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Taking ROCKET on an Efficiency Mission: Multivariate Time Series Classification with LightWaveS

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Abstract—Nowadays, with the rising number of sensors in sectors such as healthcare and industry, the problem of multivariate time series classification (MTSC) is getting increasingly relevant and is a prime target for machine and deep learning approaches. Their expanding adoption in real-world environments is causing a shift in focus from the pursuit of ever-higher prediction accuracy with complex models towards practical, deployable solutions that balance accuracy and parameters such as prediction speed. An MTSC model that has attracted attention recently is ROCKET, based on random convolutional kernels, both because of its very fast training process and its state-of-the-art accuracy. However, the large number of features it utilizes may be detrimental to inference time. Examining its theoretical background and limitations enables us to address potential drawbacks and present LightWaveS: a framework for accurate MTSC, which is fast both during training and inference. Specifically, utilizing wavelet scattering transformation and distributed feature selection, we manage to create a solution that employs just 2.5% of the ROCKET features, while achieving accuracy comparable to recent MTSC models. LightWaveS also scales well across multiple compute nodes and with the number of input channels during training. In addition, it can significantly reduce the input size and provide insight to an MTSC problem by keeping only the most useful channels. We present three versions of our algorithm and their results on distributed training time and scalability, accuracy, and inference speedup. We show that we achieve speedup ranging from 9x to 53x compared to ROCKET during inference on an edge device, on datasets with comparable accuracy.

Index Terms—distribution, time series, classification, multivariate, wavelet, scattering, feature selection, edge intelligence

I. INTRODUCTION

Time series classification is the task of characterizing a series of values observed in sequential moments in time as belonging to one of two or more categories, or classes. There has been extensive work on univariate time series classification with machine and deep learning methods, as observed in surveys such as [1]. In practice, as noted in [2], problems are increasingly described by more than one channel of information, turning the task into multivariate time series classification (MTSC). Some factors contributing to that are the development of smaller and cheaper sensors for the measurement of various quantities, the general advancement of Internet of Things, and the engagement with inherently more complex problems in

sectors such as healthcare and industry, which benefit from additional information channels [3].

Although the improvement of the prediction accuracy of MTSC models has been a prominent goal of research, the rise of edge computing and deployment of models in such real-world environments makes it necessary to also consider the conditions and resources of the computational nodes on which those models will be executed [4]. This change in perspective makes it important to include, apart from accuracy, criteria such as prediction speed or throughput in the evaluation of a model’s suitability for a given task.

In the recent evaluation of advances in MTSC [2], one solution that shows good performance is ROCKET [5], both in terms of accuracy and training time. ROCKET utilizes random convolutions to transform the time series channels and then extracts two features per convolution that are used with a linear classifier. The evolution of ROCKET, MINIROCKET [6], is proposed as the new default variant of ROCKET by its authors and utilizes only one feature per kernel (percentage of positive values), thereby halving the features. It also utilizes other optimizations to speed up ROCKET in general and follows a minimally random approach with a given set of kernels. Another variant, MultiRocket [7], uses more features per convolution to achieve better accuracy at the expense of transformation time. Both ROCKET and MINIROCKET have been developed for univariate time series. Although the authors of MINIROCKET characterize their provided repository code for multivariate time series as naive, it is the same algorithmic logic in the form of a ROCKET extension in the sktime [8] repository that achieves the impressive performance mentioned above.

In (MINI)ROCKET, the authors encourage research into more sophisticated approaches for multivariate time series. We can start by identifying potential points that can be improved. One issue with (MINI)ROCKET that we try to address in our work is that the large number of features, although beneficial to accuracy, can be highly redundant, and extreme for some datasets, leading to unnecessarily high transformation and inference times. In addition, due to the fixed process and number of generated features, there is a large discrepancy in the representation (features per channel) across datasets with different dimensions. Moreover, the indiscriminate inclusion of

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all channels in the feature generation is susceptible to uninformative series. Finally, the stochastic element, especially the random channel combination, although potentially favorable to accuracy, does not offer significant interpretability.

Based on this analysis, we propose LightWaveS, a framework for fast transformation of multivariate time series based on convolutional kernels, wavelet scattering, and feature selection, for lightweight and accurate classification with linear classifiers. Our solution aims to keep the successful aspects of the ROCKETS model family, such as the short transformation time, the arbitrary convolutional kernel approach, and the few descriptive features per kernel. On top of that, LightWaveS adds well-studied wavelet theory, multi-node¹ distribution during training and smart feature selection to address the drawbacks identified above. The trade-off that we propose compared to (MINI)ROCKET is clear: we take advantage of additional computational resources during training time, especially for larger datasets, to keep its duration short and significantly speed up inference on resource-constrained devices. Our contributions with LightWaveS are:

- We introduce the usage of minimal wavelet scattering based on arbitrary kernels.
- We achieve accuracy comparable to state-of-the-art in the majority of the UEA datasets [9], using only a fraction of the number of features used by (MINI)ROCKET.
- We achieve inference speedups on an edge device ranging from 9x to 53x compared to ROCKETS.
- We achieve reduction of the channels required for inference ranging from 7% to 86%.
- We distribute the framework and achieve training time comparable to (MINI)ROCKET on 1 node, and shorter on multiple nodes.
- We achieve linear scaling of training time with the number of channels, tested in experiments with up to 900 channels.
- Depending on the dataset size, we achieve good distributed training speedup with additional nodes, tested in experiments with up to 8 nodes.

With this work, we take an efficiency-centric approach, focusing on the practicality and the inference speed of a model that may be deployed on an edge device, without necessarily trying to surpass the state-of-the-art in terms of accuracy.

II. RELATED WORK

A. Multivariate time series classification

Due to the recent rise in popularity of the deep learning field, there is a multitude of models that can be easily adapted to incorporate the additional dimension of MTSC [10]. A detailed evaluation of recent MTSC methods appears in [2]. Convolutions in particular, either 1-D or with more dimensions, are a very popular module when dealing with time series, as seen in models such as TapNet [11], InceptionTime [12] and OS-CNN [13] among others. In these

works, convolutions are combined in various architectures with other modules, such as fully connected networks, and achieve impressive classification accuracy. The majority of those deep learning models take a significant amount of time and memory to train even on GPU nodes, ranging from hours to even days, depending on the dataset size [2]. In contrast, our method takes less than 20 minutes to transform, train and test all 30 UEA datasets on a CPU node with a linear classifier. If we distribute the solution on e.g. 8 CPU nodes, this time drops to under 4 minutes. An additional challenge is the interpretability of deep learning models. The usage of wavelets by LightWaveS and their method of application gives the potential to interpret the result based on signal theory and the input channel filtering helps to extract useful conclusions about a given time series problem.

B. Feature extraction and selection

Deep learning models implicitly extract features from the input along their first layers. In contrast, explicitly extracting features to use with classifiers has also been visited in multiple ways. We have already described how the *ROCKET family extracts features from the convolutions of random kernels with the input, an idea that has also been explored before, such as in [14]. Another example is tsfresh [15], which extracts a large number of predefined statistical features from the time series and then through feature selection reduces them to the most useful. Similarly, catch22 [16] is a solution that uses only 22 predefined characteristics to transform time series, aiming for a very fast transformation. A different approach is presented in WEASEL+MUSE [17], which extracts features based on a bag-of-patterns approach and selects the most useful ones based on a χ^2 test. LightWaveS, similarly to MINIROCKET, depends on an arbitrary set of convolutions and only 4 statistical features, extracted however from the coefficients of wavelet scattering. Due to the speed of the convolution operation and the simplicity of the features, we can achieve extremely fast training and inference times, while giving the model enough complexity to accommodate difficult datasets, where predefined statistical features on the raw time series values may not be descriptive enough.

C. Distributed training

As the size of the deep learning models and the amount of input data increase, it is increasingly difficult to perform training on a single node. For that reason, distribution of the training process across multiple nodes is becoming increasingly necessary [18]. This distribution can be implemented with methods such as data parallelism, where each node applies the same operations on different parts of the input data, with frequent communication among the nodes to update the model. Distribution can also be applied to solutions that do not depend on deep learning, such as tsfresh mentioned above, which supports operation on a cluster through Dask [19]. LightWaveS is distributed using MPI in a data-parallel way, but in contrast to the communication heavy training of DL models, there is efficient and minimal communication between the worker

¹With the term *node* we refer to a computing node in a distributed (networked) system.

nodes and the central coordinator. Specifically, the nodes only send a limited number of feature scores and descriptions once during the execution, making communication a trivial percentage of the whole process.

D. Wavelets

Wavelets are localized waveforms (as seen in Fig. 1 on the right) and are a well-studied method in signal processing that has been used extensively in the analysis of time series [20]. There is vast literature with methods and applications of wavelets on all types of problems, ranging from healthcare to audio analysis, and well-studied and developed families of wavelets suitable for specific applications [21], [22]. There are also numerous approaches that combine wavelets with machine and deep learning methods, either as implicit or explicit feature extractors [23], [24]. A seminal work is [25], where the concept of a wavelet scattering network using a Morlet wavelet is introduced, in combination with linear and support vector machine classifiers for hand-written digit classification and texture recognition. This method was constructed to be invariant to translations of the input and stable to small deformations. It has also been recently used in combination with deep learning networks for specific applications [26], [27].

LightWaveS aims to combine the strong points of these works under a single generalized framework, with a focus on efficiency. We aim to bridge the gap between ROCKET and the wavelet theory, and we progress to the next logical step of wavelet scattering. We keep this approach lightweight, both in depth and paths of the scattering, so we can apply it to time series channels on a massive scale in a very short time. The arbitrary base set of wavelets can potentially be extended based on expert opinion, backed by the solid theory behind wavelets and their applications, making LightWaveS a suitable platform for experimentation on solutions for MTSC problems. Finally, the hierarchical feature filtering leads to the most relevant output features of the scattering coefficients being selected.

III. PROPOSED FRAMEWORK

A. Preliminaries

1) *(MINI)ROCKET fundamentals*: (MINI)ROCKET is primarily based on the convolution operation, in which a kernel \mathbf{k} with size l ($\mathbf{k} \in \mathbb{R}^l$), bias β and dilation factor d is used to calculate a sliding dot product with a 1-D input $\mathbf{x} \in \mathbb{R}^L$ of size L and produce an output \mathbf{x}' , where each element is calculated as [5]:

$$\mathbf{x}'_i = \sum_{j=0}^{l-1} \mathbf{k}_j \cdot \mathbf{x}_{i+d*j} + \beta \quad (1)$$

In (MINI)ROCKET, the outputs \mathbf{x}' are either convolutions of 1-D kernels with single input channels, or the sum of the convolutions of multiple kernels with random subsets of the input channels. In the minimally random variant, MINIROCKET, the kernel weights are selected from an empirically chosen

subset of 84 kernels of length 9 with weights in $\{2, -1\}$. This has been chosen to limit the possible weight combinations but is not unique for the purpose, and other lengths, different values or weights drawn from $\sim \mathcal{N}(0, 1)$ are equally effective [6]. The only thing that is important is that the kernel weights have sum 0. The bias is drawn from the convolution output, and the dilation is drawn from the set $\mathbb{D} = \{\lfloor 2^e \rfloor\}$, where $e \sim \mathcal{U}(0, m)$, with m such that the length of the dilated kernel does not exceed that of the input. Finally, half of the kernels use padding, which appends zeros to either side of the input so that \mathbf{x}' and \mathbf{x} have the same dimension. The feature extracted from each of the 10000 outputs is the percentage of positive values and is used for the final classification.

2) *Wavelet Scattering*: Wavelet scattering is the process of applying wavelet transforms in a cascading manner [25], combined with non-linearities and pooling. The wavelet transform is a method used to approximate a signal using a set of wavelets that originate from a "mother" wavelet $\Psi(t)$, scaled by s and shifted by b [28]. Each such wavelet can be described as:

$$\Psi_{s,b}(t) = \frac{1}{\sqrt{s}} \Psi\left(\frac{t-b}{s}\right) \quad (2)$$

Intuitively, we can relate these wavelets to the convolution filters that we discussed above, with the dilation being the scale of the wavelets (how "narrow" or "wide" they are), and the shift parameter b corresponding to the starting point of the convolution on the input ($i + d * j$). This connection between convolutional networks and the scattering architecture has also been thoroughly explored in [29]. We can see an example of a wavelet convolution in Fig. 1, where the response is strong at the points where the sliding wavelet "matches" the signal. In addition, the wavelet set created from a mother wavelet is parallel to the way that MINIROCKET has a fixed set of kernel weights, for which different paddings and dilations are randomly selected, generating the child kernels.

In the wavelet scattering transform, on each level λ , the previous result is convoluted with each wavelet ψ_{λ_n} (kernel) and a complex modulus operator is applied before propagating the result to the next level, such that:

$$U[\lambda] = |U[\lambda - 1] * \psi_{\lambda_n}| \quad (3)$$

and the scattering coefficients that result from each level are

$$S[\lambda] = U[\lambda] * \phi \quad (4)$$

where ϕ is an averaging kernel. Since on every level of the scattering transform there can be multiple candidate wavelets (kernels), there is a geometric progression of potential paths, as can be seen in the graphic representation of the process in Fig. 1.

Throughout the above intuitive description, we connected the concepts of MINIROCKET with the wavelet theory. In MINIROCKET the prototype kernels have zero mean, which corresponds to a desirable constraint of mother wavelets [28]. Under this new context, we can re-consider MINIROCKET as a classifier based on convolutions with random child wavelets of an arbitrary set of mother wavelets. In addition, although

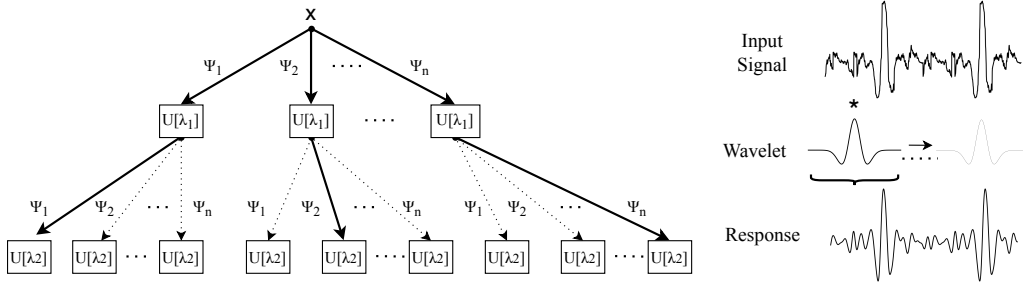


Fig. 1. 2-level wavelet scattering [25] and wavelet convolution example

not being wavelet scattering, MINIROCKET can be intuitively mapped on the first level, with its kernel set equivalent to the first-level set, $\{\Psi_{0,1,s}, \dots, \Psi_{0,n,s}\}$, with s drawn from \mathbb{D} as we said above. Since each kernel is slid across the input, we can think of b as taking all discrete values from 0 to $l_{input} - l_{kernel} * s$ for each candidate wavelet, and the convolution output (response) as being the combined response of all shifted wavelets, as portrayed in Fig. 1. However, MINIROCKET extracts the features before the application of any modulus operator, so it does not satisfy the rest of the wavelet scattering transform requirements.

B. Algorithm

Based on the above observations, we improve the approach and reach the crux of LightWaveS: Lightweight Wavelet Scattering based on random wavelets. The term lightweight refers both to the system optimizations of the framework that make it fast, such as the distribution, as well as the fact that only a reduced set of wavelet scattering paths are computed. Although it is established that not all paths need to be considered in a scattering network [25], since we are aiming for fast training and inference, we take this notion to its limit. We compute all coefficients for the given kernels and dilations for the first level, but we consider only one path per first-level output for the second level. In this way, we limit significantly the memory and computation time required for the extracted features, while accepting the trade-off of losing some descriptive coefficients.

The choice of the kernels to be applied in the second level is not immediately clear. We can consider heuristics such as selecting kernels whose first level coefficients gave features with high correlation to the classification task. However, after experimenting with such heuristics, and even with up to four second-level paths, we found that the final classification results were not noticeably different than the simple approach of applying the same kernel and dilation, a concept intuitively and loosely similar to the process of a discrete wavelet transform [30]. Thus, we end up computing only the paths shown in bold in Fig. 1, which means that the same kernel is applied twice consecutively. In addition, we limit the depth to two levels, as a good balance point between computational speed and informative coefficients, as observed in [25].

The main steps of LightWaveS are the following: Initially, the dataset is split among the nodes across the channel dimension. For larger datasets, the nodes receive only a sample of the total training examples, in order to speed up computation. This sample selection is the only source of randomness in the algorithm. Then, on each node, the kernels are generated, which for our purpose are based on the same subset of 84 kernels that MINIROCKET uses. We limit randomness even more, so each kernel is dilated with all dilations in the set $\{2^0, 2^1, \dots, 2^5\}$. We also completely remove bias, and the padding is common to all kernels so that the output dimension is equal to the input.

All those kernels are applied to each of the input channels according to the wavelet scattering process described above. The generated kernels have no complex part, so the non-linearity modulus operator is equal to the absolute value of the convolution output. We also downsample the $U[\lambda_1]$ result by a factor of 2 before propagating it, while keeping the same scale for the kernel, so it operates in lower frequencies. This is according to the insight in [25] that the most useful paths are frequency decreasing. As far as the pooling is concerned, since we want to limit the number of coefficients that will be used as features, we use max and min pooling, instead of the averaging kernel. In this way, although we accept the loss of more information, we have fewer features and we also avoid two additional convolutions per path. The features that are extracted from each scattering path are 8: the first four are the max and min values of $U[\lambda_1]$ and $U[\lambda_2]$. We selected those as the most straightforward non-linearities that can be quickly calculated during the convolution process. The other four are the percentage of positive values (ppv) and normalized longer sequence of positive values (ls) in $U[\lambda_1]$ and $U[\lambda_2]$ before the application of the modulus operator. We keep these features based on MINIROCKET and MultiROCKET respectively, since they have proven to be useful during classification.

After the feature extraction, the first selection phase is performed on each node in a supervised way using ANOVA. The main node then gathers the top-scoring features and performs the final feature selection, using the minimum-redundancy, maximum-relevance algorithm [31], incrementally selecting the feature with the highest score. This score is determined by its F-statistic (relevance to the class), divided by its average correlation to the previously selected features (redundancy).

In our case, we use the Pearson correlation coefficient as the correlation indicator. In both phases the feature selection methods are filter-based, which are fast, classifier-independent, and can be implemented to scale well with the number of features [32].

IV. EXPERIMENTS

A. Datasets

We select as benchmark the UEA collection of multivariate datasets [9], excluding *InsectWingbeat*, since due to its large size it presented issues when training ROCKET. The datasets are described in detail in [2]. In addition, we prepare and use five machinery related datasets:

- **MAFAULDA**, from Machinery Fault Database [33] is a dataset with 8 sensor measurements on a machine fault simulator, taken under normal conditions and five different fault types. We downsample the measurements so that the input length is 1000 steps and we split the dataset into train and test with ratio 85-15 %.
- **TURBOFAN** [34], is an engine degradation simulation dataset collection, containing 4 datasets with operation simulations of engines that run until failure under different conditions, with measurements from 26 sensors. The goal is to predict the remaining useful life (RUL) of the engines. In order to turn the problem into binary classification, we prepare the dataset and the labels in a suitable way with the goal being classifying RUL as more or less than 20 operational cycles.

B. Experimental setup

All training experiments were run on the DAS-5 infrastructure [35], on nodes with dual 8-core 2.4 GHz (Intel Haswell E5-2630-v3) CPUs and 64 GB of RAM. The inference experiments are executed on a Jetson Xavier board which has an 8-core ARM CPU. Both (MINI)ROCKET and LightWaveS were set to use all 8 cores during inference, an option that is not the default in the sktime implementations of the former. We ran ROCKET and MINIROCKET using the default number of features (20 and 10 thousand respectively). As for LightWaveS, we present three variants of the model, termed L1, L2, and L1L2. These versions refer to keeping the features only from the scattering level 1, level 2, or both, although we consider the L1L2 version as the default.

Following the example of [5], we selected 15 of the 30 UEA datasets to work on when developing the method, in order to draw generic conclusions and avoid overfitting the whole collection. The design choices that are not guided or restricted by theory, intuition, and related work, such as the feature scoring function, are straightforward and focused on computational efficiency. Our hyperparameter search during experimentation was limited to the initial and final number of selected features, as well as alternative options for the second-level scattering paths, as mentioned above. This has led to the selection of 500 features as the default variant, which has shown good balance between training time, inference speed and accuracy in the development set.

We use a Ridge regression classifier from the Scikit-learn package [36] for all methods. We use a critical difference diagram to present the results, a popular method of comparing classifier performance across multiple datasets [2], [10]. This shows the ranking of the classifiers and groups the ones that do not show statistical difference, based on pairwise comparisons using a Wilcoxon signed-rank test [37] with Holm's alpha correction [38], [39]. The grouped classifiers appear on the diagram connected by a thick horizontal line. The code of LightWaveS, as well as detailed metrics and the scripts used to train (MINI)ROCKET, run the inference experiments and preprocess the machinery datasets are made available² to enable reproducibility and facilitate further exploration on the topics of this work. We repeat the experiments multiple times and report average values for robustness.

C. Accuracy results

We present the performance of LightWaveS in terms of accuracy in comparison with (MINI)ROCKET, as well as other recent solutions, namely (M)OSS-CNN [13], WEASEL+MUSE [17], TapNet [11] and Catch22 [16]. Apart from LightWaveS and (MINI)ROCKET, the rest of the accuracy metrics are taken from the repositories of [13]³ and [40]⁴.

We can see the results in Fig. 2. Although lower in rank, LightWaveS belongs in the same statistical group with (MINI)ROCKET, which have the best accuracy. In addition, it is among the ranks of more complex DL methods, such as TapNet and MOS-CNN. Out of the three variants, LightWaveS-L2 performs the worst, without the benefit of faster execution that L1 has due to the fewer convolutions.

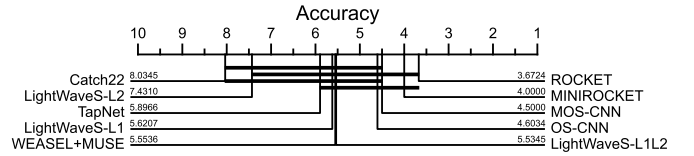


Fig. 2. Mean rank of LightWaveS methods vs recent classifiers in terms of accuracy

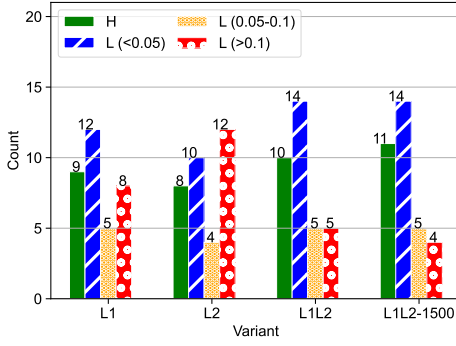
We can focus on (MINI)ROCKET for a more detailed comparison, and also include the 5 additional datasets. Since the aim of LightWaveS is to approach their state-of-the-art accuracy with fewer features, not necessarily surpass it, we place the LightWaveS results for all datasets in four accuracy bins compared to (MINI)ROCKET : one for the cases where LightWaveS achieves higher or equal accuracy, and three bins for lower accuracy, with difference less than 0.05, between 0.05 and 0.1 and more than 0.1 respectively. In Fig. 3 we see the number of datasets in each bin.

For the majority of the datasets the accuracy stays in the first 3 categories for all variants apart from L2, and the datasets with large accuracy deviation are few. In addition, we can

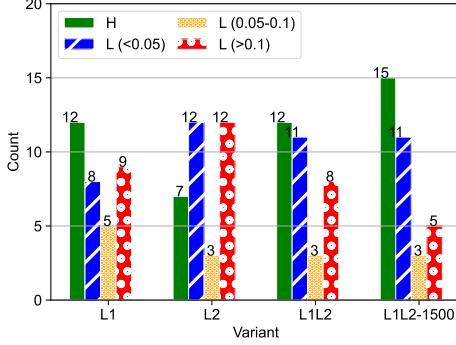
²<https://github.com/lpphd/lightwaves>

³<https://github.com/Wensi-Tang/OS-CNN>

⁴https://github.com/mlgig/mtsc_benchmark/



(a) ROCKET



(b) MINIROCKET

Fig. 3. Distribution of datasets based on average accuracy difference between LightWaveS variants and (MINI)ROCKET

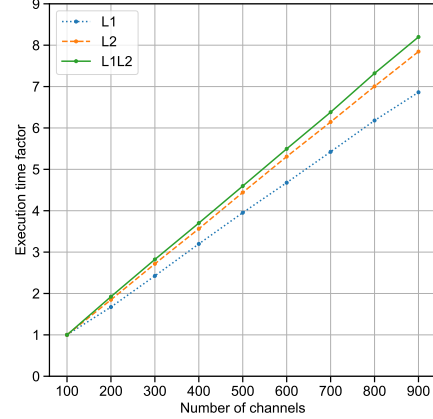
see that just increasing the number of features to 1500 leads to improvement of the comparison results, especially in the case of MINIROCKET, showing the potential of the method to successfully tackle the harder datasets as well.

D. Scaling of training time with channels and nodes

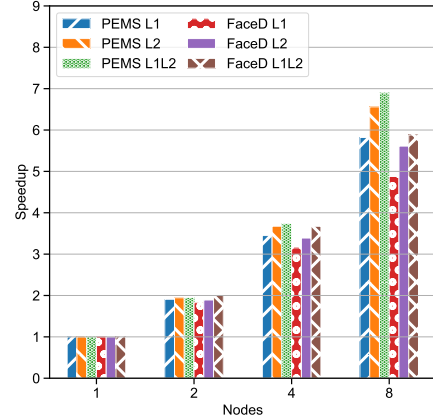
As a point of reference, ROCKET processes the whole UEA set (apart from *InsectWingbeat*) on a single node in approximately 9 minutes, MINIROCKET in 5 and LightWaveS (L1L2) in 14. (MINI)ROCKET has complexity $\mathcal{O}(\text{channels} \cdot \text{samples} \cdot \text{tslength})$. Since LightWaveS uses one more convolution per kernel it adds a fixed factor of two to the complexity, essentially keeping linear scalability with these variables. Thus, we can focus on its training time scalability with the number of channels and across the compute nodes.

We select *PEMS-SF* from UEA which has 963 channels, and we use subsets of the total dataset to train LightWaveS on 2 nodes, starting from 100 channels and incrementing by 100. We see in Fig. 4a that all variants show (sub)linear scaling with the number of channels, which is expected since each additional channel results in a fixed number of additional convolutions, and there are no combinations or permutations of channels. For the node scaling, we also select *FaceDetection*, with 144 channels and we measure the training time across 1, 2, 4 and 8 nodes. As we see in Fig. 4b, with *PEMS-SF* the gained training speedup is more close to ideal since there are many channels for each node to work on and

the distributed computation constitutes the majority of the execution time. In contrast to that, with *FaceDetection* that has fewer channels, the computational cost starts being dominated by the operations on the main node (feature selection, final transformation), so the gained speedup declines faster.



(a) Channel scalability



(b) Node scalability

Fig. 4. Scalability of LightWaveS training time with the number of (a) channels and (b) nodes

E. Inference speedup results

We manage to achieve significant speedup during inference due to the small number of features, which heavily reduces the number of convolutions required to transform a test sample. Although this speedup is achieved for all datasets and variants, we focus for fairness on the datasets in the first two accuracy bins for the default L1L2 variant, where it ranges from 9x to 53x compared to ROCKET and from 2x to 10x for MINIROCKET. In order to give a qualitative representation of the results, we show in Fig. 5 the accuracy - speedup plots for all LightWaveS variants compared to (MINI)ROCKET for the 5 machinery fault datasets. We choose these since they are representative use cases and correspond to an immediately practical and realistic scenario of edge deployment of a model in an industrial IoT environment. However, a similar relation holds for all other datasets.

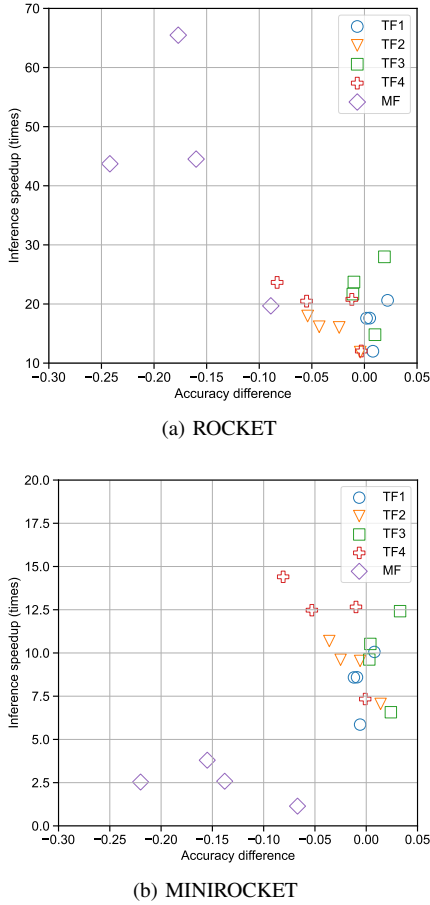


Fig. 5. Average inference speedup-accuracy difference scatterplot for the 5 machinery datasets, for each of the LightWaveS variants

Fig. 5 clearly frames the trade-off that we propose: significant inference speedup at the cost of limited reduction in accuracy (in cases where the latter is not also improved). For instance, for the TURBOFAN4 dataset, we can achieve 7.5x-24x inference speedup with an accuracy reduction of up to 0.1. The MF dataset in the MINIROCKET comparison acts as an outlier in the graph due to its large length in combination with the optimizations of MINIROCKET. Our method of applying the kernels matches ROCKET's, but could also benefit from these optimizations, restoring the discrepancy.

F. Channel reduction results

Due to its feature generation and selection pipeline, LightWaveS can filter the input channels required for inference to a subset of the originals. Similarly to the inference speedup results, we focus on the default L1L2 variant. We see in Table I that out of the 24 datasets where comparable accuracy with ROCKET is achieved, 11 were reduced, with the channel reduction ranging from 7% to 86% and the larger datasets benefiting more. We exclude from this table the 10 datasets where LightWaveS performs significantly worse than ROCKET to avoid giving LightWaveS an unfair advantage. For instance, for the *DuckDuckGeese* dataset, LightWaveS uses 98 of the

original 1345 channels but achieves accuracy of 0.44 compared to 0.51 of ROCKET.

G. Resource efficiency results

Another important aspect in edge intelligence applications is the number of operations required for inference, which directly affects the energy required, as well as the performance of other applications that potentially share the edge device resources. We can quantify the computational efficiency of LightWaveS over ROCKET by comparing the number of convolutions and consequently multiply-accumulate (MAC) operations required for inference, based on the theoretical analysis of the algorithms. We focus on ROCKET since it utilizes the same mechanism of applying the convolutions as LightWaveS, as mentioned before, making the comparison possible and precise. For the datasets in the first two accuracy bins of the L1L2 variant, LightWaveS requires approximately 16.5x to 40.5x fewer MAC operations for inference.

V. DISCUSSIONS AND CONCLUSION

Summarizing, LightWaveS offers comparable to state-of-the-art accuracy on the datasets tested, with training time similar to (MINI)ROCKET or shorter and inference time 9x-53x shorter on an edge device in the case of ROCKET and 2x-10x for MINIROCKET. Apart from the advantages we have mentioned, a significant advantage of LightWaveS is that it is based on wavelet theory, which has a strong theoretical base. A promising future direction is to explore expert tuning of the framework, by preparing and including in the base set well tested and specialized wavelets for each use case.

TABLE I
AVERAGE NUMBER OF ORIGINAL DATASET CHANNELS USED BY LIGHTWAVES

	Original channels	Channels used by LightWaveS L1L2
AWR	9	7
AtrialFib	2	2
BasicMotions	6	5
ChTrajectories	3	3
ERing	4	4
EigenWorms	6	6
Epilepsy	3	2
EthanolC	3	3
FaceDetection	144	118
FingerMov	28	28
Heartbeat	61	42
JapVowels	12	4
Libras	2	2
MotorImagery	64	64
PEMS-SF	963	132
PenDigits	2	2
RacketSports	6	6
SelfRegSCP2	7	7
SpArabicDigits	13	8
SWJump	4	4
UWaveGL	3	3
FD001	26	14
FD002	26	21
FD003	26	24

The channel reduction effect has multiple advantages: it can give insights into which channels contain useful information for the problem, leading to knowledge extraction. On edge devices, where resources are valuable, it can free up incoming signal channels. Finally, LightWaveS can act as an initial fast channel filtering method that precedes another deep learning solution, reducing the training data required.

LightWaveS can also benefit from, and is indeed orthogonal to, recent works on time series features, since additional descriptive features can be extracted from the scattering coefficients, improving accuracy. Future work can include research into such more advanced features, as well as an initial, more informed selection of the wavelets, so that the wavelet scattering network can extend to more paths. Finally, explicit, informed combinations of different channels would add value to the solution and is a worthwhile research path.

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