DNN Layers Features Reduction for Out-of-Distribution Detection

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Abstract: Decision-making in a number of industries, including environmental management, transportation, and public health, is greatly aided by artificial intelligence systems. Nonetheless, to perform well, these systems requires to follow some usage conditions. For instance, the data fed into a classification neural network must come from the same distribution as the training data to maintain the performance measured during test. In practice, however, this condition is not always met and not so easy to guarantee. In particular, for image recognition, it's possible to submit images that do not contain any learned classes and still receive a firm response from the network. This paper presents an approach to out-of-distribution observation detection applied to deep neural networks (DNNs) for image classification, called DNN Layers Features Reduction for Out-Of-Distribution Detection (DROOD). The principle of DROOD is to construct a decision statistic by successively synthesizing information from the features of all the intermediate layers of the classification network. The method is adaptable to any DNN architecture and experiments show results that outperform reference methods.

1 INTRODUCTION

From data collection to results deployment, machine learning models, particularly deep neural networks (DNN), are increasingly used in image classification tasks with remarkable performance. The traditional use of these models requires the training and test samples to be drawn independently and identically distributed. In real-life applications, this condition is not always satisfied. Thus, during inference, testing an observation whose distribution is singular from the distribution of the training data, also known as in-distribution (ID), will produce random, erroneous, or even overconfident predictions. Such observation is called out-of-distribution (OOD). In recent years, several approaches have been proposed to deal with this problem. Many of them focus on OOD detection for deep learning models (Lee et al.,), (Sastry and Oore,), (Kaur et al.,). Two groups of OOD detection approaches can be defined: (i) integrated approaches which directly integrate the detector when training the model by modifying the network architecture or by modifying the loss function (Malinin and Gales,), (Winkens et al.,), (Zhang et al.,); (ii) post-hoc approaches which integrate the detector during inference without modifying the weights of the trained network (Lee et al.,), (Zisselman and Tamar,), (Raghuram et al.,). The integrated approach is inherently computationally intensive, as it requires both calibrating the network weights and performing OOD detection simultaneously during training. The post-hoc approach can provide a significant advantage since it doesn't require retraining the network for detection. This allows detection to be implemented and adjusted without affecting the classifier's performance. Several works have applied OOD detection using information from the last layer of the neural network (Hendrycks and Gimpel,), (Liu et al.,), (Sun and Li,). This last layer is very important in image classification tasks because it is used to make the decision. It assigns a class to the image based on the output probabilities for a given input sample. These approaches have shown that applying OOD detection on the last layer of the neural network enables a good separation between in-distribution and out-of-distribution ata. Other OOD detection approaches take advantage of each layer of the neural network (Dziedzic et al.,), (Li et al.,). In DNN, each layer plays a distinct role in processing data, and the extent of their contribution can vary from one layer to another. Applying detection to the outputs of each layer allows all the sensitivities and crucial information of the data to be taken into account for robust decision-making.

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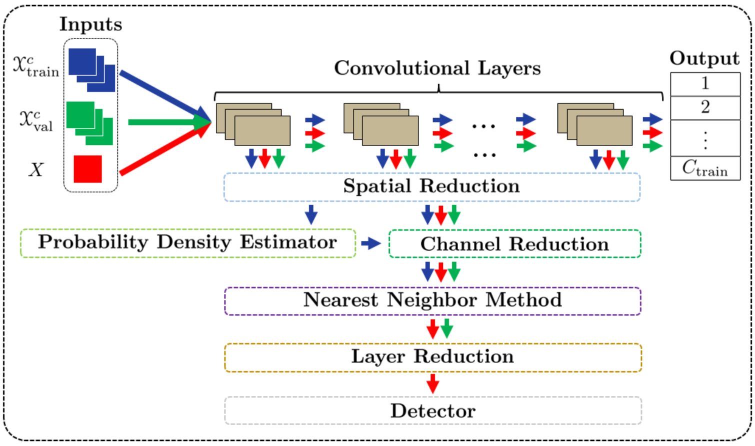


Figure 1: Overview of the DROOD approach for OOD detection in CNN classifiers. The blue arrows model the flow of the training data, the green arrows the flow of the validation data and the red arrows the flow on any data to be tested. The main steps of the DROOD approach are framed by dotted lines of different colors, also used in Figure 2, which details the DROOD flow using the equations.

The literature shows a growing trend in OOD detection methods that leverage decision statistics, achieving notable performance improvements, as seen with the MaSF (Max-Simes-Fisher) method (Haroush et al.,). The proposed DNN Layers Features Reduction for Out-Of-Distribution Detection (DROOD) method is part of the post-hoc approach to OOD detection. It can be applied to any pre-trained neural network, as it requires only the extraction of the features from all layers of the DNN to detect OOD data. Similar to MaSF, DROOD conducts OOD detection by applying decision statistics across each layer of the DNN. DROOD uses these statistics to determine the distance between elements within a space that represents the class-conditional log-densities. In Figure 1, the main steps of the DROOD approach are depicted, using a convolutional neural network (CNN) architecture (an equivalent diagram can be drawn up for transformers).

Overall, the contributions in this paper can be summarised as follows:

- We propose, for CNN classification models, to reduce each channel of each layer by estimating the probability density of the pattern of the channel input that fits best the trained convolutional filter. Equivalently, for vision transformer models, we propose to reduce the image tokens of each layer (or encoding block) by estimating the probability density of the image token pattern with the strongest response. To reduce channels, assuming their independence, we estimate their joint log-distribution per layer.
- To characterize an image, we evaluate its class-conditional log-probability density at each layer of the network. The detection statistic is deduced, in the obtained representation space, from the average nearest neighbors' distances between the test image and the training ones.
- Overall, the DROOD approach demonstrates promising performance on out-of-distribution datasets, both close to and far from the training data distribution, outperforming the methods used for comparison in this paper.

This paper is organized as follows: Section 2 reviews recent advancements in out-of-distribution detection. Section 3 describes the proposed DROOD approach. Section 4 gives some implementation details and presents the experimental results on several datasets and for several DNN classification models. Finally, section 5 presents the conclusion and perspectives for future work.

2 RELATED WORK

Detecting out-of-distribution data is essential for ensuring the safety and reliability of machine learning systems. Various methods address this challenge based on how anomalies are defined. Effective OOD detection requires detectors that can accurately reject inputs that are singular to the training distribution while accepting those within it.

Recently, advanced statistical methods for OOD detection in deep neural networks have been developed. The MLOD (Multitesting-based Layer-wise Out-of-Distribution Detection) approach (Li et al.,) is one the them. It extracts feature maps across different layers of a model, applies multiple statistical hypothesis testing techniques to control the True Positive Rate (TPR) and computes p-values based on the empirical distribution of the score function across different layers for decision-making. Another approach, called p-DkNN (Dziedzic et al.,), performs the statistical tests on latent representations of a pre-trained CNN model. p-DkNN is built on theoretical analysis of Neyman-Pearson classification and combined it with recent works in selective classification (reject option). The main idea in this approach is to abstain from predicting the out-of-distribution samples and to maintain high precision on the in-distribution datasets.

Among the various existing methods, we focused on four for comparison in this paper, namely ODIN (Liang et al.,), Mahalanobis (Lee et al.,), OpenPCS-Class (Carvalho et al.,), and MaSF (Haroush et al.,). ODIN primarily targets the behavior of the final layer by modifying it and pre-processing the input samples. The first modification involves adjusting or controlling the distribution of the network's output probabilities, while the second focuses on assessing the impact of the gradients calculated during training on perturbations applied to the input samples. The Mahalanobis detector is an approach that extracts feature maps of the training data classes across the layers of a pre-trained CNN, assuming these class-conditional feature maps follow a Gaussian distribution to estimate their probability density. The detection score is then computed using the Mahalanobis distance of each test sample with respect to the closest class-conditional distribution. OpenPCS-Class applies principal component analysis (PCA) to project the features of the model's intermediate layers, assuming that the reduced features follow a Gaussian distribution, and then computes the log-likelihood for decision-making purposes. Finally, MaSF is based on test statistics for OOD detection in CNN that used all the intermediate layers features. The process consists in spatial and channel reduction techniques to produce statistics per layer, and these statistics are combined to define a detection score. The statistical tests are based on the Simes and Fisher tests.

The proposed DROOD approach is based on a statistical framework similar to the MaSF and is described in the next section. Note that we present the DROOD method considering CNN-based classification models, but this does not affect its generality and it can easily be transposed to transformer models, which are also considered in the experiments.

3 PROPOSED APPROACH

This paper seeks to address the out-of-distribution detection problem through the use of statistical hypothesis testing. The hypothesis to be tested is as follows:

$$\begin{cases} \mathcal{H}_0 : \mathrm{X} \sim \mathcal{P}_{\text{train}} \\ \mathcal{H}_1 : \mathrm{X} \nsim \mathcal{P}_{\text{train}} \end{cases}$$

where $\mathcal{P}_{\text{train}}$ represents the training distribution.

As illustrated in Figure 1, for CNN based classification models, the DROOD approach is an OOD detection method that summarize the information brought by all channels of a classification network in a detection statistic. The statistic is build step by step synthesising each channel then aggregating all channels synthesis by layer and finally bringing all the layers together in a single statistic to decide whether an input image is in or out of $\mathcal{P}_{\text{train}}$. The proposed process to obtain the final decision statistic, considered at macro scale, is similar to MaSF but the nature of the determined statistics is different and the assumptions that underline the reduction process are also different.

Following Figure 1, the next sections provide analytical details of the DROOD steps. We can also refer to Figure 2, which gives a detailed description of the steps sequence, including the analytical expressions.

3.1 Preliminary Notations

Let $\mathcal{X}_{\text{train}} = \{(X_{\text{train}}, y)\}$ be the training set composed of N_{train} images drawn from C_{train} classes and $\mathcal{X}^c_{\text{train}} = \{(X_{\text{train}}, y) | y = c\}$ its restriction to class c. In the paper $X^{c,i}_{\text{train}}$ denotes the i^{th} image of $\mathcal{X}^c_{\text{train}}$ with i from 1 to n^c_{train}, the cardinal of $\mathcal{X}^c_{\text{train}}$.

By extension, the validation samples gathered in $\mathcal{X}_{\text{val}}$ are drawn from the same distribution than the training samples in $\mathcal{X}_{\text{train}}$ and are referred as in-distribution. The class labels in the two sets are the same, so $C_{\text{val}} = C_{\text{train}}$. These sets are used to learn the parameters of the DROOD method. Next, new images are tested to decide whether they are in-distribution or not. To keep similar notations the i^{th} image of the test set $\mathcal{X}_{\text{test}}$ is noted $X^{c,i}_{\text{test}}$, where c corresponds initially to the "unknown" label. The DNN classification model will predict the class $c \in \{1, \ldots, C_{\text{train}}\}$ (each value corresponds to a given category) if the image is detected as in-distribution otherwise the image is out-of-distribution and the class c remain "unkown". Also note that the so-called C_{test} classes in the test set (which are in fact unknown), are of course not all the same as the C_{train} classes in $\mathcal{X}_{\text{train}}$ to unable out-of-distribution performance analysis of the DROOD approach.

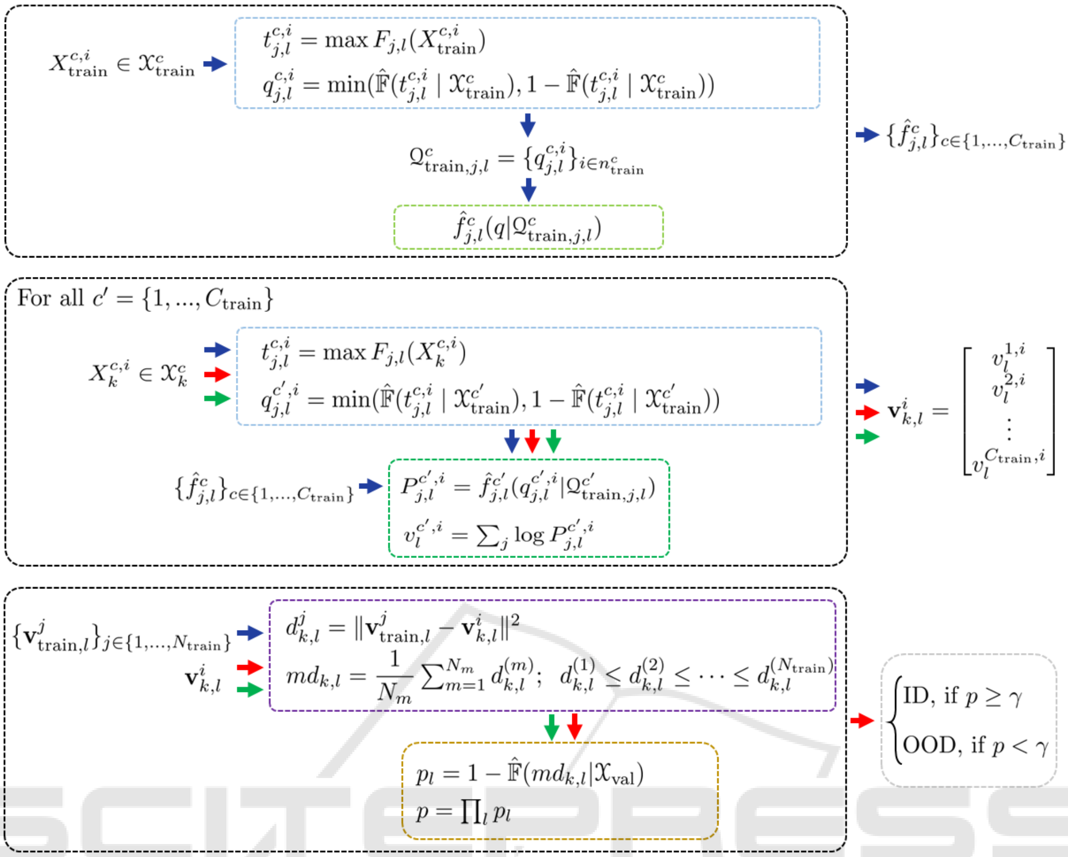


Figure 2: Details of the different steps in the DROOD approach. Frame colors correspond to those in Figure 1. Colored arrows represent the data flow as shown in the Figure 1.

The main goal of OOD detection is to decide whether an image X input in a given DNN classification model is in-distribution or not. To this end, we propose a method that use all the intermediate layers features of the DNN. Typical DNN are composed of L layers, and each layer $l \in \{1, \ldots, L\}$ consists of n_l channels. Let $F_{j,l} : X \to \mathbb{R}^{w_l \times h_l}$ be the j-th channel in the layer l. h_l and w_l refer to the size of the channels in layer l.

3.2 Spatial Reduction

The first step of DROOD is to produce a statistic for each channel at each layer (light blue frame in Figure 1 and in the two first black frames of Figure 2). A spatial reduction is first applied to summarize the information contained in each channel. Following (Haroush et al.,) the maximum value is considered for this purpose:

$$t^{c,i}_{j,l} = \max F_{j,l}(X^{c,i}_k).$$

$t^{c,i}_{j,l}$ corresponds to the largest response amplitude for channel j at layer l and for the image i of the class c in the set $k = \{\text{train}, \text{val}, \text{test}\}$. It relates to the idea of adapted filters and can be interpreted as the value at the position in the input features that fits best the trained filter.

Next, the probability $q^{c',i}_{j,l}$, to obtained a more extreme value of the statistic $t^{c'}_{j,l}$ than the observed one $t^{c,i}_{j,l}$, is estimated for all classes c'. Each probability captures how singular the obtained value is compared to the distribution of $t^{c'}_{j,l}$ for the images of class c'. It can be formalized as:

$$q^{c',i}_{j,l} = \min(\hat{\mathbb{F}}(t^{c,i}_{j,l} \mid \mathcal{X}^{c'}_{\text{train}}), 1 - \hat{\mathbb{F}}(t^{c,i}_{j,l} \mid \mathcal{X}^{c'}_{\text{train}})),$$

where $\hat{\mathbb{F}}()$ is the empirical cumulative distribution function of $t^{c'}_{j,l}$ determined using training samples $\mathcal{X}^{c'}_{\text{train}}$. Note that $q^{c',i}_{j,l}$ can be interpreted as a p-value in the context of a two-sided test.

3.3 Probability Density Estimator

To perform channel reduction, the density $f^c_{j,l}(q)$ for each class c is needed (light green frame in Figure 1 and first black frame in Figure 2). Its Parzen estimator $\hat{f}^{c}_{j,l}(q|\mathcal{Q}^{c}_{\text{train},j,l})$ based on the set $\mathcal{Q}^{c}_{\text{train},j,l} = \{q^{c,i}_{j,l}\}_{i\in n^{c}_{\text{train}}}$ is then determined using a Gaussian kernel and cross validation parameter estimation. These estimators $\{\hat{f}^{c}_{j,l}\}_{c\in\{1,\dots,C_{\text{train}}\}}$ (outputs of the first black frame in Figure 2) are used during channel reduction to estimate conditional probability densities, as described in next section.

3.4 Channel Reduction

As shown in the green frame in Figure 1 and in the second black frame in Figure 2, the probability density for each class c', $P^{c',i}_{j,l}$, of the input image $X^{c,i}_{k}$, $k \in \{\text{train}, \text{val}, \text{test}\}$ is deduced for each channel using the estimators $\{\hat{f}^{c'}_{j,l}\}_{c'\in\{1,\dots,C_{\text{train}}\}}$ and the $q^{c',i}_{j,l}$ as $P^{c',i}_{j,l} = \hat{f}^{c'}_{j,l}(q^{c',i}_{j,l}|\mathcal{Q}^{c'}_{\text{train},j,l})$.

Next, assuming channel independence, channel reduction conditionally to a class c' is deduced by computing the log-joint probability density of channels:

$$v^{c',i}_{l} = \sum_{j} \log P^{c',i}_{j,l}.$$

These log-joint conditional probabilities form a vector $\mathbf{v}^{i}_{k,l}$ in a space $\mathcal{S}_l$ of dimension C_{train}, the number of classes in the training set:

$$\mathbf{v}^{i}_{k,l} = \begin{bmatrix} v^{1,i}_{l} & v^{2,i}_{l} & \cdots & v^{C_{\text{train}},i}_{l} \end{bmatrix}^{T},$$

where T stands for the transpose operator. Its coordinates characterise how likely are jointly the most prominent channels response conditionally to each trained class.

3.5 Nearest Neighbor Method

Following channel reduction, outlier observations should be far from the origin in $\mathcal{S}_l$. To evaluate how far an observation lays from training ones, a nearest neighbor method (purple frame in Figure 1 and in the last black frame of Figure 2) is considered.

The mean euclidean distance, noted $md_{k,l}$, between $\mathbf{v}^{i}_{k,l}$ and the N_m nearest training samples $\{\mathbf{v}^{j}_{\text{train},l}\}_{j\in N_{\text{train}}}$, in $\mathcal{S}_l$, is determined. For $j \in N_{\text{train}}$:

$$d^{j}_{k,l} = \|\mathbf{v}^{j}_{\text{train},l} - \mathbf{v}^{i}_{k,l}\|^2,$$

and

$$md_{k,l} = \frac{1}{N_m}\sum_{m=1}^{N_m} d^{(m)}_{k,l},$$

where $d^{(1)}_{k,l} \leq d^{(2)}_{k,l} \leq \cdots \leq d^{(N_{\text{train}})}_{k,l}$ are the sorted distances to training neighbors. $md_{k,l}$ indicates how well the input sample resembles N_m training ones.

3.6 Layer Reduction

To obtain the detection statistics, we finally perform a layer reduction (light orange frame in Figure 1 and in the last black frame of Figure 2). To do so, the probability p_l that the mean distance between one sample at layer l and the training samples could be larger than the obtained value $md_{k,l}$ is estimated for each layer (p-value of $md_{k,l}$) using empirical cumulative distribution estimator:

$$p_l = 1 - \hat{\mathbb{F}}(md_{k,l}|\mathcal{X}_{\text{val}}).$$

To determine the empirical cumulative distribution, we use the validation set $\mathcal{X}_{\text{val}}$ to ensure the independence of the obtained p-values with the training data.

The joint probability of mean distances for all layers p is computed assuming layer independence as the product of p_l for all l:

$$p = \prod_{l=1}^{L} p_l.$$

We can therefore note that the larger this final probability is the more likely the sample belongs to one of the trained classes, leading to the detector defined below.

3.7 Detector

To implement detection (light grey frame in Figure 1 and output of the third black frame in Figure 2), p is compared to a threshold $\gamma \in [0,1]$ to decide whether the image has to be classified or discarded. The detector is defined as follows:

$$\text{The tested image is: } \begin{cases} \text{ID, if } & p \geq \gamma \\ \text{OOD, if } & p < \gamma \end{cases}$$

4 EXPERIMENTS

This section describes the data, the DNN classification models, the experiments and discusses the results. It should be noted that we carried out all the simulations of the OOD methods used to compare performance with DROOD.

4.1 Datasets

As generally considered for OOD experiments, five datasets are used in this paper. CIFAR10 (Krizhevsky,) is used as the in-distribution dataset. It consists of 10 classes and contains 50,000 train images, split in train (40,000) and validation (10,000) sets, and 10,000 test images. This dataset is made up of natural images with one dominant object per image such as vehicle, animal, or boat.

The remaining four datasets are used as out-of-distribution data. The Large-scale Scene UNderstanding (LSUN) test dataset (Yu et al.,) contains 10,000 images with 10 classes representing different environments, both natural and man-made. The Street View House Numbers (SVHN) test dataset (Netzer et al.,) contains 26,032 digits images (from 0 to 9), extracted from house numbers images captured by Google Street View. The TinyImageNet (Le and Yang,) dataset, a subset of the larger ImageNet dataset, containing 200 classes. The test set contains 10,000 images. Finally, the CIFAR100 test dataset (Krizhevsky,), which contains 10,000 images of 100 classes, is made up of natural images close to CIFAR10.

4.2 Model Architectures

The proposed DROOD method falls under post-hoc out-of-distribution detection methods. In this study, as classification models, we used two CNN: ResNet34 (He et al.,) and DenseNet-BC (Huang et al.,) and one transformer: the Vision Transformer (Dosovitskiy et al.,), referenced as ViT[1]). All these models are trained on the CIFAR10 training set, the considered in-distribution dataset. These models achieved good accuracy, reaching 0.9510 with ResNet34, 0.9400 with DenseNet-BC and 0.9852 with ViT, on the CIFAR10 test set.

In the experiments, for MaSF and DROOD methods, the spatial reduction (or max operation) is applied to the channels at each layer of the CNN models. For the ViT model, this operation is performed on all tokens, excluding the ”class token”, across the transformer encoding layers. The ”class token” is excluded because it gathers information from the other tokens within these encoding layers. Consequently, we can expect the application of spatial reduction to the remaining ”image tokens” to be equivalent to the direct consideration of the ”class token”. However, in this paper, we want to keep the flow exactly the same as for the CNN models, for fair comparison. Note that the MaSF method, initially developed for CNN has been adapted to ViT.

The OpenPCS-Class method is originally applied to the Vision Transformer architecture. For our experimental evaluation, we have adapted this approach to CNN architectures.

[1]ViT weights have been uploaded from Hugging Face web site: `https://huggingface.co/nateraw/vit-base-patch16-224-cifar10`

The Mahalanobis approach was originally proposed for CNN models. The code provided by the authors cannot be used for the Vision Transformer architecture, as it requires too much memory space. Consequently, it is only used as comparison method with the CNN models.

4.3 Evaluation Metrics

As generally considered, the following metrics are used to evaluate the detection performance: the false positive rate of the OOD data when the true positive rate of the ID data is 95%, denoted as FPR95; the true positive rate of the ID data when the FPR of the OOD data is 5%, referred to as TPR95; and the area under the receiver operating characteristic curve (AUC), which quantifies how well a detector can separate ID data from OOD data. In the tables, ↓ (or ↑) indicates that lower (or higher) values are preferable, while bold text highlights the best results in each row.

4.4 Experimental Results

All experimental results on the considered DNN classification models (CNNs and transformers) are summarized in Table 1 for ResNet34, Table 2 for DenseNet-BC and Table 3 for ViT.

The hyperparameters of the method are the kernels, the bandwidth of the kernels for estimating probability densities, the number of neighbours for calculating the mean distance and the decision threshold. For the probability density estimators, the chosen kernels are Gaussians and their bandwidth has been determined by cross-validation on the training data. The choice of the number of neighbors Nm was determined empirically. After experiments, we set the Nm to 5 which gives the best results. The detection threshold γ has been chosen according to targeted false alarm rate measured on validation set.

The detection performance of the DROOD approach is very good on both far-out-of-distribution (LSUN, SVHN and TinyImageNet) and near-out-of-distribution (CIFAR100) datasets, outperforming most of the time the reference methods. Based on these results, one can also note that OOD detection performs better when using the ViT model.

In many OOD detection methods, CIFAR10 and CIFAR100 are among the most difficult datasets to evaluate, especially when one of these datasets is used as an in-distribution, due to the close similarities of some classes. Despite this, the DROOD approach achieves the best performance in OOD detection for all DNN considered, with CIFAR10 used as the ID set and CIFAR100 as the OOD set.

Table 1: Performance results using ResNet34.

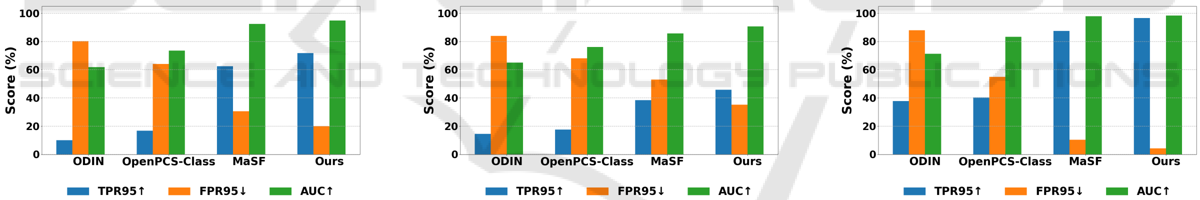
TPR95↑ / FPR95↓ / AUC↑ (%)					
OOD datasets	ODIN	Mahalanobis	OpenPCS-Class	MaSF	Ours
CIFAR100	33.50 / 52.90 / 85.90	42.68 / 37.54 / 89.08	65.98 / 28.44 / 93.30	83.61 / 20.25 / 96.40	**84.83 / 14.52 / 97.14**
LSUN	92.90 / 8.50 / 98.60	92.17 / 7.18 / 98.34	98.76 / 0.09 / 99.40	99.73 / 0.19 / 99.81	**99.91 / 0.01 / 99.91**
SVHN	41.50 / 47.90 / 88.10	98.24 / 3.03 / 99.04	82.95 / 19.23 / 95.93	99.73 / 0.06 / 99.83	**99.91 / 0.00 / 99.95**
TinyImageNet	89.20 / 17.50 / 97.40	89.82 / 7.35 / 97.91	98.76 / **0.25** / 99.41	**99.37** / 0.35 / **99.77**	98.54 / 1.12 / 99.63
Average	64.27 / 31.70 / 92.50	80.72 / 13.77 / 96.09	86.61 / 12.00 / 97.01	95.61 / 5.21 / 98.95	**95.79 / 3.91 / 99.15**

Table 2: Performance results using DenseNet-BC.

TPR95↑ / FPR95↓ / AUC↑ (%)					
OOD datasets	ODIN	Mahalanobis	OpenPCS-Class	MaSF	Ours
CIFAR100	33.25 / 55.43 / 84.99	33.96 / 56.40 / 83.60	67.17 / 40.48 / 91.85	55.99 / 42.80 / 89.89	**68.00 / 25.58 / 93.90**
LSUN	91.00 / 10.15 / 98.07	90.23 / 7.66 / 98.06	85.85 / 27.58 / 95.65	99.61 / 0.14 / 99.86	**99.98 / 0.00 / 99.98**
SVHN	61.48 / 42.95 / 91.12	96.95 / 3.30 / 98.89	91.04 / 16.23 / 97.24	99.57 / 0.01 / 99.89	**99.98 / 0.00 / 99.98**
TinyImageNet	86.70 / 16.61 / 97.02	65.26 / 17.47 / 94.63	82.86 / 29.66 / 95.00	98.23 / 2.08 / 99.51	**98.27 / 1.96 / 99.53**
Average	68.10 / 31.28 / 92.80	71.60 / 21.20 / 93.79	81.73 / 28.48 / 94.93	88.35 / 11.25 / 97.28	**91.55 / 6.88 / 98.34**

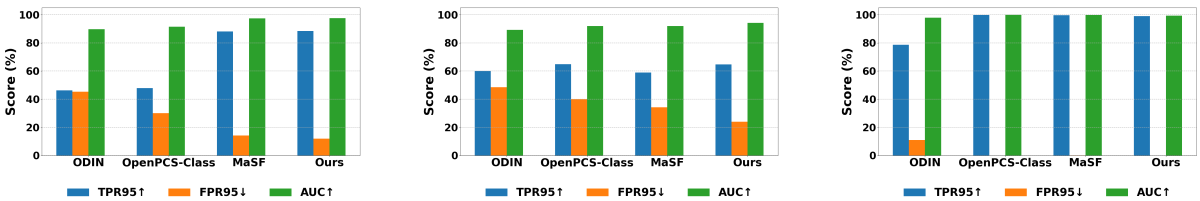
Table 3: Performance results using ViT.

TPR95↑ / FPR95↓ / AUC↑ (%)				
OOD datasets	ODIN	OpenPCS-Class	MaSF	Ours
CIFAR100	71.40 / 16.90 / 95.50	94.51 / 5.34 / 98.70	98.39 / 2.01 / 99.53	**99.64 / 0.06 / 99.75**
LSUN	93.10 / 6.00 / 98.60	99.75 / 0.15 / 99.80	**99.92 / 0.00 / 99.95**	99.71 / **0.00** / 99.83
SVHN	93.90 / 5.90 / 98.60	98.83 / 0.60 / 99.60	**99.95/ 0.00 / 99.96**	99.71 / **0.00** / 99.83
TinyImageNet	80.10 / 11.20 / 97.60	98.38 / 1.34 / 99.65	**99.92 / 0.00 / 99.95**	99.71 / **0.00** / 99.78
Average	84.62 / 10.00 / 97.57	97.86 / 1.85 / 99.43	99.54 / 0.50 / **99.84**	**99.69** / **0.01** / 99.79



(a) ResNet34 (b) DenseNet-BC (c) ViT

Figure 3: Performance results of the CIFAR100 ”bus” class.



(a) ResNet34 (b) DenseNet-BC (c) ViT

Figure 4: Performance results of the CIFAR100 ”cockroach” class.

Finally, we propose to focus on the ”bus” (Figure 3) and ”cockroach” (Figure 4) classes of CIFAR100. The first one is very similar to CIFAR10 ”automobile” class, while ”cockroach” is not close to any CIFAR10 classes. DROOD is particularly effective for the ”bus” class detection, whatever the DNN model, and outperforms reference methods. The ”cockroach” class is perfectly detected by almost all methods, as expected.

5 CONCLUSION

The DROOD method is based on a statistical framework for OOD detection. It is a successive synthesis of statistics using all the features produced by a DNN. The experimental study shows very good detection performances compared to state-of-the-art methods with two image classification networks based on CNNs and one based on transformers, which also demonstrates its ability to perform whatever the model.

We observed variations in performance depending on the DNN chosen and the OOD method, which seems in a certain way normal. However, some existing OOD detection methods appear to be linked to specific neural network architectures, since performances vary considerably when applied with others. Experiments suggest that our DROOD detection approach is more robust than others.

As further work, It would be of course interesting to test other distances than the Euclidean distance. As mentioned above, in the transformer architecture, the ”class token” gathers information from the ”image tokens” across the transformer encoding layers for the final classification task. One can therefore expect that the max operation in MaSF and DROOD methods can be effectively replaced by the use of this ”class token”. Finally, it would also be interesting to experiment with this type of approach in other application fields, such as audio analysis or image segmentation.

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