A benchmark of data stream classification for human activity recognition on connected objects

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Abstract—This paper evaluates data stream classifiers from the perspective of connected devices, focusing on the use case of HAR. We measure both classification performance and resource consumption (runtime, memory, and power) of five usual stream classification algorithms, implemented in a consistent library, and applied to two real human activity datasets and to three synthetic datasets. Regarding classification performance, results show an overall superiority of the HT, the MF, and the NB classifiers over the FNN and the Micro Cluster Nearest Neighbor (MCNN) classifiers on 4 datasets out of 6, including the real ones. In addition, the HT, and to some extent MCNN, are the only classifiers that can recover from a concept drift. Overall, the three leading classifiers still perform substantially lower than an offline classifier on the real datasets. Regarding resource consumption, the HT and the MF are the most memory intensive and have the longest runtime, however, no difference in power consumption is found between classifiers. We conclude that stream learning for HAR on connected objects is challenged by two factors which could lead to interesting future work: a high memory consumption and low F1 scores overall.

Index Terms—Application Platform, Data Management and Analytics, Smart Environment, Data Streams, Classification, Power, Memory Footprint, Benchmark, Human Activity Recognition, MCNN, Mondrian, Hoeffding Tree.

I. INTRODUCTION

Internet of Things applications may adopt a centralized model, where connected objects transfer data to servers with adequate computing capabilities, or a decentralized model, where data is analyzed directly on the connected objects or on nearby devices. While the decentralized model limits network transmission, increases battery life [2], [9], and reduces data privacy risks, it also raises important processing challenges due to the modest computing capacity of connected objects. Indeed, it is not uncommon for wearable devices and other smart objects to include a processing memory of less than 100 KB, little to no storage memory, a slow CPU, and no operating system. With multiple sensors producing data at a high frequency, typically 50 Hz to 800 Hz, processing speed and memory consumption become critical properties of data analyses.

Data stream processing algorithms are precisely designed to analyze virtually infinite sequences of data elements with reduced amounts of working memory. Several classes of stream processing algorithms were developed in the past decades, such as filtering, counting, or sampling algorithms [16]. These algorithms must follow multiple constraints such as a constant processing time per data element, or a constant space complexity [12]. Our study focuses on supervised classification, a key component of contemporary data models.

We evaluate supervised data stream classifiers from the point of view of connected objects, with a particular focus on Human Activity Recognition (HAR). The main motivating use case is that of wearable sensors measuring 3D acceleration and orientation at different locations on the human body, from which activities such as gym exercises have to be predicted. A previously untrained supervised classifier is deployed directly on the wearables or on a nearby object, perhaps a watch, and aggregates the data, learns a data model, predicts the current activity, and episodically receives true labels from the human subject. Our main question is to determine whether on-chip classification is feasible in this context.

We evaluate existing classifiers from the complementary angles of (1) classification performance, including in the presence of concept drift, and (2) resource consumption, including memory usage and classification time per element (latency). We consider six datasets in our benchmark, including three that are derived from the two most popular open datasets used for HAR, and three simulated datasets.

Compared to the previous works reviewed in Section II, the contributions of our paper are the following:

- We compare the most popular data stream classifiers on the specific case of HAR;
- We provide quantitative measurements of memory and power consumption, as well as runtime;
- We implement data stream classifiers in a consistent software library meant for deployment on embedded systems.

The subsequent sections present the materials, methods, and results of our benchmark.

II. RELATED WORK

To the best of our knowledge, no previous study focused on the comparison of data stream classifiers for HAR in the context of limited memory and available runtime that characterizes connected objects.

A. Comparisons of data stream classifiers

Data stream classifiers were compared mostly using synthetic datasets or real but general-purpose ones (Electrical, CoverType, Poker), which is not representative of our use case. In addition, memory and runtime usage are rarely reported, with the notable exception of [6].
The work in [23] reviews an extensive list of classifiers for data streams, comparing the Hoeffding Tree (HT), the Naive Bayes (NB), and the k-nearest neighbor (k-NN) online classifiers. The paper reports an accuracy of 92 for online k-NN, 80 for the HT, and 60 for NB. The study is limited to a single dataset (CoverType).

The work in [15] compares four classifiers (Bayesnet, HT, NB, and Decision Stump) using synthetic datasets. It reports a similar accuracy of 90 for the Bayesnet, the HT, and NB classifiers, while the Decision Stump one only reaches 65. Regarding runtimes, Bayesnet is found to be four times slower than the HT which is itself three times slower than NB and Decision Stump.

The work in [24] compares ensemble classifiers on imbalanced data streams with concept drifts, using two real datasets (Electrical, Intrusion), synthetic datasets, and six classifiers, including the NB and the HT ones. The HT is found to be the second most accurate classifier after the Accuracy Updated Ensemble.

The authors in [11] have analyzed the resource trade-offs of six online decision trees applied to edge computing. Their results showed that the Very Fast Decision Tree and the Strict Very Fast Decision Tree were the most energy-friendly, the latter having the smallest memory footprint. On the other hand, the best predictive performances were obtained in combination with OLBoost. In particular, the paper reports an accuracy of 89.6% on the Electrical dataset, and 83.2% on an Hyperplane dataset.

Finally, the work in [6] describes the architecture of StreamDM-C++ and presents an extensive benchmark of tree-based classifiers, covering runtime, memory, and accuracy. Compared to other tree-based classifiers, the HT classifier is found to have the smallest memory footprint while the Hoeffding Adaptive Tree classifier is found to be the most accurate on most of the datasets.

### B. Offline and data stream classifiers for HAR

Several studies evaluated classifiers for HAR in an offline (non data stream) setting. In particular, the work in [14] compared 293 classifiers using various sensor placements and window sizes, concluding on the superiority of k nearest neighbors (k-NN) and pointing out a trade-off between runtime and classification performance. Resource consumption, including memory and runtime, was also studied for offline classifiers, such as in [18] for the particular case of the R programming language.

In addition, the work in [28] achieved an offline accuracy of 99.4% on a five-class dataset of HAR. The authors used AdaBoost, an ensemble method, with ten offline decision trees. The work in [1] proposes a Support Vector Machine enhanced with feature selection. Using smartphone data, the model showed above 90% accuracy on day-to-day human activities. Finally, the work in [25] applies three offline classifiers to smartphone and smartwatch human activity data. Results show that Convolutional Neural Network and Random Forest achieve F1 score of 0.98 with smartwatches and 0.99 with smartphones.

In a data stream (online) setting, the work in [26] presents a wearable system capable of running pre-trained classifiers on the chip with high classification accuracy. It shows the superiority of the proposed Feedforward Neural Network (FNN) over k-NN.

### III. MATERIALS AND METHODS

We evaluate 5 classifiers implemented in either StreamDM-C++ [6] or OrpailleCC [17]. StreamDM-C++ is a C++ implementation of StreamDM [5], a software to mine big data streams using Apache Spark Streaming. StreamDM-C++ is usually faster than StreamDM in single-core environments, due to the overhead induced by Spark.

OrpailleCC is a collection of data stream algorithms developed for embedded devices. The key functions, such as random number generation or memory allocation, are parametrizable through class templates and can thus be customized on a given execution platform. OrpailleCC is not limited to classification algorithms, it implements other data stream algorithms such as the Cuckoo filter [10] or a multi-dimensional extension of the Lightweight Temporal Compression [21]. We extended it with a few classifiers for the purpose of this benchmark.

This benchmark includes five popular classification algorithms. The Mondrian forest (MF) [19] builds decision trees without immediate need for labels, which is useful in situations where labels are delayed [13]. The Micro-Cluster Nearest Neighbors [27] is a compressed version of the k-nearest neighbor (k-NN) that was shown to be among the most accurate classifiers for HAR from wearable sensors [14]. The NB [20] classifier builds a table of attribute occurrence to estimate class likelihoods. The HT [8] builds a decision tree using the Hoeffding Bound to estimate when the best split is found. Finally, Neural Network classifiers have become popular by reaching or even exceeding human performance in many fields such as image recognition or game playing. We use a Feedforward Neural Network (FNN) with one hidden layer, as described in [26] for the recognition of fitness activities on a low-power platform.

The remainder of this section details the datasets, classifiers, evaluation metrics and parameters used in our benchmark.

#### A. Datasets

1) Banos et al: The Banos et al dataset [3] is a human activity dataset with 17 participants and 9 sensors per participant. Each sensor samples a 3D acceleration, gyroscope, and magnetic field, as well as the orientation in a quaternion format, producing a total of 13 values. Sensors are sampled at 50 Hz, and each sample is associated with one of 33 activities. In addition to the 33 activities, an extra activity labeled 0 indicates no specific activity.

We pre-process the Banos et al dataset using non-overlapping windows of one second (50 samples), and using only the 6 axes (acceleration and gyroscope) of the right forearm sensor. We compute the average and the standard deviation over the window as features for each axis. We assign

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1Banos et al dataset available [here](#)
the most frequent label to the window. The resulting data points were shuffled uniformly.

In addition, we construct another dataset from Banos et al., in which we simulate a concept drift by shifting the activity labels in the second half of the data stream. This is useful to observe any behavioral change induced by the concept drift such as an increase in power consumption.

2) Recofit: The Recofit dataset [22] is a human activity dataset containing 94 participants. Similarly to the Banos et al. dataset, the activity labeled 0 indicates no specific activity. Since many of these activities were similar, we merged some of them together based on the table in [7].

We pre-processed the dataset similarly to the Banos et al. one, using non-overlapping windows of one second, and only using 6 axes (acceleration and gyroscope) from one sensor. From these 6 axes, we used the average and the standard deviation over the window as features. We assigned the most frequent label to the window.

3) MOA dataset: Massive Online Analysis [4] (MOA) is a Java framework to compare data stream classifiers. In addition to classification algorithms, MOA provides many tools to read and generate datasets. We generate three synthetic datasets: a hyperplane, a RandomRBF, and a RandomTree dataset. We generate 200,000 data points for each of these synthetic datasets. The hyperplane and the RandomRBF both have three features and two classes, however, the RandomRBF has a slight imbalance toward one class. The RandomTree dataset is the hardest of the three, with six attributes and ten classes. Since the data points are generated with a tree structure, we expect the decision trees to show better performances than the other classifiers.

B. Algorithms and Implementation

In this section, we describe the algorithms used in the benchmark, their hyperparameters, and relevant implementation details.

1) Mondrian forest (MF) [19]: Each tree in a MF recursively splits the feature space, similar to a regular decision tree. However, the feature used in the split and the value of the split are picked randomly. The probability to select a feature is proportional to its normalized range, and the value for the split is uniformly selected in the range of the feature.

In OrpailleCC, the amount of memory allocated to the forest is predefined, and it is shared by all the trees in the forest, leading to a constant memory footprint for the classifier. This implementation is memory-bounded, meaning that the classifier can adjust to memory limitations, for instance by stopping tree growth or replacing existing nodes with new ones. This is different from an implementation with a constant space complexity, where the classifier would use the same amount of memory regardless of the amount of available memory. For instance, in our study, the MF classifier is memory-bounded while NB classifier has a constant space complexity.

Mondrian trees can be tuned using three parameters: the base count, the discount factor, and the budget. The base count is used to initialize the prediction for the root. The discount factor influences the nodes on how much they should use their parent prediction. A discount factor closer to one makes the prediction of a node closer to the prediction of its parent. Finally, the budget controls the tree depth.

Hyperparameters used for MF are available in the repository readme. Additionally, the MF is allocated with 600 KB of memory unless specified otherwise. On the Banos et al. and Recofit datasets, we also explore the MF with 3 MB of memory in order to observe the effect of available memory on performances (classification, runtime, and power).

2) Micro Cluster Nearest Neighbor [27]: The Micro Cluster Nearest Neighbor (MCNN) is a variant of k-nearest neighbors where data points are aggregated into clusters to reduce storage requirements. The space and time complexities of MCNN are constant since the maximum number of clusters is fixed. The reaction to concept drift is influenced by the participation threshold and the error threshold. A higher participation threshold and a lower error threshold increase reaction speed to concept drift. Since the error thresholds used in this study are small, we expect MCNN to react quite fast and efficiently to concept drifts.

We implemented two versions of MCNN in OrpailleCC, differing in the way they remove clusters during training. The first version (MCNN Origin) is similar to the mechanism described in [27], based on participation scores. The second version (MCNN OrpailleCC) removes the cluster with the lowest participation only when space is needed. A cluster slot is needed when an existing cluster is split and there is no more slot available because the number of active clusters already reached the maximum defined by the user.

MCNN OrpailleCC has only one parameter, the error threshold after which a cluster is split. MCNN Origin has two parameters: the error threshold and the participation threshold. The participation threshold is the limit below which a cluster is removed. Hyperparameters used for MCNN are available in the repository readme.

3) Nave Bayes (NB) [20]: The NB algorithm keeps a table of counters for each feature value and each label. During prediction, the algorithm assigns a score for each label depending on how the data point to predict compares to the values observed during the training phase.

The implementation from StreamDM-C++ was used in this benchmark. It uses a Gaussian fit for numerical attributes. Two implementations were used, the OrpailleCC one and the StreamDM one. We used two implementations to provide a comparison reference between the two libraries.

4) Hoeffding Tree (HT) [8]: Similar to a decision tree, the HT recursively splits the feature space to maximize a metric, often the information gain or the Gini index. However, to estimate when a leaf should be split, the HT relies on the Hoeffding bound, a measure of the score deviation of the splits. We used this classifier as implemented in StreamDM-C++. The HT is common in data stream classification, however, the internal nodes are static and cannot be re-considered.
Therefore, any concept drift adaption relies on the new leaves that will be split.

The HT has three parameters: the confidence level, the grace period, and the leaf learner. The confidence level is the probability that the Hoeffding bound makes a wrong estimation of the deviation. The grace period is the number of processed data points before a leaf is evaluated for a split. The leaf learner is the method used in the leaf to predict the label. In this study, we used a confidence level of 0.01 with a grace period of 10 data points and the NB classifier as leaf learner.

5) Feedforward Neural Network (FNN): A neural network is a combination of artificial neurons, also known as perceptrons, that all have input weights and an activation function. In this benchmark, we used a fully-connected FNN, that is, a network where perceptrons are organized in layers and all output values from perceptrons of layer $n - 1$ serve as input values for perceptrons of layer $n$. We used a 3-layer network with 120 inputs, 30 perceptrons in the hidden layer, and 33 output perceptrons. Because a FNN takes many epochs to update and converge it barely adapts to a concept drifts even though it trains with each new data point.

In this study, we used histogram features from [26] instead of the ones presented in Section III-A because the network performed poorly with these features. The histogram features produce 20 bins per axis. This neural network can be tuned by changing the number of layers and the size of each layer. Additionally, the activation function and the learning ratio can be changed. The learning ratio indicates by how much the weights should change during backpropagation.

6) Hyperparameters Tuning: For each classifier, we tuned hyperparameters using the first subject from the Banos et al dataset. The data from this subject was pre-processed as the rest of the Banos et al dataset (window size of one second, average and standard deviation on the six-axis of the right forearm sensor, ...). We did a grid search to test multiple values for the parameters. The classifiers start the sequential phase with no knowledge from the first subject. We made an exception for the FNN because we noticed that it performed poorly with random weights and it needed many epochs to achieve better performances than a random classifier. Therefore, we decided to pre-train the FNN and re-use the weights as a starting point for the sequential phase.

For other classifiers, only the hyperparameters were taken from the sequential phase. We selected the hyperparameters that maximized the F1 score on the first subject.

7) Offline Comparison: We compared data stream algorithms with an offline $k$-NN. The value of $k$ were selected using a grid search.

C. Evaluation

We computed four metrics: the F1 score, the memory footprint, the runtime, and the power usage. The F1 score and the memory footprint were computed periodically during the execution of a classifier. The power consumption and the runtime were collected at the end of each execution.

\begin{itemize}
\item[a)] Classification Performance: We monitor the true positives, false positives, true negatives, and false negatives using the sequential evaluation, meaning that with each new data point the model is first tested and then trained. From these counts, we compute the F1 score every 50 elements. We do not apply any fading factor to attenuate errors throughout the stream. We compute the F1 score in a one-versus-all fashion for each class, averaged across all classes (macro-average, code available here). When a class has not been encountered yet, its F1 score is ignored. We use the F1 score rather than the accuracy because the real data sets are imbalanced.

\item[b)] Memory: We measure the memory footprint by reading file \texttt{/proc/self/statm} every 50 data points.

\item[c)] Runtime: The runtime of a classifier is the time needed for the classifier to process the dataset. We collect the runtime reported by the \texttt{perf} command, which includes loading of the binary in memory, setting up data structures, and opening the dataset file. To remove these overheads from our measurements, we use the runtime of an empty classifier that always predict class 0 as a baseline.

\item[d)] Power: We measure the average power consumed by classification algorithms with the \texttt{perf} command. The power measurement is done multiple times in a minimal environment.
\end{itemize}

D. Experimental Conditions

We automated our experiments with a Python script that defines classifiers and their parameters, randomizes all the repetitions, and plots the resulting data. The datasets and output results were stored in memory through a memfs filesystem mounted on /tmp, to reduce the impact of I/O time. We averaged metrics across repetitions (same classifier, same parameters, and same dataset).

The experiment was done with a single core of a cluster node with two Intel(R) Xeon(R) Gold 6130 CPUs and a main memory of 250G.

IV. RESULTS

This section presents our benchmark results and the corresponding hyperparameters tuning experiments.

A. Overall classification performance

Figure 1 compares the F1 scores obtained by all classifiers on the six datasets. The graphs also show the standard deviation of the MF classifier observed across all repetitions (the other classifiers do not involve any randomness).

F1 scores vary greatly across the datasets. While the highest observed F1 score is above 0.95 on the Hyperplane and RandomRBF datasets, it barely reaches 0.65 for the Banos et al dataset, and it remains under 0.40 on the Recofit and RandomTree datasets. This trend is consistent for all classifiers.

The offline $k$-NN classifier used as baseline achieves better F1 scores than all other classifiers, except for the MF on the Hyperplane and the RandomRBF datasets. On the Banos et al dataset, the F1 score is 0.95, which is 0.05 higher than the next best classifier, the RF.

\begin{itemize}
\item[4)] \texttt{perf} website
\end{itemize}
Fig. 1: F1 scores for the six datasets (average over 20 repetitions). The horizontal dashed black line indicates the offline $k$-NN F1 score (the value of $k$ was obtained by grid search in [2, 20]). The blue shades represent a $\pm \sigma$ interval of the MF classifier across repetitions.
dataset, the difference of 0.23 with the best stream classifier remains very substantial, which quantifies the remaining performance gap between data stream and offline classifiers. On the Recofit dataset, the difference between stream and offline classifiers is lower, but the offline performance remains very low.

It should be noted that the F1 scores observed for the offline k-NN classifier on the real datasets are substantially lower than the values reported in the literature. On the Banos et al. dataset, the original study in [3] reports an F1 score of 0.96, the work in [7] achieves 0.92, but our benchmark only achieves 0.86. Similarly, on the Recofit dataset, the original study reports an accuracy of 0.99 and the work in [7] reaches 0.65 while our benchmark only achieves 0.40. This is most likely due to our use of data coming from a single sensor, consistently with our motivating use case, while the other works used multiple ones (9 in the case of Banos et al.).

The HT appears to be the most robust to concept drifts (Banos et al. with drift), while the MF and NB classifiers are the most impacted. MCNN classifiers are marginally impacted. The low resilience of MF to concept drifts can be attributed to two factors. First, existing nodes in trees of a MF cannot be updated. Second, when the memory limit is reached, Mondrian trees cannot grow or reshape their structure anymore.

B. HT and NB

The NB and the HT classifiers stand out on the two real datasets (Banos et al. and Recofit) even though the F1 scores observed remain low (0.6 and 0.35) compared to offline k-NN (0.86 and 0.40). Additionally, the HT performs outstandingly on the RandomTree dataset and Banos et al. dataset with a drift. Such good performances were expected on the RandomTree dataset because it was generated based on a tree structure.

Except for the Banos et al. dataset, the HT performs better than NB. For all datasets, the performance of both classifiers is comparable at the beginning of the stream, because the HT uses a NB in its leaves. However, F1 scores diverge throughout the stream, most likely because of the HT’s ability to reshape its tree structure. This occurs after a sufficient amount of elements, and the difference is more noticeable after a concept drift.

Finally, we note that the StreamDM-C++ and OrpailleCC implementations of NB are indistinguishable from each other, which confirms the correctness of our implementation in OrpailleCC.

C. MF

On two synthetic datasets, Hyperplane and RandomRBF, the MF (RAM x 1.0) with 10 trees achieves the best performance (F1 > 0.95), above offline k-NN. Additionally, the MF with 5 or 10 trees ranks third on the two real datasets.

Surprisingly, a MF with 50 trees performs worse than 5 or 10 trees on most datasets. The only exception is the Hyperplane dataset where 50 trees perform between 5 and 10 trees. This is due to the fact that our MF implementation is memory-bound, which is useful on connected objects but limits tree growth when the allocated memory is full. Because 50 trees fill the memory faster than 10 or 5 trees, the learning stops earlier, before the trees can learn enough from the data. It can also be noted that the variance of the F1 score decreases with the number of trees, as expected.

The dependency of the MF to memory allocation is shown in Banos et al. and Recofit datasets, where an additional configuration with five times more memory than the initial configuration was run (total of 3 MB). The memory increase induces an F1 score difference greater than 0.1, except when only one tree is used, in which case the improvement caused by the memory is less than 0.05. Naturally, the selected memory bound may not be achievable on a connected object. Overall, MF seems to be a viable alternative to NB or the HT for HAR.

D. MCNN

The MCNN OrpailleCC stands out on the Banos et al. (with drift) dataset where it ranks second thanks to its adaptation to the concept drift. On other datasets, MCNN OrpailleCC ranks below the MF and the HT, but above MCNN Original. This difference between the two MCNN implementations is presumably due to the fact that MCNN Origin removes clusters with low participation too early. On the real datasets (Banos et al. and Recofit), we notice that the MCNN OrpailleCC appears to be learning faster than the MF, although the MF catches up after a few thousand elements. Finally, we note that MCNN remains quite lower than the offline k-NN.

E. FNN

Figure 1a shows that the FNN has a low F1 score (0.36) compared to other classifiers (above 0.5), which contradicts the results reported in [26] where the FNN achieves more than 95% accuracy in a context of offline training. The main difference between [26] and our study lies in the definition of the training set. In [26], the training set includes examples from every subject, while we only use a single one, to ensure an objective comparison with the other stream classifiers that do not require offline training (except for hyperparameter tuning, done on the first subject of the Banos et al. dataset). When we use a random sample of 10% of the datpoints across all subjects for offline training, we reach an F1 score of 0.68, which is higher than the performance of the NB classifier.

F. Power

Figure 2 shows the power usage of each classifier on four datasets (results are similar for the other two datasets). All classifiers exhibit comparable power consumptions, close to 102 W.

This observation is explained by two factors. First, the benchmarking platform was working at minimal power. To ensure no disturbance by a background process, we run the classifiers on an isolated cluster node with eight cores. Therefore, the power difference on one core is not noticeable.

Another reason is the dataset sizes. Indeed, the slowest run is about 10 seconds with 50 Mondrian trees on Recofit dataset. Such short executions do not leave time for the CPU to switch P-states because it barely warms a core. Further experiments would be required to check how our power consumption observations generalize to connected objects.
Fig. 2: Power usage for the Banos et al. dataset. Results are similar across datasets.

Fig. 3: Runtime with the Banos et al. dataset (20 repetitions). Runtime results are similar across datasets.

G. Runtime

Figure 3 shows the classifier runtimes for the two real datasets. The MF is the slowest classifier, in particular for 50 trees which reaches 2 seconds on Banos et al. dataset. This represents roughly 0.35 ms/element with a slower CPU. The second slowest classifier is the HT, with a runtime comparable to the MF with 10 trees. The HT is followed by the two NB implementations, which is not surprising since NB classifiers are used in the leaves of the HT. The MCNN classifiers are the fastest ones, with a runtime very close to the empty classifier. Note that allocating more memory to the MF substantially increases runtime.

We observe that the runtime of StreamDM-C++’s NB is comparable to OrpailleCC’s. This suggests that the performance of the two libraries is similar, which justifies our comparison of HT and MF.

H. Memory

Figure 4 shows the evolution of the memory footprint for the Banos et al. dataset. Results are similar for the other datasets and are not reported for brevity. Since the memory footprint of the NB classifier was almost indistinguishable from the empty classifier, we used the two NB as a baseline for the two libraries. This enables us to remove the 1.2 MB overhead induced by StreamDM-C++. The StreamDM-C++ memory footprint matches the result in [6], where the HT shows a memory footprint of 4.8 MB.

We observe that the memory footprints of the MF and the HT are substantially higher than for the other classifiers, which makes their deployment on connected objects challenging. Overall, memory footprints are similar across datasets, due to the fact that most algorithms follow a bounded memory policy or have a constant space complexity. The only exception is the HT that constantly selects new splits depending on new data points. The MF has the same behavior but the OrpailleCC implementation is memory-bounded, which makes its memory footprint constant.

V. Conclusion

We conclude that the HT, the MF, and the NB data stream classifiers have an overall superiority over the FNN and the MCNNs ones for HAR. However, the prediction performance remains quite low compared to an offline k-NN classifier, and it varies substantially between datasets. Noticeably, the HT and the MCNNs classifiers are more resilient to concept drift that the other ones.

Regarding memory consumption, only the MCNN and NB classifiers were found to have a negligible memory footprint, in the order of a few kilobytes, which is compatible with connected objects. Conversely, the memory consumed by a MF, a FNN or a HT is in the order of 100 kB, which would only be available on some connected objects. In addition, the classification performance of a MF is strongly modulated by the amount of memory allocated. With enough memory, a MF
is likely to match or exceed the performance of the HT and NB classifiers.

The amount of energy consumed by classifiers is mostly impacted by their runtime, as all power consumptions were found comparable. The HT and MF are substantially slower than the other classifiers, with runtimes in the order of 0.35 ms/element, a performance not compatible with common sampling frequencies of wearable sensors.

Future research will focus on reducing the memory requirements and runtime of the HT and the MF classifiers. In addition to improving the deployability of these classifiers on connected objects, this would also potentially improve their classification performance, since memory remains a bottleneck in the MF.

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