Adapting Open-Set Recognition Method to Various Time-Series Data

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Keywords: Open-Set Recognition, Time-Series.

Abstract: In real-world scenarios, conventional classifier methods often stumble when faced with the unexpected emergence of unknown samples or classes previously unseen during training. Open-Set Recognition (OSR) models have emerged as a solution to this ubiquitous challenge. Our previous work introduced a robust OSR method leveraging synthesized – or "fake" – features to delineate the uncharted territory of unknowns, focusing on image datasets. Recognizing the imperative to extend this capability to diverse data types, we have successfully transposed this model to time-series datasets. A pivotal feature of the original model was its modular architecture, allowing for focused modification in feature extraction. Consequently, the core components remained intact, including feature extraction, sample generation, and feature transformation. This paper illuminates our initial strides, employing a one-dimensional convolutional network for feature extraction and showcasing promising preliminary OSR results using that network. Additionally, our adapted model maintains its advantageous edge in terms of time complexity, achieved through the discreet generation of fake features in a simplified hidden layer. Future investigations will further delve into alternative feature extraction methodologies, promising to broaden the scope of applications for this adaptable OSR model.

1 INTRODUCTION

In the realm of machine learning, remarkable achievements have been made across various classification and recognition tasks, often surpassing human-level performance. For instance, take the current pinnacle: a model that achieves a staggeringly low error rate of just 0.21% on the MNIST dataset (Wan et al., 2013). At first glance, the field has conquered all its challenges. However, these triumphs come with a crucial caveat – these exceptional results have been achieved within closed-set scenarios, where the assumption is that all classes are known during training. The open-set scenario prevails in the real world, where new classes can emerge during testing, demanding our models make informed rejections.

We engaged in prior research endeavors to address this fundamental challenge, wherein we introduced a highly effective Open-Set Recognition (OSR) methodology. At its core, our approach revolves around a pivotal concept: creating a representation of the unknown space by generating synthetic samples derived from authentic data instances. A noteworthy observation emerges: the process of training the model to discern and reject these artificially generated samples yields a substantial improvement in its capacity to identify and reject genuine unknown samples during testing appropriately. Our innovation, however, departs from the conventional path. Instead of fabricating entirely new inputs, we generated synthetic features within a concealed layer. This strategic departure led to a notable enhancement in accuracy and delivered a remarkable reduction in computational overhead. The generative model responsible for crafting these features adopted a leaner and more streamlined structure than the input layer, optimizing computational efficiency. Furthermore, placing these synthetic samples within a hidden layer enabled them to circumvent the initial segments of the model, resulting in significant computational resource savings. Worth noting is that this sample generation process continues to leverage Generative Adversarial

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Halász, A., Daubner, L., Al-Hemeary, N., Juhász, J., Zsedrovits, T. and Tornai, K.
Adapting Open-Set Recognition Method to Various Time-Series Data.
DOI: 10.5220/0012265700003584
In *Proceedings of the 19th International Conference on Web Information Systems and Technologies (WEBIST 2023)*, pages 595-601
ISBN: 978-989-758-672-9; ISSN: 2184-3252

Networks (GANs) (Goodfellow et al., 2014), albeit with refined and simplified generator and discriminator networks.

Conceived initially to operate with image datasets employing convolutional networks, our OSR model boasts remarkable adaptability, accommodating diverse data types. The crux of this adaptability rests upon a critical component – the feature extraction module, situated just before the concealed layer where synthetic samples are generated. Once we successfully extract the requisite features, the generative and feature-classifier components synergize seamlessly. Our latest endeavor has tailored this model to effectively classify multi-channel time series data, specifically focusing on biometric signals. Our objective revolves around the precise identification of users based on the vibrational patterns of their hands, captured via the accelerometer and gyroscope sensors within a mobile phone held by the subjects (Jiokeng et al., 2022). For feature extraction, we harnessed the capabilities of one-dimensional convolutional neural networks, a natural choice given the one-dimensional nature of the data. Notably, our preliminary findings in this domain have been exceedingly promising, all while retaining the crucial advantage of the model's low time complexity, which was a hallmark of its original design.

This paper unfolds as follows: We commence with an exhaustive literature review, providing a comprehensive backdrop to contextualize our work. Subsequently, we offer an overview of the original OSR model. Following this introduction, we delve into particular detail regarding the adaptation of our model to accommodate this novel data type, encompassing comprehensive discussions on data preprocessing and feature extraction methodologies. In closing, we present our preliminary results, illuminating the future prospects of this model's continued development.

2 RELATED WORKS

In this section, the corresponding literature is briefly reviewed. It starts with the Open Set Recognition theory and then presents the dataset the model was adapted to.

2.1 Theory of Open-Set Recognition

There have been algorithms for a long time that solve classification tasks where only some samples belong to any known class (Bodesheim et al., 2015), or the machine needs to be more confident (Fumera and Roli, 2002; Grandvalet et al., 2008) to classify them. Finally introduced the formal theory of Open-set Recognition (Scheirer et al., 2013). In this paper, their definitions are followed.

Let O denote the open space (i.e., the space far from any known data). The Open Space Risk is defined as follows

$$R_O(f) = \frac{\int_O f(x)dx}{\int_{S_O} f(x)dx} \tag{1}$$

where S_O denotes the space containing both the positive training examples and the positively labeled open space, and f is the recognition function with $f(x) = 1$, if the sample x is recognized as as a known class, $f(x) = 0$ otherwise.

Definition 1. Open Set Recognition Problem: Let V be the set of training samples, R_O the open space risk, R_ε the empirical risk (i.e., the closed set classification risk, associated with misclassifications). Then, the Open Set Recognition is the task to find an $f \in H$ measurable recognition function, where $f(x) > 0$ means classification into a known class, and f minimizes the Open Set Risk:

$$arg\min_{f \in H}\{R_O(f) + \lambda_r R_\varepsilon(f(V))\} \tag{2}$$

where λ_r is a regularization parameter balancing open space risk and empirical risk.

Definition 2. *The Openness of an Open Set Recognition problem is defined as follows.*

$$O = 1 - \sqrt{\frac{2x|C_{TR}|}{|C_{TA}| + |C_{TE}|}} \tag{3}$$

where $C_{TR}, C_{TA}, andC_{TE}$ denote the training, target, and test classes, respectively.

2.2 Existing Approaches

(Scheirer et al., 2013), after formalizing the problem of Open Set Recognition, immediately presented the first solution to it, the 1-vs-Set Machine, which is an SVM specialized for open set recognition. After training an SVM model, the 1-vs-Set Machine adds a second hyperplane parallel to the first one, and only inputs between the hyperplanes will be classified as positive. The argument is that comparing the measure of a d-dimensional ball and the positively labeled slab inside that ball, the open space risk of such a model approaches zero as the radius of the ball grows. Although it is true, the positively labeled space is still unbounded. (Júnior et al., 2016) use RBF (Radial Base Function) kernel to the SVM model. As $\lim_{d(x,x')\to\infty} K(x,x') = 0$ with radial kernel function K, a necessary and sufficient condition to bounded positively labeled open space is a negative bias term. They ensure this using a regularization term on bias in the objective function.

SVM-s, as well as softmax classifiers - are initially designed for the closed-set scenario. Although these can be modified to reject open-set samples to some extent, fundamentally different approaches are needed to achieve better results as the first solutions did.

Distance-based methods inherently fit into the open-set scenario. In addition to deciding which class is the most similar to the sample in question, they provide a value on the extent of the similarity. Using this value, e.g., applying a threshold on it, one can decide whether the sample belongs to the most similar class or is unknown.

(Júnior et al., 2017) extended the nearest neighbor classifier to the open-set scenario. To decide where sample s belongs, its nearest neighbor t is first taken, then the nearest neighbor u s.t. u and t are of different classes. If the ratio of the distances $R = d(t,s)/d(u,s)$ is less than a threshold T, s is classified with the same label as t; otherwise, it is rejected as unknown.

Instead of using the distances between individual instances, (Miller et al., 2021) used predefined (so-called anchored) class means. A network projects each input into the logit space. Then, the decision is made according to the Euclidean distances between the logit vectors and the class means.

The vast majority of OSR models are made for the purpose of processing images. It is highly needed to develop algorithms working on time series. Among the first were (Tornai and Scheirer, 2019), who, after extracting statistical features, applied the $P_I - SVM$ (Jain et al., 2014) and EVM (Rudd et al., 2018) models on them. It showed that OSR is possible on time series, although the results left room to improve.

2.3 Authors' Previous Work

Previously, we have implemented a distance-based model instead of using soft-max (inherently a closed-set approach) in the last layer. The training is simplified into a quadratic regression with the fixed class centers. The model is prepared for the later occurring unknown inputs with generated fake samples. These are, however, generated in a hidden feature layer instead of the input space. The neural network model is cut into two halves. The output of the first half is the layer where the features are generated. This way, the training goes as shown on Algorithm **??**. First, both parts of the model are pre-trained, as they would be a single model. Then, the outputs of the pre-trained first part of the model are saved. These serve as real inputs to train the generative model. After that, the real features, together with the ones created by the generative model, are used to train the second half of the model further. Figure 1 shows an overview of the model.

```
Data: X = (x_1, ...x_n) training samples,
      numbers of iterations n_1, n_2
Initialize N_1, N_2, N_G, N_D with random
  parameters, class centres Y = (y_1, ...y_k) ;
X ← x;
N ← n;
for i = {0..n_1} do
    for j in batches do
        out ← N_2(N_1(x_j));
        loss ← quadratic loss(out, Y);
        Update N_1 and N_2 with the gradient of
          the loss;
    end
end
f_1(X) = (f_1(x_1), ...f_1(x_n) ←
  (N_1(x_1)), ...N_1(x_n));
(N_G, N_D) ← GAN(N_G, N_D, f_1(X));
z ← random noise;
X_G ← N_G(z);
for i = {0..n_2} do
    for j in batches do
        out ← N_2(f_1(X)_j);
        loss ← quadratic loss(out, Y);
        out ← N_2((X_G)_j);
        loss ← loss + quadratic loss(out, Y);
        Update N_2 with the gradient of the
          loss;
    end
end
```

Algorithm 1: The training algorithm of the model. It is sufficient to modify N_1 in order to adapt the algorithm for different kinds of data.

The model outperformed most competitors' methods on the commonly used image datasets. On CIFAR10, for example, the open-set detection AUC was 0.839, while the closed-set accuracy was 0.914. Both values are the best among the tested OSR algorithms, and the closed-set accuracy falls behind only very well-optimized closed-set classifiers (Halász et al., 2023).

2.4 Dataset

The primary motivation for developing this model lies in its application to user classification based on hand gestures, primarily through data collected from mobile devices. In essence, the objective is to create a robust biometric authentication system. A database containing measurements specifically tailored to this

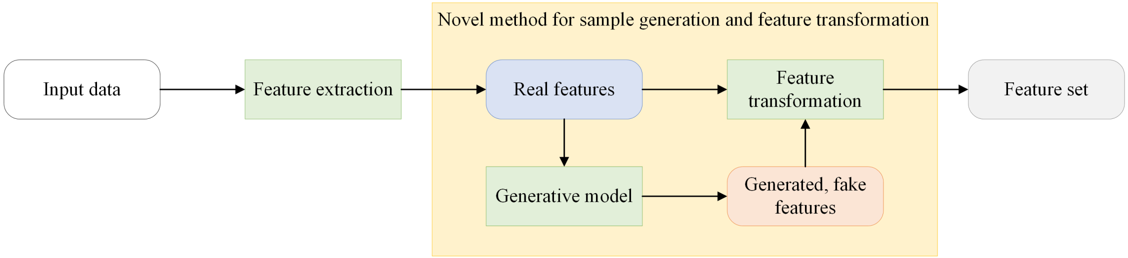

Figure 1: Schematic representation of the model. Adapted to time-series data, it remains the same; only the feature extraction module had to be changed.

purpose was under construction when the research was carried out. However, while the database is incomplete, preliminary tests were conducted using an available public dataset. In a related endeavor, Jiokeng et al. devised a distinct biometric authentication system, which relies on classifying the subject's heart signal, detected through the vibrations in their hand while holding a mobile phone. Their study encompassed 112 users, but it posed unique challenges due to the meaningful signal's relatively faint and intricate nature. Substantial preprocessing efforts were required to filter out extraneous information. Impressively, the authors' model achieved a commendable level of accuracy. Notably, their experiments were conducted within a closed-set scenario, wherein the model's task was to identify and grant access only to registered users it had been trained on (Jiokeng et al., 2022). In contrast, the novel model exhibits the capacity to maintain high-performance levels within a closed-set scenario and discern and reject users whose data it has not encountered during training, thereby addressing open-set recognition challenges with considerable accuracy. This attribute enhances the security and adaptability of the biometric authentication system the authors are working on, marking a significant advancement in this domain.

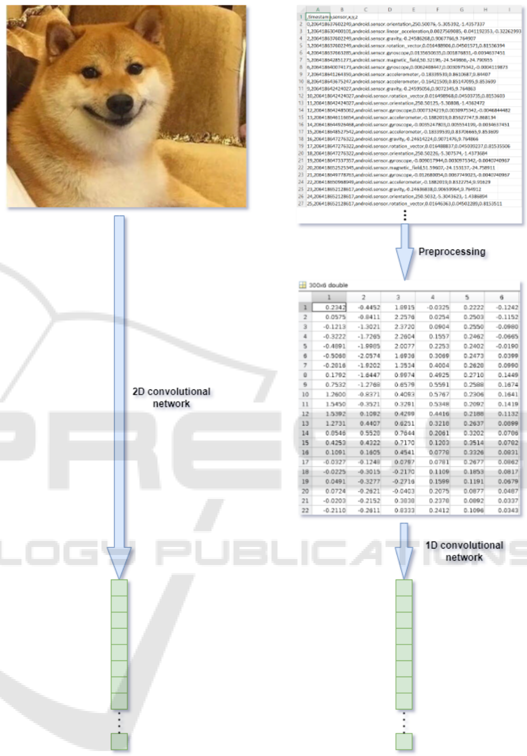

Figure 2: Comparison of the feature extraction part of the model in case of image and time-series data. Due to the different nature of the inputs, different processing methods were needed, but at the end of the part, both were converted into a feature vector of the same size. Thus, the rest of the model works the same way.

3 ADAPTING THE MODEL FOR TIME-SERIES

The model's first part aims to extract appropriate features capable of training the generative model. The second part of the model classifies these features. This means that neither the generative part nor the second part of the model depends on the input data type; the only concern is to get the features.

The preprocessing broadly followed the method described in (Jiokeng et al., 2022). The sensors' measurements were in a single file for each measurement session. First, the data from the accelerometer and gyroscope sensors were extracted. The measurements were, of course, made on different timestamps by the two sensors. Moreover, the sampling of the individual sensors could have been more perfectly uniform, too. A single time series with six channels was gained by resampling the data to a fixed sampling frequency, as both sensors measure along three axes. A bandpass filter was applied to isolate the relevant frequencies. The data were also sliced into shorter parts with some overlap, thus resulting in plenty of training samples.

Once the data is preprocessed, appropriate features need to be extracted. Similar to the case of

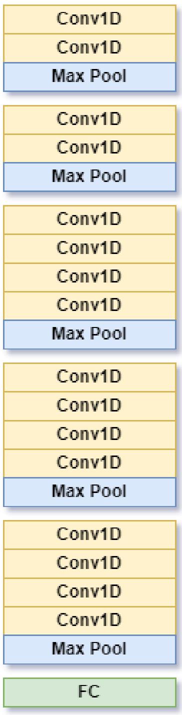

Figure 3: The structure of the convolutional network responsible for feature extraction.

images, the primary approach was using neural networks. Convolutional networks work very well on images that have two spatial dimensions. As time series has only one dimension (not counting multiple channels, which are also present in colored images), it is self-explanatory to use convolutional layers with 1D convolutional layers. The one shown in Figure 3 proved to be the best performing of the several structures that have been tried. It consists of five blocks with a doubling number of channels in each block. The blocks are built of some one-dimensional convolutional layers with ReLU activation function, followed by a max pooling layer. The structure closely resembles VGG networks (Simonyan and Zisserman, 2014). The output of the network is a feature vector with the same size as it was with image datasets. This is in the spirit of the modular nature of the model, as it is illustrated in Figure 2.

4 EXPERIMENTAL RESULTS

The model has been comprehensively evaluated by using the dataset, the details of which are expounded upon in Section 2.4. It is important to note that to the best of our knowledge, there is no existing Open-Set Recognition (OSR) solution specifically tailored for this dataset. Consequently, our evaluation primarily focuses on closed-set accuracy, drawing a comparison with the work presented by (Jiokeng et al., 2022) as a baseline reference. The first component of the model, namely the feature extraction module, is meticulously designed and illustrated in Figure 3. While adapting the model for the new dataset, the generative model and the classifier network were retained without any alterations, adhering to the architecture initially described in our prior work, (Halász et al., 2023). This decision ensures the preservation of the model's proven effectiveness and performance while making necessary adjustments for the new data domain. The relevant hardware specifications were as follows.

- Intel(R) Core(TM) i7-9800X CPU @ 3.80 GHz;
- NVIDIA(R) GeForce RTX(TM) 2080 Ti;
- 128 GB RAM.

4.1 Evaluation Metrics

According to a thorough survey on OSR methods by Geng et al., the most common metrics for evaluating open-set performance are AUC and F1 measure (Geng et al., 2018). In terms of overall accuracy or F1 measure, the metric is highly sensitive to its calibration, in addition to the real effectiveness of a model. Hence, open-set recognition performance was evaluated with the two metrics described below.

AUC: The receiver operating characteristic (ROC) curve is obtained by plotting the true positive rate (sensitivity) against the false positive rating (1–specificity) at every relevant threshold setting. The area under this curve gives a calibration-free measure of the open-set detection performance (Fawcett, 2006).

Closed Set Accuracy: It is essential that the model, while being able to reject unknown samples, retains its closed-set performance. Therefore, the closed-set accuracy on the test samples of known classes was also measured.

4.2 Results

The tests were run with different numbers of known classes, from 10 to 60, increasing by 10 a time. Each setup was run five times, with different random known classes each time. To the authors best knowledge, there were no results published of OSR solution on this database; only the closed-set accuracy by (Jiokeng et al., 2022) can be observed. With different classifiers, this accuracy ranged between 98.27% and over 99%. Our results are shown in Table 1. In

Table 1: Closed-set accuracy and Open-set detection AUC performance of the model on time-series data trained on a different number of classes. With all number of known classes, the measurements were run five times, and the results were averaged. Also, the standard deviation of the results is presented.

Known classes	**10**	**20**	**30**	**40**	**50**	**60**
Accuracy	0.954	0.940	0.889	0.933	0.915	0.902
STD	0.029	0.025	0.030	0.028	0.023	0.029
AUC	0.700	0.727	0.782	0.770	0.800	0.803
STD	0.046	0.085	0.032	0.062	0.031	0.040

terms of closed-set accuracy, the result fell behind the closed-set approaches, but it is still high. Besides that, the model could reject most of the unknown samples. Moreover, its performance even increases with more classes it was trained on. The deviation of the results is very low, indicating the robustness of the model to the choice of known classes.

A significant advantage of the model over other generative approaches is that it almost completely eliminates the cost of generating and using fake samples while benefiting from the performance gain in terms of accuracy. This is achieved by generating the samples in a hidden layer of a much simpler structure, which needs a much smaller generative model structure to create appropriate samples, and the fact that the generated samples do not have to be run through the first part of the model, which is the more heavyweight part with convolutional layers. Measurements show that this gain in time complexity still holds. The average runtime of a training epoch of the generative model on one batch is **5.2ms**. This is very close to the case of training on image datasets, which is unsurprising considering that the real inputs are features of the same size. The runtime of a generative model creating samples in the input space cannot be shown this time, as there were no published GAN structures specialized for time-series data. The runtime of the first part of the model on a batch is **2.1ms**, on the second part **0.23ms**. Since the generated samples have to be run only through the second part of the model, **91%** of runtime required to run the generated samples on the model can be saved.

5 CONCLUSIONS

In conclusion, our exploration into Open-Set Recognition (OSR) within the context of time-series data brings forth several critical insights and implications. OSR represents an invaluable extension of traditional classification methods, and its paramount relevance becomes abundantly clear when applied to real-life scenarios, particularly in the authentication domain, which is our research's primary objective.

The very essence of authentication demands a system that recognizes known users and effectively discerns unknown or unauthorized individuals. This is precisely where OSR steps in, acting as a vital shield against potential security breaches and unauthorized access. Our findings underscore the profound importance of OSR in enhancing the robustness and reliability of authentication systems, reinforcing the need for its widespread adoption in practical applications.

Furthermore, our research highlights a notable gap in the existing literature: the need for OSR methods tailored to time-series data. Our preliminary results demonstrate promising feasibility in adapting OSR techniques to time-series datasets, so we anticipate a burgeoning interest in this field. The fusion of OSR and time-series data analysis augments the security and reliability of authentication systems and opens doors to new possibilities in various other domains where recognizing unknown patterns within sequential data is paramount.

There is still room for improvement regarding the feature extraction. Different neural network models and utterly different feature mining approaches can be considered. (Tornai and Scheirer, 2019), (Jiokeng et al., 2022) show that using statistical features without training can also be efficient. Another possible approach is to take the Fourier transform of the signal and use the data in the frequency domain as an input for various neural network structures. Future work includes exploring these approaches as well as finding the best-performing combination of them.

ACKNOWLEDGEMENT

This research was supported by the National Research, Development, and Innovation Office through the grant TKP2021-NVA-26.

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