prototypes.

The  $l_2$ -norm performs reasonably when combined with the three classifiers. Although the method enables ECP-Median- $l_2$  with ROCKET to perform similar to the default version ECP-Median with euclidean distance, overall it is not better than the distance-based selection strategies. The reason for this could be that the  $l_2$ -norm of class-prototypes is highly susceptible to data noise for each channel, where a slight jitter could mislead results. Hitherto, from Tables 4, 5 and 6, we conclude that distance-based selection strategies with the ECP-MAD as class prototype works best in comparison to other strategies.

## 5.2 Sensitivity Analysis

The above section shows that channel selection significantly reduces the computation time while maintaining accuracy. In this section, we take a more refined look into the data and analyse the performance of these techniques on the UEA datasets.

### 5.2.1 Channel Utilisation for Different Class Prototypes

Figure 6 shows the percentages of channels utilised by the three class prototypes. Interestingly, the higher the number of channels in the dataset, the fewer channels are helpful. Datasets like DuckDuckGeese has 1345 channels; however, only 538 channels are selected by ECP-MAD. As the number of channels decreases, more channels get utilised, which is logical as they tend to possess more information.

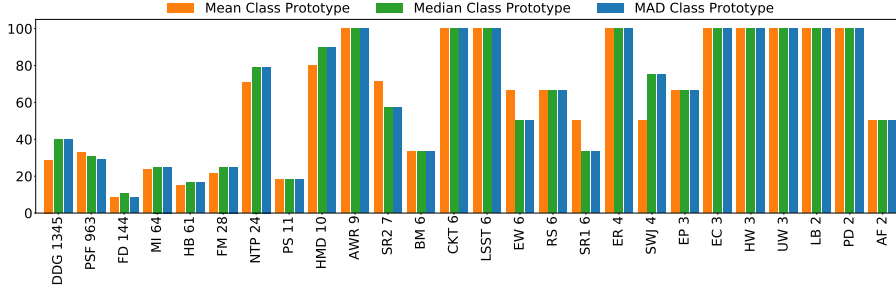


Fig. 6: Channel utilisation for the three class prototypes with ECP selection.

### 5.2.2 Runtime by Different Class Prototypes

Table 7 presents time and memory required by different class prototypes along with various channel selection techniques. The time taken by MAD is highest among the three, as it iterates over data points for every class (as described in Section 3). The table also illustrates the memory required for different datasets. The proposed methods significantly reduce the memory required, as compared to the 1.2GB required to store the 26 UEA datasets.

Class Prototype→ Channel Selection→	Mean		Median		MAD	
	ECS	ECP	ECS	ECP	ECS	ECP
Time (minutes)	0.26	0.27	0.31	0.32	0.64	0.67
Memory (GB)	0.28	0.42	0.27	0.42	0.25	0.41

Table 7: Total runtime of channel selection methods and the memory required to store the 26 UEA datasets after selection.

### 5.2.3 Analysis by Datasets

As mentioned in Section 4.1, the UEA MTSC archive is a heterogeneous collection of problems. In this section, we discuss the performance of ECP on the benchmark datasets.

Figure 7,8 and 9 illustrates the change in accuracy on different class prototypes versus the number of channels utilized by each dataset for ROCKET, MrSEQL and Weasel-Muse. We note that the accuracy is largely preserved, with a significant reduction in the number of channels, especially for datasets with more than 10 channels. Although the set of channels recommended by the proposed techniques is identical for all classifiers, the performance of classifiers varies for the same set of datasets. The DuckDuckGeese (DDG) dataset gains significant accuracy for ROCKET and MrSEQL but loses some for Weasel-Muse. Similarly, for the MotorImagery( MI), MrSEQL-SAX performs better than the default, but ROCKET and Weasel-Muse are not as accurate. These results may arise due to the type of classifier, and the study of the classifier is outside the current study's scope.

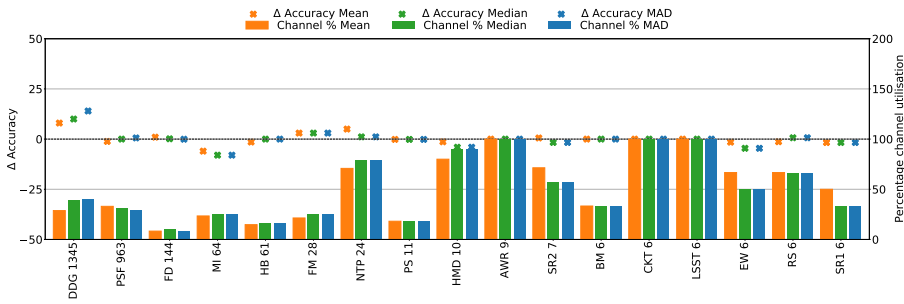


Fig. 7: Rocket ECP accuracy and channel utilisation for three class-prototypes.

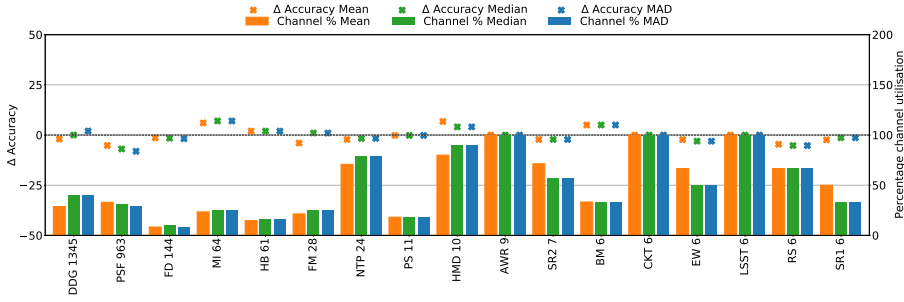


Fig. 8: MrSEQL-SAX ECP accuracy and channel utilisation for three class-prototypes.

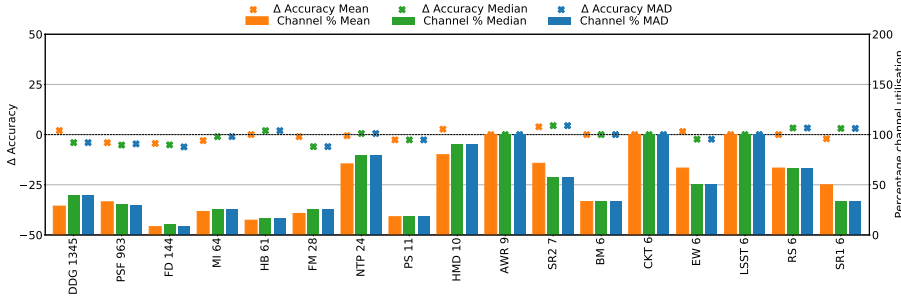


Fig. 9: Weasel-Muse ECP accuracy and channel utilisation for three class-prototypes.

#### 5.2.4 Analysis by the Number of Channels

The UEA datasets vary in the number of channels. It contains three datasets with more than 100 channels and six datasets with between 10 and 100 channels. Table 8 and Table 9 demonstrate the performance of channel selection for datasets in these groups. ROCKET outperforms the other two classifiers when the channels are greater than 100. It gains 4.48% average accuracy on the three datasets at the cost of 13.8 (7.04%) seconds more than the default setting.

Although the channel selection for the other two classifiers does not help them as much as in the case of Rocket, it helps them reduce the time significantly. Moreover, the MrSEQL-SAX performs better than Rocket and Weasel Muse for datasets between 10 and 100 channels.

Class Prototype→	Mean		Median		MAD	
Classifiers↓	ΔAcc	%Time	ΔAcc	%Time	ΔAcc	%Time
Rocket	+2.60	2.30	+3.38	1.13	+4.84	-7.04
WeaselMuse	-2.15	76.52	-4.77	74.33	-4.92	79.06
MrSEQL-SAX	-2.86	74.26	-2.83	72.62	-2.65	84.40

Table 8: ECP channel selection on datasets with channels  $\geq 100$

Class Prototype→	Mean		Median		MAD	
Classifiers↓	ΔAcc	%Time	ΔAcc	%Time	ΔAcc	%Time
Rocket	+0.08	20.96	-0.81	20.27	-0.81	20.47
WeaselMuse	-1.44	76.32	-1.42	75.03	-1.42	84.40
MrSEQL-SAX	+0.31	55.91	+1.62	55.74	+1.62	73.52

Table 9: ECP channel selection on datasets with channels  $> 10$  and  $< 100$

### 5.2.5 Analysis by Problem Domains

The application of multivariate data varies across domains. In the UEA archive, the data comes from 5 different domains, namely, Audio Spectra Classification (ASC), EEG/MEG Classification (EEG), Human Activity Recognition (HAR), Motion Classification (MC), ECG Classification (ECG).

Table 49 illustrates the performance of the classifiers on the mentioned domains when using the ECP-MAD selection. Channel selection improves the performance of Rocket in ASR and MC domains, while in the case of EEG, MrSEQL performs slightly better with channel selection than its default setting. Channel selection also aids Weasel-Muse in the case of HAR and MC.

Classifiers→	Rocket	MrSEQL	WM
ASR (3)	+4.48	+1.26	-1.55
ECG (2)	-4.00	-6.67	-6.66
EEG (6)	-0.28	+1.10	-2.29
HAR (9)	-1.20	-0.55	+0.18
MC (3)	0.00	-0.24	+0.01
Other (3)	+4.44	-2.69	-1.54

Table 10:  $\Delta$  Accuracy ECP-MAD channel selection for datasets from different domains.

### 5.2.6 Analysis of Channel Selection on Minority Classes

Although most of the datasets in the UEA benchmark are balanced with regard to the number of samples in each class, we analyse the impact of channel selection on the imbalanced datasets in this section. The significantly imbalanced datasets from the UEA benchmark are reported below with the F1 score (refer to Table 48 for class counts). Table 11 compares ECP-MAD based channel selection (F1-CS) with the default classifier performance (F1-Default).

Dataset (#Channels)	#Channels Selected	F1-Default	F1-CS	Best-Setting
EW (6)	4	83.36	86.58	ECP+Mean
HW (3)	3	55.72	55.72	ECP+Med
LSST (6)	6	43.66	43.66	ECP+Med
HB (61)	10	63.41	66.87	ECS+MAD

Table 11: Analysis of channel-selection on imbalanced datasets.

The datasets EW, HW, LSST, and HB maintain or improve F1 scores with channel selection. For dataset HW and LSST, the channel selection method recommends using all channels; however, for EW and HB, it is recommended to use the fewer channels, especially HB sees a significant reduction in the number of channels to be used. Also, it should be noted that in most cases,

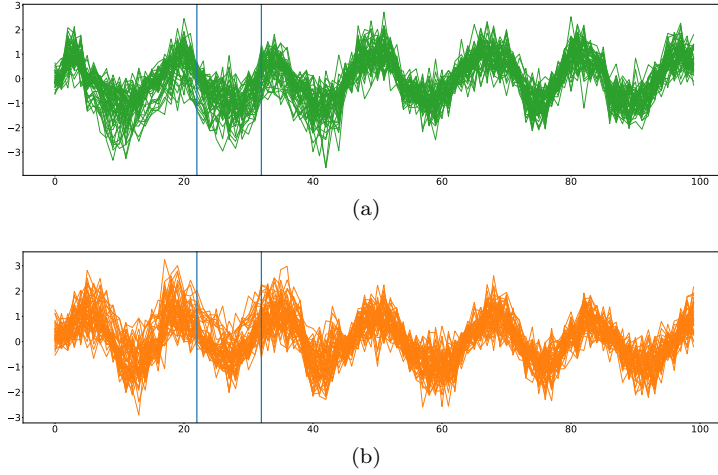


Fig. 10: Two synthetic (multivariate) time series of different classes generated by the Pseudo Periodic process. The important time steps are 22-32 where the values in (a) are typically lower than (b).

ECP works well; however, the class prototypes are crucial for different types of channel selection (refer to Table 19).

## 6 Case Study 1: Synthetic Datasets

The UEA benchmark suggests that our channel selection methods can reduce the computation time and memory while at least maintaining the same level of classification accuracy. However, other than using the resulting accuracy, we were unable to ascertain the effectiveness of the channel selection (i.e., did it select the right channels?) because we have no such ground truth.

To address this problem, we make use of synthetic datasets from the work of (Ismail et al., 2020), where the important channels and timepoints are set during the data generation process. We select the RareTime setting, where a small part of the time series is informative. The dataset type is generated using three signal types: Gaussian Process (GP), Pseudo Periodic (PP), and AutoRegressive (AR). The position of the signal can be stationary or moving (can change position within the channel). The length of time series is fixed to 100, and length of the important time series segment is 10. There are two classes.

The number of important channels is fixed to 40. Therefore, as the number of channels increases, the ratio of the important channel to all channels decreases. For example, from 40%, it goes to 20% and then 10% for 100, 200 and 400 channels, so the problem becomes more difficult with an increasing number of channels. Figure 11 presents the performance of ROCKET on the synthetic data. ROCKET is the most accurate classifier among the three we

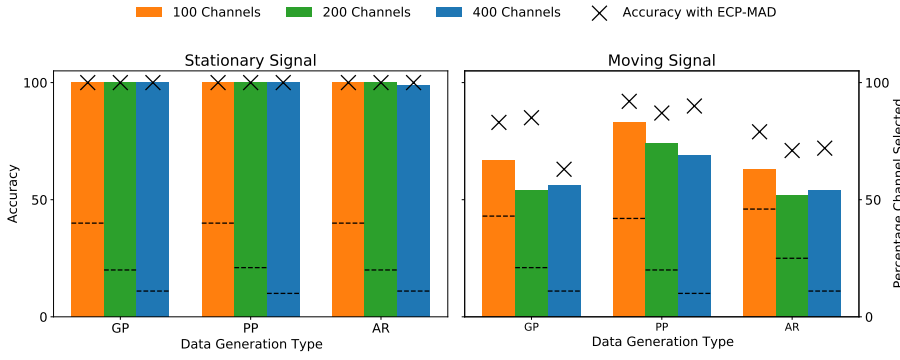


Fig. 11: Synthetic datasets generated using the procedure in (Ismail et al., 2020) using the RareTime setting. The dashed black line indicates the percentage of channels selected.

studied; therefore, we use ROCKET to analyse the synthetic data. ROCKET achieves 100 percent accuracy for the stationary signal; however, it struggles to perform accurately when the signal is moving. When we use ROCKET with our channels selection method, ECP-MAD, then ROCKET achieves the same accuracy as without channel selection in the case of the stationary signal data; furthermore, in the case of moving signal, channel selection enables ROCKET to perform significantly better.

The interesting point is that channel selection extracts approximately the same number of important channels mentioned during dataset generation. For 40% of important channels in 100 channel stationary signal data, the channel selection recommends 40% channels in static signal data for all three signals, and 43%, 42% and 46% for moving signal for GP, PP, and AR signal data, respectively. Similarly, for 200 channel data, the important channels created are 40, the number of channels recommended is 20%, 21% and 20% for stationary signal data and 21, 20 and 25 for moving signal data in GP, PP and AR, respectively. With the 400 channels, the number of important channels in the dataset reduces to 10%, and it becomes harder for the classifier to find useful signal; however, the channel selection algorithm reduces the efforts required by the classifier. The method selects 11%, 10% and 11% for stationary GP, PP and AR signal data and 14%, 11% and 13% for moving GP, PP and AR signal data, respectively.

### 6.1 Performance of Channel Selection on Minority Classes

In continuation to Section 5.2.6, we analyse the impact of channel selection on minority classes in synthetic data using ROCKET. Table 12 presents the F1 score for moving and stationary signals in GP, PP and AR datasets with 100 channels across the different scenarios of class imbalance. We vary the

class ratio to evaluate the performance of channel selection. This enables us to study how the channel selection performs with different cardinalities.

Datasets	Class Ratio #0 : #1	F1-Moving		F1-Stationary	
		Default	CS	Default	CS
GP	50:50	83.00	82.98	100	100
	90:10	34.21	34.21	81.00	97.99
	80:20	34.21	40.78	93.93	100
PP	50:50	92.00	92.00	100	100
	90:10	33.33	35.51	100	100
	80:20	35.52	61.55	100	100
AR	50:50	79.00	78.64	100	100
	90:10	29.07	29.07	77.52	94.97
	80:20	29.07	34.54	97.99	98.99

Table 12: Analysis of ECP-MAD channel selection in minority class on synthetic data.

Similar to the analysis above, we find that the cardinality of a class does not impact the channel selection. However, with various levels of imbalance, even a good classifier like ROCKET struggles to perform better. The channel selection, on some occasions, improves accuracy; however, not as much as in the case of balanced data.

## 7 Case Study 2: Military Press Dataset

The experiments in the above sections confirm that our channel selection methods enable the state-of-the-art classifiers to achieve better accuracy in significantly smaller amounts of time and memory and, in the worst case, saves time and memory with minimal loss of accuracy. However, to perform a sanity check on real-world data, we provide an additional study on Military Press data, collected and verified at University College Dublin with the help of domain experts.

### 7.1 Dataset

A total of 56 healthy volunteers (34 males and 22 females; age:  $26 \pm 5$  years, height:  $1.73 \pm 0.09$  m and body mass:  $72 \pm 15$  kg) participated in a study aimed at analysing the execution of the Military Press strength and conditioning exercise. The participants completed ten repetitions of the normal form and ten repetitions of induced forms. The NSCA guidelines were applied under the guidance of sports physiotherapists and conditioning coaches to ensure standardisation. The dataset was extracted from the video of individuals performing the exercise with the help of the human body pose estimation library

OpenPose<sup>6</sup>. There are four classes in the dataset, namely: Normal (N), Asymmetrical (A), Reduced Range (R) and Arch (arch). The N refers to the correct execution of the exercise; A refers to when the barbell is lopsided and asymmetrical, R refers to the form where the bar is not brought down completely to the shoulder level and Arch refers to when participants arch their back. A total of 25 body parts were tracked along X and Y axis, as seen in Figure 4. These 50 body trackers ( $25 \times 2$ ) act as channels for the MTSC task. The train and test size for this dataset is 1452 and 601 respectively and the length of time-series is 160.

## 7.2 Evaluation

When used with all 50 channels, ROCKET takes 1.45 minutes and achieves an accuracy of 77.53%. In this setting, the normalisation hyperparameter of ROCKET is switched off; this is because the signal magnitude contains crucial information. Table 13 shows accuracy and computation results before and after channel selection.

Classifiers ↓	Before Selection			After Selection			Best Setting
	Acc	Time	Mem (MB)	Acc	Time	Mem (MB)	
ROCKET	77.53	1.45	98.5	84.02	1.52	13.80	ECS-Median
Weasel Muse	57.57	71.55	98.5	59.90	38.87	43.38	ECP-Median
MrSEAL-SAX	61.56	633.56	98.5	59.07	360.80	43.38	ECP-Median

Table 13: The SOTA classifiers on 50 Channel Military Press dataset.

## 7.3 Performance of SOTA Classifiers on MP Dataset

Table 14 demonstrates the performance of channel selection on the Military Press dataset. The ECS with Median as class prototype outperforms any other setting; the gain in accuracy is about 7%. All the other channel selection methods perform better than ROCKET in its default setting.

Center→ Channel Selection→	Median				MAD			
	ECS		ECP		ECS		ECP	
Classifier↓	Acc	Time	Acc	Time	Acc	Time	Acc	Time
ROCKET	84.02	1.52	81.03	1.78	82.59	1.59	80.20	1.75
Weasel Muse	54.57	10.28	59.90	38.87	54.57	10.23	58.57	48.35
MrSEQL-SAX	58.90	58.63	59.07	360.80	58.90	58.63	51.32	382.08

Table 14: Performance of SOTA classifiers on MP dataset.

<sup>6</sup> <https://github.com/CMU-Perceptual-Computing-Lab/openpose>

**Ranking:** The channel ranking using the best method here, ECS with median prototype, is as follows: 'RWrist\_Y', 'LWrist\_Y', 'RElbow\_Y', 'LElbow\_Y', 'RElbow\_X', 'LElbow\_X', 'RHeel\_Y'. We note that out of 50 channels, this method selects only a subset of 7 channels, which not only reduces the data drastically, but also results in significantly increased accuracy. We consider this a very good result, also considering that it makes it easier to provide feedback to the participant executing the exercise, by pointing to the most important body parts for the execution.

#### 7.4 Performance of Channel Selection with Two Classes

With the help of domain experts, we know that the Military Press exercises with classes Asymmetric, Reduced, and Arch, are exercises done incorrectly. All three classes have different signal magnitudes. To study the impact of channel selection when one of the classes has a group of different behaviours, we group the classes mentioned above into Abnormal and train a binary classifier, Abnormal, against the Normal class in the dataset. Since there are only two classes, ECS and ECP strategies are identical.

All	Mean	Median	MAD
72.05	73.71	77.05	77.50

Table 15: F1 score for ROCKET when using two classes

Table 15 illustrates the performance of ROCKET on the three prototypes used. We see that channel selection helps ROCKET to distinguish between the two classes. Furthermore, MAD is the most effective strategy. Since this is an imbalanced dataset, we also compared precision and recall in Table 16 and found that, with channel selection, there is an improvement in both precision and recall.

	Precision	Recall	F1		Precision	Recall	F1	Support
Abnormal	0.86	0.86	0.86		0.90	0.87	0.88	451
Normal	0.59	0.57	0.58		0.64	0.69	0.67	150

F1 results with all channels.

F1 results for the MAD prototype.

Table 16: Comparison of performance of ROCKET with and without channel selection.

## 8 Limitations & Future Work

While ECP performs better than ECS in most datasets, it may collect some noisy channels when iterating through the different class pairs in the distance matrix. These noisy channels, along with useful channels, are then used for classification and this could negatively impact the classifier accuracy. The proposed methods rely on the euclidean distance between two class prototypes; however, if a class prototype is too noisy, it could amplify the euclidean distance. With the help of the signal’s magnitude, the euclidean distance could be regularised. In our future work we want to further analyse the impact of combining information from the prototype magnitude and the distance-based computation to address this issue.

We also plan to investigate whether combining multiple class prototypes can further improve results. At the moment we only use one class prototype to represent each class and for classes with subgroups of behaviours this could be an issue. We can consider first clustering the behaviours in each class and representing each subgroup with a prototype. In that case, we also need to investigate whether all class prototypes are equally important, or if some are more important than others.

The current study focuses on channel selection based on euclidean distance and does not use time-series attributes or statistical properties of each class to adjust the selection strategy. Similar to channel selection, we could also explore the time series segments that contribute most to the classification, providing another avenue to make existing MTSC algorithms more scalable.

## 9 Conclusion

This study shows that for many MTSC datasets, state-of-the-art classifiers do not require all the channels to achieve the best accuracy. Some channels are very noisy for the classification task and act as a bottleneck for the classifier to achieve its maximum potential. We observed that our channel selection methods remove data noise and drastically reduce the required computation time for existing MTSC methods. The current study showed that the distance between the class prototypes of various channels plays a crucial role in identifying the noisy channels. Our channel selection strategies, ECP and ECS, can select the useful channels based on euclidean distance between class prototypes. Our techniques significantly reduced the runtime and memory required to run MTSC classifiers. There is some accuracy loss for some datasets, however, this is minimal, and the benefit of data reduction and computation savings outweighs the small accuracy loss. Channel selection saves approximately 75% time and around 60% memory. The proposed channel selection techniques have more impact on the datasets with a higher number of channels. We verified the performance of our channel selection methods on various types of signals with varying levels of difficulty, ranging from the popular UEA MTSC benchmark, to synthetic data and a real-world case study. The channels selected performed

very well on those datasets, enhancing the performance of the most accurate classifier, ROCKET. On our case study with a real-world dataset, Military Press, our channel selection methods combined with ROCKET improved the accuracy by more than 5%. The proposed channel selection techniques are classifier-agnostic, they can be plugged into any classification pipeline, before training an MTSC classifier. They are also simple, fast and at the same time robust to different types of noise, which leads to preserved classifier accuracy as shown in our extensive experiments.

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## Appendix

Evaluation metrics

$$\text{Accuracy} = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

$$\text{F1 score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

$$\Delta\text{Acc} = \text{Accuracy after channel selection} - \text{Accuracy with default classifier}$$

$$\% \text{Time} = \frac{\text{Time taken with Channel Selection} - \text{Time taken without Channel Selection}}{\text{Time taken without Channel Selection}}$$

Domain	Problem	Acronym	Train Size	Test Size	Num Channels	Series Length	Num Classes
ASC	DuckDuckGeese	DDG	50	50	1345	270	5
Other	PEMS-SF	PSF	267	173	963	144	7
EEG	FaceDetection	FD	5890	3524	144	62	2
EEG	MotorImagery	MI	278	100	64	3000	2
ASC	Heartbeat	HB	204	205	61	405	2
EEG	FingerMovements	FM	316	100	28	50	2
HAR	NATOPS	NTP	180	180	24	51	6
ASC	PhonemeSpectra	PS	3315	3353	11	217	39
EEG	HandMovementDirection	HMD	160	74	10	400	4
Mot	ArticulatoryWordRecognition	AWR	275	300	9	144	25
EEG	SelfRegulationSCP2	SR2	200	180	7	1152	2
HAR	BasicMots	BM	40	40	6	100	4
HAR	Cricket	CKT	108	72	6	1197	12
HAR	EigenWorms	EW	128	131	6	17984	5
HAR	LSST	LSST	2459	2466	6	36	14
HAR	RacketSports	RS	151	152	6	30	4
EEG	SelfRegulationSCP1	SR1	268	293	6	896	2
HAR	ERing	ER	30	270	4	65	6
ECG	StandWalkJump	SWJ	12	15	4	2500	3
Mot	Epilepsy	EP	137	138	3	206	4
Other	EthanolConcentration	EC	261	263	3	1751	4
HAR	Handwriting	HW	150	850	3	152	26
HAR	UWaveGestureLibrary	UW	120	320	3	315	8
ECG	AtrialFibrillation	AF	15	15	2	640	3
Other	Libras	LB	180	180	2	45	15
Mot	PenDigits	PD	7494	3498	2	8	10

Table 17: Data Dictionary for 26 equal length UCR datasets.

Channels ↓	← Classes →					
	CP_a_arch	CP_a_n	CP_a_r	CP_arch_n	CP_arch_r	CP_n_r
RWrist_Y	51.00	56.27	103.15	48.93	123.44	82.84
RElbow_Y	50.66	51.67	98.55	35.13	87.03	75.97
LWrist_Y	40.12	45.61	99.03	45.41	123.17	90.40
REar_Y	39.44	5.29	11.39	36.79	31.18	9.85
LEar_Y	38.68	3.26	4.04	39.84	37.40	5.99
RShoulder_Y	35.43	11.63	23.36	34.42	18.33	23.77
RElbow_X	30.66	43.73	76.51	30.60	70.06	68.05
RHip_Y	28.88	6.41	11.38	27.95	19.21	10.52
MidHip_Y	28.23	8.10	9.16	25.60	21.45	7.49
LElbow_Y	27.72	40.91	95.98	33.26	92.82	83.06
LElbow_X	27.51	40.61	55.97	28.79	68.01	68.89
LShoulder_Y	27.22	16.11	10.78	37.82	25.27	20.57
Neck_Y	25.91	14.47	15.41	36.49	18.38	25.95
RSmallToe_X	25.09	24.26	29.78	32.07	33.48	36.95
RWrist_X	24.63	19.88	17.88	14.93	29.84	28.10
LHip_Y	23.97	9.02	7.78	23.49	19.12	8.11
RBigToe_Y	20.66	20.10	16.96	29.57	25.34	30.02
RSmallToe_Y	20.05	14.86	12.26	26.29	19.48	20.93
Neck_X	17.27	6.37	20.87	15.78	26.78	22.75
MidHip_X	16.87	10.10	11.46	13.77	15.98	9.30
LBigToe_X	13.31	6.06	5.71	13.76	11.98	6.10
LWrist_X	13.27	10.90	14.93	9.98	15.47	10.37
LKnee_X	11.57	7.31	9.04	11.69	14.93	8.73
LAnkle_X	11.02	6.89	10.52	10.02	15.16	12.29
RBigToe_X	10.45	6.22	5.57	11.79	11.26	8.36
RHeel_Y	10.40	1.90	4.40	10.55	12.48	4.58
LSmallToe_Y	10.10	7.58	11.15	9.87	10.42	10.03
LHip_X	9.59	7.26	6.46	10.97	13.94	9.65
RKnee_X	9.54	8.88	6.95	12.40	11.68	7.27
REar_X	8.92	16.58	7.71	16.50	7.16	14.55
LHeel_Y	8.81	5.90	6.90	6.53	10.84	6.74
LKnee_Y	7.69	6.18	6.07	6.77	7.70	4.85
RAnkle_Y	7.60	1.19	6.49	7.36	9.31	6.41
LEar_X	7.09	2.14	3.22	6.27	6.74	2.59
RShoulder_X	6.87	10.69	6.45	10.55	7.39	12.42
LBigToe_Y	6.85	6.74	6.54	5.68	5.50	3.37
RHip_X	6.43	7.97	6.47	3.46	1.20	3.89
LShoulder_X	6.38	20.07	11.29	20.81	13.67	20.76
RKnee_Y	6.20	5.50	6.16	4.06	5.35	4.75
LSmallToe_X	5.89	27.39	7.29	29.62	7.87	28.84
RAnkle_X	4.28	2.47	0.15	5.06	4.28	2.47
RHeel_X	3.99	2.20	0.12	4.90	4.02	2.19
LAnkle_Y	0.44	1.78	3.62	1.75	3.66	4.03
LHeel_X	0.16	16.05	13.26	16.08	13.29	17.56
Nose_X	0.00	0.00	0.00	0.00	0.00	0.00
REye_X	0.00	0.00	0.00	0.00	0.00	0.00
LEye_X	0.00	0.00	0.00	0.00	0.00	0.00
Nose_Y	0.00	0.00	0.00	0.00	0.00	0.00
REye_Y	0.00	0.00	0.00	0.00	0.00	0.00
LEye_Y	0.00	0.00	0.00	0.00	0.00	0.00

Table 18: Distance matrix for the Median class-prototype on the MP dataset with 50 channels.

	Before Channel Selection			After Channel Selection			Best classifier & Accuracy							
Dataset	Rocket			WM			SEQL			Best Classifier	Best Accuracy	Δ Acc	Best CS	Best CP
DDG 1345	46.00	44.00	34.00	60.00	50.00	42.00	Rocket	60.00	14.00	ECP	MAD			
PSF 963	84.39	98.27	95.95	84.97	94.22	90.75	WM	94.22	-4.05	ECP	MEAN			
FD 144	62.74	65.21	55.90	63.71	60.81	54.51	Rocket	63.71	0.97	ECP	MED			
MI 64	57.00	55.00	51.00	51.00	63.00	58.00	WM	63.00	8.00	ECS	MEAN			
HB 61	74.15	73.17	73.17	74.15	75.12	75.12	WM	75.12	1.95	ECP	MED			
FM 28	53.00	54.00	56.00	56.00	60.00	57.00	WM	60.00	6.00	ECS	MEAN			
NTP 24	87.22	91.67	87.22	92.22	92.22	85.56	Rocket	92.22	5.00	ECP	MED			
PS 11	27.62	31.46	26.27	27.47	29.29	26.10	WM	29.29	-2.17	ECS	MED			
HMD 10	54.05	28.38	14.86	54.05	31.08	22.97	Rocket	54.05	0.00	ECP	MED			
AWR 9	99.33	99.33	99.33	99.33	99.33	99.33	Rocket	99.33	0.00	ECP	MED			
SR2 7	53.89	47.78	50.56	55.00	56.11	48.33	WM	56.11	8.33	ECS	MEAN			
BM 6	100.00	100.00	95.00	100.00	100.00	100.00	Rocket	100.00	0.00	ECP	MED			
CKT 6	100.00	100.00	98.61	100.00	100.00	98.61	Rocket	100.00	0.00	ECP	MED			
EW 6	54.62	89.31	73.28	54.62	90.84	70.99	WM	90.84	1.53	ECP	MEAN			
LSST 6	89.31	61.27	58.80	87.79	61.27	58.80	Rocket	87.79	-1.52	ECP	MED			
RS 6	90.79	86.18	86.84	91.45	89.47	82.24	Rocket	91.45	0.66	ECP	MED			
SR1 6	84.64	78.50	68.26	82.94	81.57	66.89	Rocket	82.94	-1.70	ECP	MED			
ER 4	98.15	96.67	87.78	98.15	96.67	87.78	Rocket	98.15	0.00	ECP	MED			
SWJ 4	53.33	46.67	33.33	53.33	60.00	40.00	WM	60.00	13.33	ECP	MED			
EP 3	98.55	100.00	99.28	100.00	100.00	98.55	Rocket	100.00	1.45	ECP	MED			
EC 3	43.35	36.50	55.51	49.81	44.49	58.17	SEQL	58.17	2.66	ECP	MAD			
HW 3	59.53	26.12	47.41	59.53	26.12	47.41	Rocket	59.53	0.00	ECP	MED			
UW 3	94.06	90.63	87.19	94.06	90.63	87.19	Rocket	94.06	0.00	ECP	MED			
AF 2	6.67	40.00	26.67	20.00	13.33	40.00	SEQL	40.00	13.33	ECS	MED			
LB 2	90.56	93.33	87.22	90.56	93.33	87.22	WM	93.33	0.00	ECP	MED			
PD 2	98.20	93.85	92.28	98.20	93.85	92.28	Rocket	98.20	0.00	ECP	MED			

Table 19: Accuracy performance of channel selection on UEA MTSC datasets with different channel selection and channel prototypes.

Dataset	Time before channel selection			Time after channel selection			Storage	
	Time Rocket	Time WM	Time SEQ	Best Time Rocket	Best Time WM	Best Time SEQ	Full Storage	Best Storage
DDG 1345	0.13	302.52	249.73	0.20	40.58	106.66	147.25	58.68
PSF 963	0.33	621.38	688.13	0.43	229.96	491.53	315.83	104.29
FD 144	2.88	987.31	3979.68	2.81	102.13	650.56	511.20	53.25
MI 64	5.90	928.27	730.60	5.95	212.61	317.84	409.53	95.98
HB 61	0.57	95.55	37.13	0.55	30.26	22.32	40.06	6.57
FM 28	0.11	10.38	4.00	0.10	5.12	6.44	4.52	0.97
NTP 24	0.06	6.07	2.58	0.07	10.60	9.56	2.24	1.77
PS 11	4.94	309.61	990.72	2.56	58.13	448.86	65.10	11.84
HMD 10	0.43	11.40	13.18	0.42	17.78	32.61	5.09	4.58
AWR 9	0.26	8.68	9.30	0.26	17.47	35.42	3.04	3.04
SR2 7	1.41	37.63	16.78	1.12	41.00	33.81	12.49	8.92
BM 6	0.02	0.54	0.18	0.02	0.44	0.15	0.21	0.07
CKT 6	0.74	16.15	16.61	0.75	28.20	53.75	6.00	6.00
EW 6	0.54	344.38	511.94	0.54	207.33	476.45	105.47	6.00
LSST 6	13.73	11.60	15.39	10.25	22.61	49.92	5.97	5.97
RS 6	0.03	0.54	0.11	0.03	1.02	0.44	0.32	0.22
SR1 6	1.37	36.05	14.47	0.84	25.17	19.56	11.20	3.73
ER 4	0.01	0.90	0.09	0.01	2.46	0.50	0.08	0.08
SWJ 4	0.15	2.88	1.54	0.07	4.89	3.39	0.92	0.69
EP 3	0.12	1.94	0.72	0.10	3.13	2.16	0.70	0.47
EC 3	1.96	31.19	25.89	0.97	21.66	29.92	10.56	10.56
HW 3	0.10	4.42	1.85	0.11	10.00	9.35	0.58	0.58
UW 3	0.16	3.57	2.16	0.16	7.98	10.05	0.91	0.91
AF 2	0.03	0.44	0.24	0.02	0.47	0.60	0.15	0.08
LB 2	0.03	0.37	0.20	0.04	1.07	1.22	0.17	0.17
PD 2	0.91	0.71	0.82	0.90	2.05	5.19	2.86	2.86

Table 20: Time (mins) &amp; memory (MB) required on different UEA MTSC datasets to achieve the best accuracy.

## 10 Minority Class Classification Report for Synthetic Datasets

Classification report for minority class study in synthetic datasets having 100 channels and 100 signal length, with varying level of class imbalance.

### 10.1 Moving Signal: No channel Selection

This section presents the performance of standalone ROCKET on the minority class where the signal is moving randomly.

#### 10.1.1 Data Imbalance Ratio 90:10

The below classification reports presents ROCKET performance on dataset with class imbalance of 90:10.

	precision	recall	f1-score	support
0	0.52	1	0.68	52
1	0	0	0	48
accuracy	0.52	0.52	0.52	0.52
macro avg	0.26	0.5	0.34	100
weighted avg	0.27	0.52	0.35	100

Table 21: Classification report for moving signal in GP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.50	1	0.67	50.00
1	0.00	0.00	0.00	50.00
accuracy	0.50	0.50	0.50	0.50
macro avg	0.25	0.50	0.33	100.00
weighted avg	0.25	0.50	0.33	100.00

Table 22: Classification report for moving signal in PP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.41	1.00	0.58	41.00
1	0.00	0.00	0.00	59.00
accuracy	0.41	0.41	0.41	0.41
macro avg	0.21	0.50	0.29	100.00
weighted avg	0.17	0.41	0.24	100.00

Table 23: Classification report for moving signal in AR dataset with training dataset in 90:10 ratio.

### 10.1.2 Data Imbalance Ratio 80:20

The below classification reports presents ROCKET performance on dataset with class imbalance of 80:20.

	precision	recall	f1-score	support
0	0.52	1.00	0.68	52.00
1	0.00	0.00	0	48.00
accuracy	0.52	0.52	0.52	0.52
macro avg	0.26	0.50	0.34	100.00
weighted avg	0.27	0.52	0.36	100.00

Table 24: Classification report for moving signal in GP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	0.51	1.00	0.67	50.00
1	1.00	0.02	0.04	50.00
accuracy	0.51	0.51	0.51	0.51
macro avg	0.75	0.51	0.36	100.00
weighted avg	0.75	0.51	0.36	100.00

Table 25: Classification report for moving signal in PP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	0.41	1.00	0.58	41.00
1	0.00	0.00	0.00	59.00
accuracy	0.41	0.41	0.41	0.41
macro avg	0.21	0.50	0.29	100.00
weighted avg	0.17	0.41	0.24	100.00

Table 26: Classification report for moving signal in PP dataset with training dataset in 80:20 ratio.

## 10.2 Moving Signal: Channel Selection

This section presents the performance of ROCKET with channel selection on minority class where signal is moving randomly.

### 10.2.1 Data Imbalance Ratio 90:10

	precision	recall	f1-score	support
0	0.52	1.00	0.68	52.00
1	0.00	0.00	0.00	48.00
accuracy	0.52	0.52	0.52	0.52
macro avg	0.26	0.50	0.34	100.00
weighted avg	0.27	0.52	0.36	100.00

Table 27: Classification report for moving signal in GP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.51	1.00	0.67	50.00
1	1.00	0.02	0.04	50.00
accuracy	0.51	0.51	0.51	0.51
macro avg	0.75	0.51	0.36	100.00
weighted avg	0.75	0.51	0.36	100.00

Table 28: Classification report for moving signal in PP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.41	1.00	0.58	41.00
1	0.00	0.00	0.00	59.00
accuracy	0.41	0.41	0.41	0.41
macro avg	0.21	0.50	0.29	100.00
weighted avg	0.17	0.41	0.24	100.00

Table 29: Classification report for moving signal in PP dataset with training dataset in 90:10 ratio.

### 10.2.2 Data imbalance ratio 80:20

	precision	recall	f1-score	support
0	0.54	1.00	0.70	52.00
1	1.00	0.06	0.12	48.00
accuracy	0.55	0.55	0.55	0.55
macro avg	0.77	0.53	0.41	100.00
weighted avg	0.76	0.55	0.42	100.00

Table 30: Classification report for moving signal in GP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.60	1.00	0.75	50.00
1	1.00	0.32	0.48	50.00
accuracy	0.66	0.66	0.66	0.66
macro avg	0.80	0.66	0.62	100.00
weighted avg	0.80	0.66	0.62	100.00

Table 31: Classification report for moving signal in PP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	0.42	1.00	0.59	41.00
1	1.00	0.05	0.10	59.00
accuracy	0.44	0.44	0.44	0.44
macro avg	0.71	0.53	0.35	100.00
weighted avg	0.76	0.44	0.30	100.00

Table 32: Classification report for moving signal in AR dataset with training dataset in 80:20 ratio.

### 10.3 Stationary Signal: No channel Selection

This section presents the performance of standalone ROCKET on minority class where signal stationary.

#### 10.3.1 Data Imbalance Ratio 90:10

The below classification reports presents ROCKET performance on dataset with class imbalance of 90:10.

	precision	recall	f1-score	support
0	0.74	1.00	0.85	52.00
1	1.00	0.63	0.77	48.00
accuracy	0.82	0.82	0.82	0.82
macro avg	0.87	0.81	0.81	100.00
weighted avg	0.87	0.82	0.81	100.00

Table 33: Classification report for moving signal in GP dataset with training dataset in 90:10 ratio

	precision	recall	f1-score	support
0	1.00	1.00	1.00	53.00
1	1.00	1.00	1.00	47.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	100.00
weighted avg	1.00	1.00	1.00	100.00

Table 34: Classification report for moving signal in PP dataset with training dataset in 90:10 ratio

	precision	recall	f1-score	support
0	0.70	1.00	0.82	51.00
1	1.00	0.55	0.71	49.00
accuracy	0.78	0.78	0.78	0.78
macro avg	0.85	0.78	0.77	100.00
weighted avg	0.85	0.78	0.77	100.00

Table 35: Classification report for moving signal in AR dataset with training dataset in 90:10 ratio

### 10.3.2 Data Imbalance Ratio 80:20

The below classification reports presents ROCKET performance on dataset with class imbalance of 80:20.

	precision	recall	f1-score	support
0	0.90	1.00	0.95	52.00
1	1.00	0.88	0.93	48.00
accuracy	0.94	0.94	0.94	0.94
macro avg	0.95	0.94	0.94	100.00
weighted avg	0.95	0.94	0.94	100.00

Table 36: Classification report for stationary signal in GP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	53.00
1	1.00	1.00	1.00	47.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	100.00
weighted avg	1.00	1.00	1.00	100.00

Table 37: Classification report for stationary signal in PP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0.00	0.96	1.00	0.98	51.00
1.00	1.00	0.96	0.98	49.00
accuracy	0.98	0.98	0.98	0.98
macro avg	0.98	0.98	0.98	100.00
weighted avg	0.98	0.98	0.98	100.00

Table 38: Classification report for stationary signal in AR dataset with training dataset in 80:20 ratio.

## 10.4 Stationary Signal: Channel Selection

This section presents the performance of ROCKET with channel selection on minority class where signal is stationary.

#### 10.4.1 Data Imbalance Ratio 90:10

The below classification reports presents ROCKET performance on dataset with class imbalance of 90:10.

	precision	recall	f1-score	support
0	0.96	1.00	0.98	52.00
1	1.00	0.96	0.98	48.00
accuracy	0.98	0.98	0.98	0.98
macro avg	0.98	0.98	0.98	100.00
weighted avg	0.98	0.98	0.98	100.00

Table 39: Classification report for stationary signal in GP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	53.00
1	1.00	1.00	1.00	47.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	100.00
weighted avg	1.00	1.00	1.00	100.00

Table 40: Classification report for stationary signal in PP dataset with training dataset in 90:10 ratio.

	precision	recall	f1-score	support
0	0.91	1.00	0.95	51.00
1	1.00	0.90	0.95	49.00
accuracy	0.95	0.95	0.95	0.95
macro avg	0.96	0.95	0.95	100.00
weighted avg	0.95	0.95	0.95	100.00

Table 41: Classification report for stationary signal in AR dataset with training dataset in 90:10 ratio.

#### 10.4.2 Data Imbalance Ratio 80:20

The below classification reports presents ROCKET performance on dataset with class imbalance of 80:20.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	52.00
1	1.00	1.00	1.00	48.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	100.00
weighted avg	1.00	1.00	1.00	100.00

Table 42: Classification report for stationary signal in GP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	1.00	1.00	1.00	53.00
1	1.00	1.00	1.00	47.00
accuracy	1.00	1.00	1.00	1.00
macro avg	1.00	1.00	1.00	100.00
weighted avg	1.00	1.00	1.00	100.00

Table 43: Classification report for stationary signal in PP dataset with training dataset in 80:20 ratio.

	precision	recall	f1-score	support
0	0.98	1.00	0.99	51.00
1	1.00	0.98	0.99	49.00
accuracy	0.99	0.99	0.99	0.99
macro avg	0.99	0.99	0.99	100.00
weighted avg	0.99	0.99	0.99	100.00

Table 44: Classification report for stationary signal in AR dataset with training dataset in 80:20 ratio.

Channel Selection →	ECS						ECP					
Class Prototype →	Mean		Median		MAD		Mean		Median		MAD	
Distance function →	EU	DTW	EU	DTW	EU	DTW	EU	DTW	EU	DTW	EU	DTW
Rocket	67.17	67.17	66.56	66.56	67.05	67.05	71.58	71.53	71.69	71.60	71.86	71.58
WeaselMuse	66.48	68.18	64.1	64.1	64.51	64.51	68.71	70.30	68.96	68.56	68.94	68.62
MrSEQL-SAX	63.14	63.14	63.32	63.32	63.68	63.68	67.44	66.63	67.35	66.83	67.37	66.79

Table 45: Accuracy for channel selection using Euclidean vs DTW distance.

Channel Selection →	ECP					
Class Prototype →	Mean		Median		MAD	
Distance function →	EU	DTW	EU	DTW	EU	DTW
Rocket	23.13	25	26.40	28.24	26.74	28.79
WeaselMuse	871.85	988.55	843.87	1027.60	634.50	985.07
MrSEQL-SAX	2067.11	2004.19	2117.61	2358.81	1178.24	2269.91

Table 46: Euclidean vs DTW distance computation time (minutes) (Part ECS)

Channel Selection →	ECP					
Class Prototype →	Mean		Median		MAD	
Distance function →	EU	DTW	EU	DTW	EU	DTW
Rocket	31.69	52.02	30.17	49.63	30.4	48.38
WeaselMuse	1208.8	1700.2	1206.94	1294.82	966.51	1271.76
MrSEQL-SAX	2951.17	3684.17	2950.34	3262.07	1674.18	3303.49

Table 47: EU vs DTW computation time (minutes) (Part ECP)

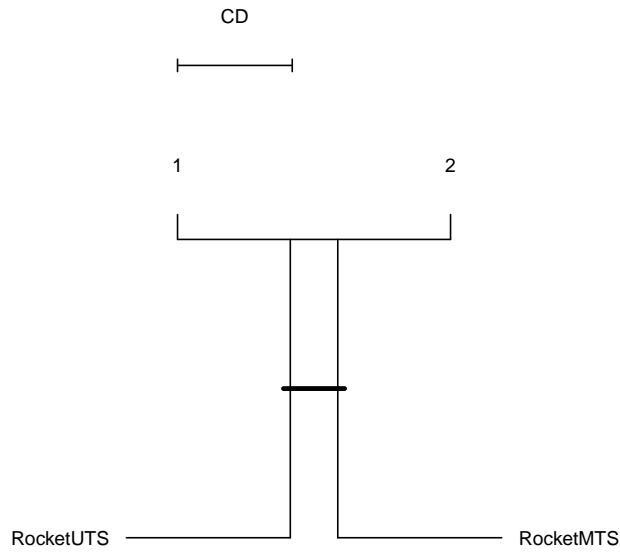


Fig. 12: Examination of channel interdependence on 23 UEA datasets. There is no significant difference in accuracy between using kernels across all channels versus single-channel kernels.

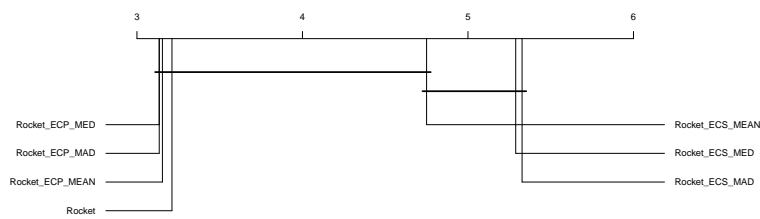


Fig. 13: Critical difference diagram of Rocket with and without channel selection.

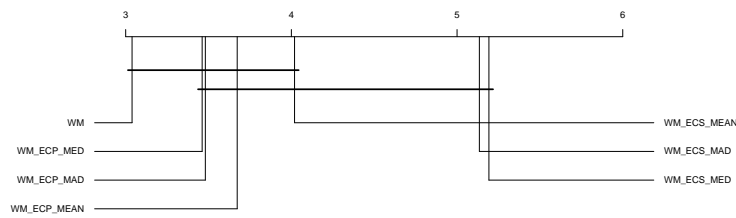


Fig. 14: Critical difference diagram of Weasel Muse with and without channel selection.

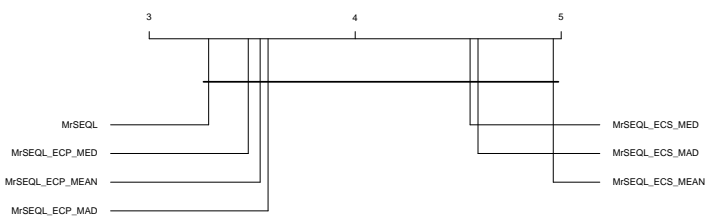


Fig. 15: Critical difference diagram of MrSEQL with and without channel selection.

dataset	class counts
ArticularyWordRecognition	{'1.0': 12, '2.0': 12, '3.0': 12, '4.0': 12, '5.0': 12, '6.0': 12, '7.0': 12, '8.0': 12, '9.0': 12, '10.0': 12, '11.0': 12, '12.0': 12, '13.0': 12, '14.0': 12, '15.0': 12, '16.0': 12, '17.0': 12, '18.0': 12, '19.0': 12, '20.0': 12, '21.0': 12, '22.0': 12, '23.0': 12, '24.0': 12, '25.0': 12}
AtrialFibrillation	{'n': 5, 's': 5, 't': 5}
BasicMotions	{'standing': 10, 'running': 10, 'walking': 10, 'badminton': 10}
Cricket	{'1.0': 6, '2.0': 6, '3.0': 6, '4.0': 6, '5.0': 6, '6.0': 6, '7.0': 6, '8.0': 6, '9.0': 6, '10.0': 6, '11.0': 6, '12.0': 6}
DuckDuckGeese	{'blackbellied_whistling_duck': 10, 'canadian_goose': 10, 'greylag_goose': 10, 'pinkfooted_goose': 10, 'whitefaced_whistling_duck': 10}
ERing	{'2': 45, '5': 45, '3': 45, '6': 45, '1': 45, '4': 45}
EigenWorms	{'1': 55, '2': 22, '3': 18, '4': 23, '5': 13}
Epilepsy	{'epilepsy': 34, 'walking': 37, 'running': 37, 'sawing': 30}
EthanolConcentration	{'e35': 66, 'e38': 66, 'e40': 66, 'e45': 65}
FaceDetection	{'0': 1762, '1': 1762}
FingerMovements	{'right': 51, 'left': 49}
HandMovementDirection	{'right': 14, 'forward': 30, 'left': 15, 'backward': 15}
Handwriting	{'15.0': 29, '1.0': 36, '23.0': 32, '9.0': 27, '2.0': 34, '17.0': 32, '14.0': 35, '24.0': 37, '25.0': 26, '11.0': 25, '12.0': 37, '7.0': 29, '3.0': 29, '21.0': 34, '6.0': 30, '20.0': 31, '5.0': 34, '4.0': 43, '26.0': 32, '8.0': 32, '16.0': 33, '13.0': 40, '19.0': 33, '10.0': 26, '18.0': 31, '22.0': 43}
Heartbeat	{'normal': 57, 'abnormal': 148}
LSST	{'6': 35, '15': 124, '16': 270, '42': 382, '52': 63, '53': 7, '62': 153, '64': 24, '65': 313, '67': 68, '88': 121, '90': 777, '92': 77, '95': 52}
Libras	{'1': 12, '2': 12, '3': 12, '4': 12, '5': 12, '6': 12, '7': 12, '8': 12, '9': 12, '10': 12, '11': 12, '12': 12, '13': 12, '14': 12, '15': 12}
MotorImagery	{'tongue': 50, 'finger': 50}
NATOPS	{'4.0': 30, '5.0': 30, '6.0': 30, '1.0': 30, '3.0': 30, '2.0': 30}
PEMS-SF	{'4.0': 23, '2.0': 25, '7.0': 20, '3.0': 26, '1.0': 30, '5.0': 22, '6.0': 27}
PenDigits	{'8': 336, '9': 336, '1': 364, '4': 364, '7': 364, '0': 363, '2': 364, '5': 335, '3': 336, '6': 336}
PhonemeSpectra	{'aa': 86, 'ae': 86, 'ah': 86, 'ao': 86, 'aw': 86, 'ay': 86, 'b': 86, 'ch': 86, 'd': 86, 'dh': 86, 'eh': 86, 'er': 86, 'ey': 86, 'f': 86, 'g': 86, 'hh': 86, 'ih': 86, 'iy': 86, 'jh': 86, 'k': 86, 'l': 86, 'm': 86, 'n': 86, 'ng': 86, 'ow': 86, 'oy': 86, 'p': 86, 'r': 86, 's': 86, 'sh': 86, 't': 86, 'th': 86, 'uh': 86, 'uw': 86, 'v': 86, 'w': 86, 'y': 86, 'z': 86, 'zh': 85}
RacketSports	{'badminton_smash': 40, 'badminton_clear': 43, 'squash_forehandboast': 35, 'squash_backhandboast': 34}
SelfRegulationSCP1	{'positivity': 146, 'negativity': 147}
SelfRegulationSCP2	{'positivity': 90, 'negativity': 90}
StandWalkJump	{'standing': 5, 'walking': 5, 'jumping': 5}
UWaveGestureLibrary	{'1.0': 40, '2.0': 40, '3.0': 40, '4.0': 40, '5.0': 40, '6.0': 40, '7.0': 40, '8.0': 40}

Table 48: Class counts for UEA dataset.

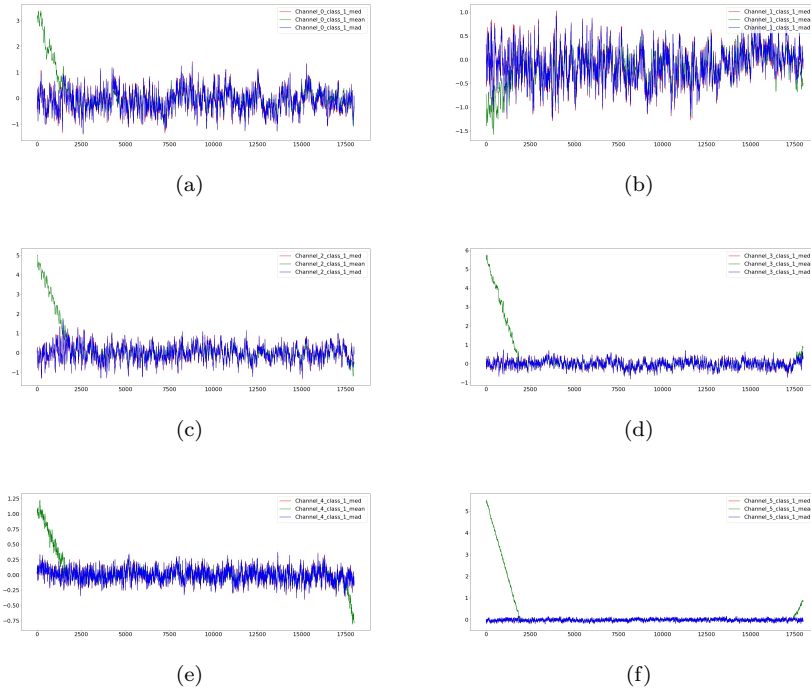


Fig. 16: Class prototype for 6 channels in class 1 for EW dataset.

Class Prototype→ Classifiers→	Mean			Median			MAD		
	Rocket	MrSEQL	WM	Rocket	MrSEQL	WM	Rocket	MrSEQL	WM
ASR (3)	+2.61	-0.07	-0.20	+3.38	+0.59	-1.55	+4.48	+1.26	-1.55
ECG (2)	-3.73	+1.0	-16.66	-4.00	-6.67	-6.66	-4.00	-6.67	-6.66
EEG (6)	+1.18	+0.45	-0.64	-0.29	+1.15	-2.12	-0.28	+1.10	-2.29
HAR (9)	-2.31	-0.43	+0.11	-1.20	-0.55	+0.18	-1.20	-0.55	+0.18
MC (3)	0.00	-0.48	+0.01	0.00	-0.24	+0.01	0.00	-0.24	+0.01
Other (3)	+4.44	-1.74	-1.34	+4.44	-2.31	-1.73	+4.44	-2.69	-1.54

Table 49:  $\Delta$  Accuracy ECP channel selection for datasets from different domains.