НЕЙРОІНФОРМАТИКА ТА ІНТЕЛЕКТУАЛЬНІ СИСТЕМИ

NEUROINFORMATICS AND INTELLIGENT SYSTEMS

UDC 004.8

ENSEMBLE OF SIMPLE SPIKING NEURAL NETWORKS AS A CONCEPT DRIFT DETECTOR

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ABSTRACT

Context. This paper provides a new approach in concept drift detection using an ensemble of simple spiking neural networks. Such approach utilizes an event-based nature and built-in ability to learn spatio-temporal patterns of spiking neurons, while ensemble provides additional robustness and scalability. This can help solve an active problem of limited time and processing resources in tasks of online machine learning, especially in very strict environments like IoT which also benefit in other ways from the use of spiking computations.

Objective. The aim of the work is the creation of an ensemble of simple spiking neural networks to act as a concept drift detector in the tasks of online data stream mining.

Method. The proposed approach is primary based on the accumulative nature of spiking neural networks, especially Leaky Integrate-and-Fire neurons can be viewed as gated memory units, where membrane time constant τ_m is a balance constant between remembering and forgetting information. A training algorithm is implemented that utilizes a shallow two-layer SNN, which takes features and labels of the data as an input layer and the second layer consists of a single neuron. This neuron's activation implies that an abrupt drift has occurred. In addition to that, such model is used as a base model within the ensemble to improve robustness, accuracy and scalability.

Results. An ensemble of shallow two-layer SNNs was implemented and trained to detect abrupt concept drift in the SEA data stream. The ensemble managed to improve accuracy significantly compared to a base model and achieved competitive results to modern state-of-the-art models.

Conclusions. Results showcased the viability of the proposed solution, which not only provides a cheap and competitive solution for resource-restricted environments, but also open doors for further research of SNN's ability to learn spatio-temporal patters in the data streams and other fields.

KEYWORDS: machine learning, online learning, spiking neural networks, concept drift, drift detector, artificial neural networks, data stream mining, artificial intelligence, leaky integrate-and-fire neuron.

ABBREVIATIONS

ANN is an artificial neural network;
GRU is a gated recurrent unit;
LSTM is a long short-term memory;
ML is a machine learning;
PLIF is a parametric leaky integrate-and-fire neuron;
RNN is a recurrent neural network;
SEA is a streaming ensemble algorithm;
SNN is a spiking neural network.

NOMENCLATURE

τ_m is a membrane time variable that determines the decay rate;
$f(V_{t-1}, X_t)$ is a LIF's neural dynamics function;
$g(X)$ is an ensemble's function;
$h_j(X)$ is an ensemble's j-th base model function;
N is a number of base models used in ensemble;
T is a number of iterations the SNN receives the input;
V_t is a membrane potential at a time point t;
X_t is an input vector at a time point t;
x_i is a data stream's i-th feature;
y is a data stream's true label.
y' is a model's output of drift detection.

INTRODUCTION

Data stream mining in the online manner is a complex task that involves strict restrictions on time and processing resources, while still requiring adequate results and a need to process huge volumes of data. This implies con-

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siderable limitations on used algorithms, even making many state-of-the-art ML models unusable. In addition, many models are unable to adapt quickly to the changing environment and therefore become obsolete. This is especially prominent with ANNs which fail to adjust their trainable parameters to the concept drift without utilizing resource-hungry recurrent architectures [1].

Many approaches have been proposed to solve existing online learning problems. In recent years, interest has spiked greatly in applying more biologically inspired systems to solve ML tasks. SNNs are one such system. They are considered to be the third generation of ANNs that closely mimic the inner work of biological neurons in human brains [2]. In comparison to regular ANNs, spiking neurons implement biological mechanisms like the accumulation of membrane potential, refractory period, charge decay and simulation of neurotransmitters' explosions. Such mechanisms result in lower power consumption [3], analogue and event-based nature, as well as an ability to learn temporal patterns in the data [4].

These characteristics make SNNs a viable solution for listed problems of online learning, especially in the most resource limited environments like IoT, which also benefit from other advantages of spiking computations. Recent research showcased that SNNs are able to adapt to the concept drift [5] and to be used as drift detectors as well when combined with evolving architectures [6].

But overall, the research on spiking drift detectors is very limited. In addition to that and to our knowledge, no research was proposed to utilize ensembling techniques with SNNs to detect the concept drift, while ensembles of ANNs were showcased to be efficient in such task, as well as improving SNNs performance (as described in section 2).

The object of study is the process of concept drift detection during online learning and data stream mining.

The subject of study is the use of spiking neural networks as concept drift detectors.

The purpose of the work is to broad the existing research by exploring how SNN's built-in abilities to learn spatio-temporal patterns can be utilized to build spiking detectors with shallow architectures and exploring how ensemble of such detectors can create a more robust system.

1 PROBLEM STATEMENT

This study aim is to develop an ensemble of simple SNNs to identify the abrupt concept drift in the artificially generated data stream and to analyze whether such approach improves the performance of the base model.

To do so, a training pipeline is to be implemented that trains a model in the online manner by providing the input vector X that consists of both the input features and the true label of the data stream:

$$X = (x_1, x_2, ..., x_n, y), \tag{1}$$

where x_i represents a stream's feature and y is its true label.

As a result, two experiments are to be performed: one with just the SNN model and one with the ensemble; and their metrics are to be compared.

2 REVIEW OF THE LITERATURE

In regular ANNs, memorization is achieved by implementing recurrent layers or by using gating mechanisms, like in LSTM [7] or GRU [8]. Previously, researchers tried to reimplement similar memory blocks for SNNs [9], but recently, they focused more on built-in short-term memory capacity. SNNs have an accumulative nature due to the membrane potential and authors of [10] noted that the Leaky Integrate-and-Fire (LIF) model can be viewed as a gated memory unit if the formula is rewritten the next way:

$$f(V_{t-1}, X_t) = V_{t-1} + \frac{1}{\tau_m}(-(V_{t-1} - V_{reset}) + X_t). \tag{2}$$

Which in case of $V_{reset} = 0$ looks like:

$$f(V_{t-1}, X_t) = \left(1 - \frac{1}{\tau_m}\right)V_{t-1} + \frac{1}{\tau_m}X_t. \tag{3}$$

As noted in the original research, the integration process and the leak can be viewed as update and reset gates, while the accumulated membrane potential V_{t-1} functions as a hidden state. With such interpretation, the membrane time constant τ_m is a balance constant between remembering and forgetting information. A larger τ_m allows for a better estimate of the frequency of input spikes, but requires more time to charge and fire, which works well with a stable input signal. On the contrary, a smaller τ_m means a faster voltage decay, which makes the LIF neuron sensitive to time-varying input signals and able to respond quickly – at the cost of losing the accuracy of distinguishing between different input signals. Furthermore, the same research proposed to make the τ_m trainable to help to find the balance without an additional hyperparameter tuning. Such solution they named as PLIF model.

Therefore, LIF nodes can be used as a cheap memory unit which also have an event-based nature. In addition, LIFs have perks of regular dense layers, like being able to combine inputs and capture relationships between different features. In this context, LIF nodes can function as two layers at the same time. This makes them even more suitable to be used as concept drift detectors, especially when faced with sudden or recurring drifts.

A popular and a common technique in ML is usage of ensemble learning techniques. Ensembles combine predictions of multiple base models which provides an improved generalization, better handling of class imbalance and overall robustness. In addition to that, ensembles can be more resource-efficient than training a single and complex model. Due to these, ensembles gathered attention to

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be used in online learning scenarios and have been already showcased to be effective in them [11, 12], especially when used in IoT systems [13] (where SNNs shine as well [14]). They also showcased the ability to detect the concept drift [15].

The human nervous system also appears to utilize some ensemble effects or techniques: groups of neurons or neural circuits act together to improve motor skills, as was noted in the [16]. The same research also developed and tested Spiking Voter Ensemble Network which was built on ensemble of simplified three-neuron models with utilization of the input timing dependent synaptic plasticity. The proposed model achieved improved MNIST [17] performance. Other research also showcased general improvements for simple SNNs when combined with ensemble techniques: authors of [18] achieved state-of-the-art results for MNIST, NMNIST [19] and DSV Gesture [20] datasets while lowering the number of trainable parameters by half; and authors of [21] also achieved state-of-the-art results for MNIST and CIFAR-10 [22] datasets.

3 MATERIALS AND METHODS

The key part of any ensemble algorithm is a base model. As was noted previously, the use of online learning sets restrictions for such models: the model should be simple to not consume large amounts of resources, while also being able to adapt to new patterns in the data stream. In our proposed solution, we utilize a shallow two-layer PLIF-based with the next key characteristics:

1) The first layer takes the input vector X to learn patterns between the features and the labels;

2) The second layer consists of a single PLIF neuron, activation of which indicates if the concept drift occurred;

3) The PLIF's membrane state does not reset between the iterations. This allows the model's internal state to accumulate information over time and capture subtle changes in the data stream that may indicate a potential drift.

The architecture is shown in Fig. 1:

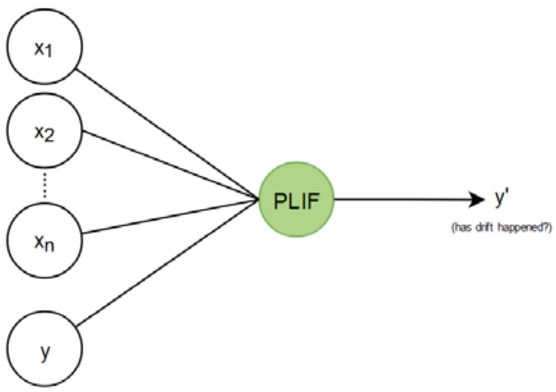

Figure 1 – The proposed model architecture

This approach does not use any additional helping models and only analyzes the stream's data. Ideally, it can learn both virtual and real drifts. In addition, the refractory period, that comes after the action potential, prevents excessive neural activity. Meaning, it won't fire again right after the drift detection. This lowers chances of recurring false-positive activations and removes the need to develop additional timeout mechanisms for the model when it successfully detected the drift. Also, as was mentioned in the section 2, the initial τ_m controls how sensitive the neuron is. Though it is different for each task, normally it is expected that data stream will be stable and concept drift won't occur often. Because of that, higher values of the initial τ_m will prevent the fast charge decay and can further decrease false-positive activations.

The main drawback of such SNN model (which will be referred as the base model) comes from its simplicity, meaning it will fail to learn complex patterns without changes in the architecture. To overcome this, an ensemble is used. The ensemble trains up to N base models, each receiving the input vector X. The verdict whether concept drift has occured is determined by the formula (4):

$$g(X) = \max(h_1(X), h_2(X), ..., h_N(X)), \tag{4}$$

where $h_j(X)$ represents the base model function. If any of the models are activated, then we conclude that the drift has occurred.

For the model training, a backpropagation algorithm is used. And to ease the experiment, it has a few restrictions on the concept drift: an abrupt concept drift occurs after the set number of iterations and a new drift cannot occur before the previous one was successfully detected.

The whole process is visualized in the Fig. 2.

4 EXPERIMENTS

The developed training algorithm was tested using the SEA (streaming ensemble algorithm) artificial data stream generator [23] with an abrupt concept drift. This data stream generates 3 features $\{x_1, x_2, x_3\}$ (where x_3 doesn't take part in the classification) and a binary target variable that is calculated by one of the (5–8) equations that switch during the drift:

$$y = (x_1 + x_2) \leq 8, \tag{5}$$

$$y = (x_1 + x_2) \leq 9, \tag{6}$$

$$y = (x_1 + x_2) \leq 7, \tag{7}$$

$$y = (x_1 + x_2) \leq 9.5. \tag{8}$$

As was mentioned in section 1, two experiments were performed: one with just the base model and second one with the ensemble of multiple such models. Both experiments run with the next configuration:

– the initial membrane time variable was set at $\tau_m = 5$ for slower charge decay;

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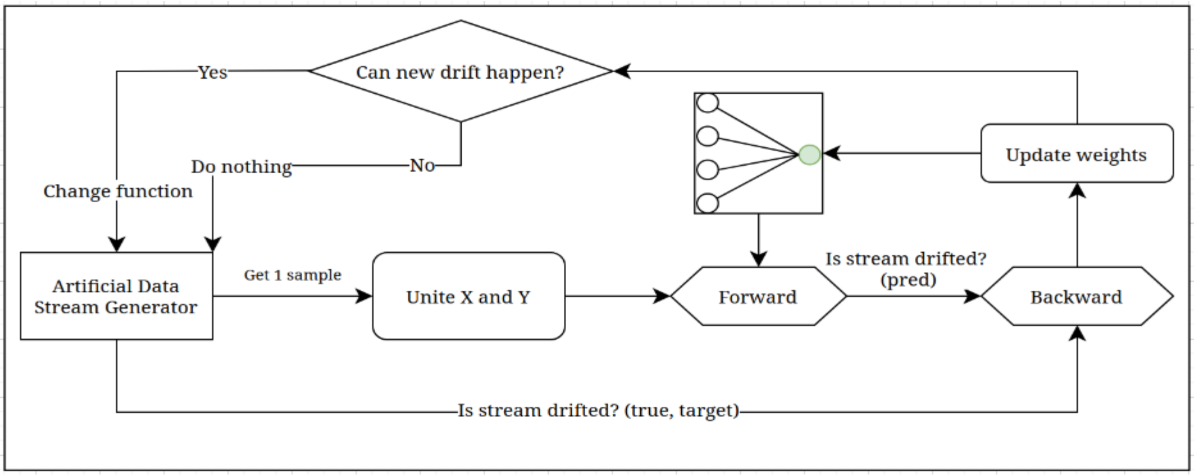

Figure 2 – Flowchart of the training algorithm

– training is done with 20000 iterations, testing is done with 2000 iterations;

– spiking neurons "see" the data only for a $T = 1$ number of iterations;

– a new drift occurs once in 200 iterations.

Initial weights are randomly generated and no additional hyperparameter tuning was performed. The ensemble uses $N = 5$ base models which are trained on the same data. Also, the random seed was freezed.

The tools used for the program realization are Python, PyTorch [24] and SpikingJelly [25].

The results of these experiments are shown in the section 5.

5 RESULTS

The first experiment with a simple base model did not yield good results. While this SNN was capable of identifying the drift, the accuracy of predictions stayed very low, with the last accuracy being equal to 29% and the average accuracy stagnating only around 34%. The accuracy history graph is shown in Fig. 3.

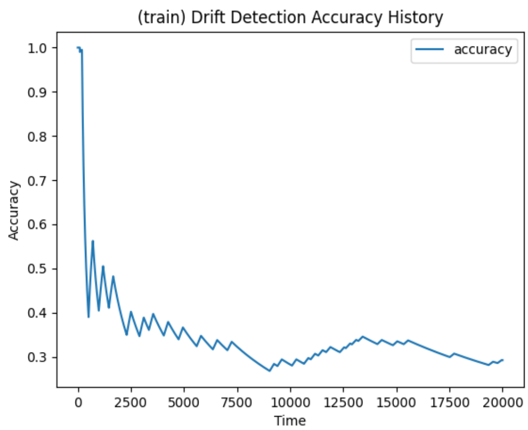

Figure 3 – The training accuracy history of the base spiking model

The situation with the testing is similar with the last accuracy being equal to 43% as shown in Fig. 4 (it also shows when the drift has happened and has been identified). Though, the fact that the metric stayed consistent between the training-testing phases is promising. In addition to that, on average, SNN required 285 iterations before identifying the drift. Also, the overall efficiency is very sensitive to the initial hyperparameters.

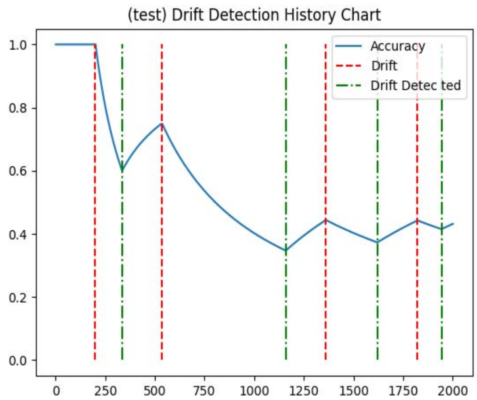

Figure 4 – The testing accuracy history of the base spiking model

The ensemble method managed to produce much better results: the average train accuracy increased to 87% (as shown in Fig. 5) on the train data and maintained the test accuracy around 91% (as shown in Fig. 6). In addition to that, the drift detection time improved as well: on average, the drifts were detected in 22.65 iterations during the training and in 8.44 iteration during the testing.

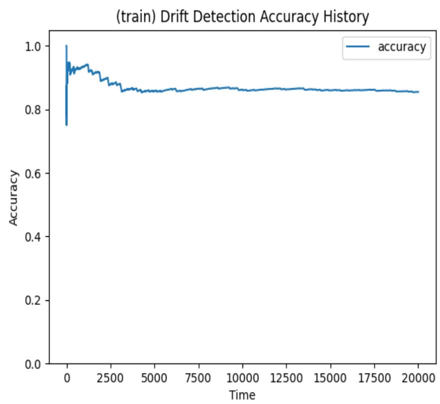

Figure 5 – The training history of the ensemble

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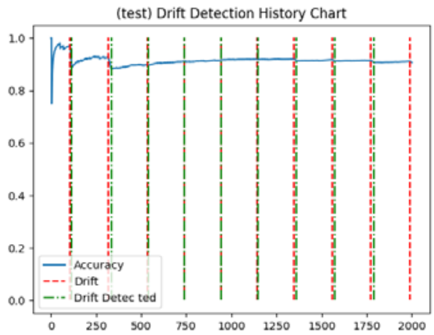

Figure 6 – The testing accuracy history of the ensemble

6 DISCUSSION

As evident from the results, the provided base model was very weak and non-robust, making it non-applicable to real-world tasks, especially with more complex data. Still, it showcased the ability to learn the patterns. But when it was used within the ensemble, the overall accuracy and detection time improved significantly.

Moreover, the achieved results are comparable to the current state-of-the-art accuracy which include classical ML algorithms [26] like Naïve Bayes with an 86% accuracy and another ensemble-based Hoeffding Tree classifier which also produced an 86% accuracy score (or 88% when combined with the adaptive sliding window algorithm [11]). Besides, the proposed solution achieved similar results to the current state-of-the-art RNN-based (recurrent neural network) solution [27], which produced an accuracy of 91.70%, in addition to having a much smaller number of trainable parameters.

This indicates the viability of the proposed solution to be used in data streams analysis when faced with resource-restricted environments. Also, such methodology allows for an easier integration into the IoT systems, where each SNN can be implemented as a small separate circuit with analogue sensors as an input. Also, it can function as a plausible alternative to the deep learning with which SNNs often struggle [28].

Nonetheless, additional testing on different data streams is required to improve the proposed architecture and algorithm and to test robustness. As already mentioned, the solution has its own disadvantages: it will struggle with more complex data and will likely require significant changes in the base model architecture.

CONCLUSIONS

This paper proposed a new approach in developing concept drift detectors that focuses on utilizing SNN's abilities to spot the changes in spatio-temporal patterns in data stream inflicted by the drift, and further improving it with ensembling techniques. Experiments with a common for such tasks artificial data were performed that gave adequate and competitive results, which validated the viability of the approach.

The scientific novelty of this work is that the method of using an ensemble of simple spiking drift detectors is firstly proposed. Ensemble's base models take in features and label to learn spatio-temporal patters and fire if the abrupt drift has occurred; while the ensemble of multiple such models itself significantly improves the overall accuracy and gives state-of-the-art results on the tested artificial data, in addition to having small number of trainable parameters.

The practical significance of obtained results is that such approach provides a cheap and efficient solution for extremely resource-limited environments that face constant dangers of concept drift occurrences, like many IoT systems that also benefit from analog and event-based nature of SNNs. Moreover, the use of ensembles provides an additional scalability by allowing the increase or decrease of model quantity to fit the practical needs.

Prospects for further research are to applying similar approach of drift detection to more complex data structures, as well as a further study of SNN's ability to learn spatio-temporal patters in the data streams.

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АНСАМБЛЬ ПРОСТИХ СПАЙКОВИХ НЕЙРОННИХ МЕРЕЖ В ЯКОСТІ ДЕТЕКТОРІВ ДРЕЙФУ КОНЦЕПЦІЇ

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АНОТАЦІЯ

Актуальність. У цій статті запропоновано новий підхід до виявлення дрейфу концепцій з використанням ансамблю простих спайкових нейронних мереж. Такий підхід використовує подієву природу та вбудовану здатність нейронів вивчати просторово-часові патерни, а ансамбль забезпечує додаткову робастність та масштабованість. Це може допомогти вирішити актуальну проблему обмеженості часових та обчислювальних ресурсів у задачах онлайн машинного навчання, особливо в дуже суворих середовищах, таких як IoT, які також мають інші переваги від використання шипінг-обчислень.

Мета роботи. Метою роботи є створення ансамблю простих спайкових нейронних мереж для роботи в якості детектора концептуального дрейфу в задачах інтелектуального аналізу потоків даних в Інтернеті.

Метод. Запропонований підхід в першу чергу базується на накопичувальній природі спайкових нейронних мереж, особливо негерметичних нейронів інтеграції-та-пострілу, які можна розглядати як одиниці пам'яті із затворами, де мембранна постійна часу τ_m є константою балансу між запам'ятовуванням та забуванням інформації. Реалізовано алгоритм навчання, який використовує неглибоку двошарову SNN, що використовує ознаки та мітки даних як вхідний шар, а другий шар складається з одного нейрона. Активація цього нейрона означає, що відбувся різкий дрейф. Крім того, така модель використовується як базова модель в ансамблі для покращення робастності, точності та масштабованості.

Результати. Ансамбль неглибоких двошарових SNN було реалізовано та навчено для виявлення різкого дрейфу концепції в потоці даних SEA. Ансамблю вдалося значно підвищити точність порівняно з базовою моделлю та досягти конкурентних результатів із сучасними передовими моделями.

Висновки. Результати показали життєздатність запропонованого рішення, яке не тільки забезпечує дешеве і конкурентоспроможне рішення для середовищ з обмеженими ресурсами, але і відкриває двері для подальших досліджень здатності спайкових нейромереж вивчати просторово-часові патерни в потоках даних та інших областях.

КЛЮЧОВІ СЛОВА: машинне навчання, онлайн навчання, спайкові нейронні мережі, дрейф концепцій, детектор дрейфу, штучні нейронні мережі, інтелектуальний аналіз потоку даних, штучний інтелект, негерметичний нейрон інтеграції-та-пострілу.

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