ON OUT-OF-DISTRIBUTION DETECTION FOR AUDIO WITH DEEP NEAREST NEIGHBORS

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ABSTRACT
Out-of-distribution (OOD) detection is concerned with identifying data points that do not belong to the same distribution as the model’s training data. For the safe deployment of predictive models in a real-world environment, it is critical to avoid making confident predictions on OOD inputs as it can lead to potentially dangerous consequences. However, OOD detection largely remains an under-explored area in the audio (and speech) domain. This is despite the fact that audio is a central modality for many tasks, such as speaker diarization, automatic speech recognition, and sound event detection. To address this, we propose to leverage feature-space of the model with deep k-nearest neighbors to detect OOD samples. We show that this simple and flexible method effectively detects OOD inputs across a broad category of audio (and speech) datasets. Specifically, it improves the false positive rate (FPR@TPR95) by 17% and the AUROC score by 7% than other prior techniques.

Index Terms—out-of-distribution, audio, speech, uncertainty estimation, deep learning, nearest neighbors

1. INTRODUCTION
Out-of-distribution (OOD) detection is the task of identifying inputs that are not drawn from the same distribution as the training data or are not truly representative of them. Neural networks are known to produce overconfident scores even for samples that do not belong to the training distribution [1]. This is a challenging problem for deploying machine learning in safety-critical applications, where making confident predictions on OOD inputs can lead to potentially dangerous consequences. Besides the capability to generalize well for samples from the familiar distribution, a robust machine learning model should be aware of uncertainty stemming from unknown examples. It is an important competency for real-world applications, where the distribution of data can change over time or vary across different user groups.

A broad range of approaches has been proposed to tackle the OOD detection issue and develop reliable methods that successfully detect in-distribution (ID) and OOD inputs. A set of common techniques is to deduce uncertainty measurements around predictions of the neural network based on model outputs [1, 2, 3, 4], feature space [5, 6], and gradient norms [7]. Similarly, distance-based methods [5] has also gained significant attention recently for identifying OOD inputs with promising capabilities. Distance-based methods leverage representations extracted from a pre-trained model and act on the assumption that out-of-distribution test samples are isolated from the ID data. Nevertheless, OOD detection is severely understudied in the audio domain, although audio recognition models are being widely deployed in real-world settings. As well as, audio is an important modality for many tasks, such as speaker diarization, automatic speech recognition, and sound event detection. The prior works mainly focus on vision tasks raising an important question about the efficacy and applicability of existing methods to audio and speech.

Our work follows the same intuition as of the distance-based method [5], and we aim to explore the richness of model representation space to derive a meaningful signal that can help solve the task of OOD detection. Formally, we propose a simple yet effective system for out-of-distribution detection for audio inputs with deep k-nearest neighbors. In particular, we leverage nearest neighbor distance centered on a non-parametric approach without making strong distributional assumptions regarding underlying embedding space. To identify OOD samples, we extract embedding for a test input, compute its distance to k-nearest neighbors in the training set and use a threshold to flag the input, i.e., a sample far away in representation space is more likely to be OOD.

We demonstrate the effectiveness of kNN-based approach on a broad range of audio recognition tasks and different neural network architectures and provide an extensive comparison with both recent and classical approaches as baselines. Importantly, we note that to the best of our knowledge, we make a first attempt at studying out-of-distribution detection and setting up a benchmark for audio across a variety of datasets ranging from keyword spotting and emotion recognition to environmental sounds and more. Empirically, we show that for a MobileNet [8] model (trained on in-distribution data of human vocal sounds), the non-parametric nearest neighbor method improves FPR@TPR95 by 17% and AUROC scores by 7% than approaches that leverage output or gradient space of the model.
2. APPROACH

2.1. Preliminaries

Learning Regime We focus on supervised learning regime, specifically, multi-class classification tasks, where, $\mathcal{X}$ and $\mathcal{Y} = \{1, \ldots, C\}$ denote input and label spaces, respectively. A classifier $f_\theta(\cdot)$ utilizes training set $D_T = \{(x_i, y_i)\}_{i=1}^M$, which is drawn i.i.d from the joint distribution $P$ defined over $\mathcal{X} \times \mathcal{Y}$. The deep model $f_\theta(x) : \mathcal{X} \rightarrow \mathbb{R}^{|\mathcal{Y}|}$ minimizes negative log-likelihood (or similar) objective with back-propagation to produce logits that are then translated to predicted labels being assigned to the input samples.

Problem Formulation Out-of-distribution (OOD) detection is generally formulated as a binary classification problem with the objective of identifying samples from unknown data distribution at inference time. For instance, samples from an unrelated distribution whose label set does not overlap with the task labels (of a trained deep model) should be deferred instead of producing incorrect prediction [1]. Formally, given a pre-trained classifier $f_\theta(\cdot)$ that is learned to solve a task $t$ using data $D_T$ from in-domain data distribution, the aim of OOD is to have a decision function:

$$
\mathcal{U}_s(x) = \begin{cases} 
\text{ID} & H(x) \geq \gamma \\
\text{OOD} & H(x) < \gamma 
\end{cases}
$$

that flags whether a sample $x \in \mathcal{X}$ does not belong to $D_T$. $\gamma$ represents a threshold that is chosen such that a large fraction (e.g., 95%) of ID samples are correctly identified. The domain of OOD detection is concerned with the development of a scoring function $H$ that captures the uncertainty of data being outside of the training data distribution. Previous approaches largely rely on output [1, 2, 4, 3], feature [6] and gradient [7] spaces of the model, with [5] proposing to leverage nearest neighbors in the feature space to determine uncertainty. Along similar lines, we propose to leverage the non-parametric nearest neighbors approach to detect OOD samples in audio, as we describe in the subsequent section.

2.2. OOD Detection with Deep $k$-Nearest Neighbor

We aim to exploit the representation space of a pre-trained neural network for detecting out-of-distribution samples with $k$-nearest neighbor approach. We provide a high-level illustration of our approach in Figure 1. The key driving factor behind distance-based non-parametric methods is that distances in the embedding space provide a meaningful way to compare data from distributions. Hence, they can be utilized to identify OOD samples as ID samples are closer to each other in the feature space as compared to OOD data points. Inspired by the simplicity and success of the deep nearest neighbor method for OOD detection in vision domain [5], we propose to leverage and study whether we can use it to reliably detect samples different than the ID training set in audio (and speech) domain.

Given a pre-trained classification model $f_\theta(x) : \mathcal{X} \rightarrow \mathbb{R}^{|\mathcal{Y}|}$, we extract normalized representations (features or embeddings) $z = \frac{\psi(x)}{||\psi(x)||_2}$ from penultimate layer of the model, where $\psi$ can be seen as a feature extractor. With $Z_m = (z_1, \ldots, z_n)$ be the embedding vectors from an ID training set and $z^*$ be an embedding for a test sample. We compute Euclidean distance of test input $||z_i - z^*||_2$ with each example in $Z_m$ and reorder element in $Z_m$ based on increasing distance. Finally, we use a decision function from [5] to check if sample is OOD as: $H(z^*, k) = 1\{ -d_k(z^*) \geq \gamma \}$, where, $d_k = ||z_k - z^*||_2$ denotes distance to $k$-th nearest neighbor and $1\{ \cdot \}$ is an indicator function. In practice, the threshold $\gamma$ can be chosen to correctly classify a large percentage (e.g., 95%) of ID samples. It is important to note that picking the optimal value of $\gamma$ does not depend on OOD data.

There are several advantages of using deep nearest neighbor over other methods for out-of-distribution detection. First, it is scalable and can be used with large data sets using an efficient similarity search library, such as Faiss [9]. Second, it is easy to use as it does not require access to out-of-distribution data for defining threshold. Third, it is model-agnostic in the sense that we can use it with a variety of neural network architectures and different training regimes (i.e., both supervised and unsupervised). Finally, it also offers an interpretability into the process of identifying OOD samples by letting human
Table 1: OOD detection results in comparison with other strong approaches on different audio datasets. All results are based on a MobileNet [8] (YAMNet) model trained only on ID data (i.e., MSWC (Micro-EN) and Vocalsound). ↑ and ↓ indicate larger and smaller values are better, respectively. All values are percentages.

(a) Vocalsound

| OOD Dataset        | MSP FPR95↓ | AUROC↑ | ODIN FPR95↓ | AUROC↑ | GradNorm FPR95↓ | AUROC↑ | kNN FPR95↓ | AUROC↑ |
|--------------------|------------|--------|-------------|--------|----------------|--------|------------|--------|
| MSWC (Micro-EN)    | 82.44      | 76.41  | 87.79       | 75.80  | 83.73          | 76.81  | 53.70      | 89.61  |
| Voxforge           | 39.84      | 94.22  | 31.45       | 95.33  | 31.48          | 95.10  | 39.43      | 94.28  |
| CREMA-D            | 51.74      | 91.64  | 46.92       | 93.03  | 46.34          | 92.48  | 28.28      | 95.53  |
| ESC-50             | 58.25      | 85.51  | 53.75       | 86.75  | 54.75          | 86.17  | 49.0       | 91.33  |
| MSWC (Micro-ES)    | 81.58      | 76.86  | 88.23       | 75.21  | 83.64          | 76.84  | 46.20      | 90.91  |
| SpeechCommands     | 79.59      | 78.55  | 83.72       | 76.67  | 80.51          | 78.55  | 48.96      | 91.49  |
| FluentSpeech       | 57.58      | 90.49  | 55.87       | 91.52  | 52.41          | 91.38  | 42.05      | 93.65  |
| Average            | 64.43      | 84.85  | 63.96       | 84.90  | 61.84          | 85.33  | 43.94      | 92.40  |

(b) MSWC (Micro-EN)

| OOD Dataset        | MSP FPR95↓ | AUROC↑ | ODIN FPR95↓ | AUROC↑ | GradNorm FPR95↓ | AUROC↑ | kNN FPR95↓ | AUROC↑ |
|--------------------|------------|--------|-------------|--------|----------------|--------|------------|--------|
| Vocalsound         | 36.23      | 95.53  | 2.87        | 99.26  | 12.20          | 97.67  | 4.65       | 98.80  |
| Voxforge           | 31.24      | 95.92  | 2.40        | 99.40  | 11.26          | 97.81  | 2.73       | 98.94  |
| CREMA-D            | 31.17      | 95.79  | 2.51        | 99.39  | 11.57          | 97.71  | 2.63       | 99.25  |
| ESC-50             | 34.0       | 95.91  | 5.50        | 98.89  | 9.75           | 98.0   | 9.75       | 98.59  |
| MSWC (Micro-ES)    | 67.33      | 87.81  | 56.21       | 89.42  | 56.39          | 88.74  | 39.37      | 93.11  |
| SpeechCommands     | 73.01      | 76.12  | 63.44       | 77.58  | 64.83          | 76.81  | 52.29      | 84.14  |
| FluentSpeech       | 42.82      | 94.40  | 7.30        | 98.47  | 21.91          | 96.27  | 7.62       | 98.33  |
| Average            | 45.11      | 91.64  | 20.03       | 94.62  | 26.84          | 93.29  | 17.0       | 95.88  |

operator listen to the $k$ closest training samples to the test one.

3. EXPERIMENTS

3.1. Datasets and Evaluation

We use MSCW (Micro-EN) [10] and Vocalsound [11] as in-distribution datasets, and they also act as OOD for each other. The former is curated for learning keyword spotting models with 31 classes, and the latter is related to human vocal sound monitoring (e.g., coughing and sneezing) with 6 classes. We use standard training, validation, and test splits as provided with these datasets with audio sampled at 16kHz. For the OOD test dataset, we employ six additional datasets to cover wide range of audio and speech, including Voxforge [12] (spoken language identification, 6 classes), CREMA-D [13] (emotion recognition, 6 classes), ESC-50 [14] (environmental sound classification, 50 classes), MSWC (Micro-ES) [10] (Spanish keyword spotting, 20 classes), SpeechCommands [15] (spoken commands detection, 12 classes), and FluentSpeech [16] (action recognition, 6 classes). We note that the model is not exposed to any OOD data during its training phase, and test sets of OOD datasets are used to report results. For evaluation, we closely follow prior work on OOD detection in vision [5, 1, 7] and compute the false positive rate (FPR95) of

![Fig. 2: Distribution of the $k$NN distance with the normalized features from MobileNet. The ID data is MSWC (Micro-EN).](image-url)
Owed examples when the true positive rate of in-distribution examples is set at 95%. Further, we also report the area under the receiver operating characteristic curve (AUROC).

### 3.2. Models and Implementation Details

We use MobileNet [8] (YAMNet) architecture for training audio classification models from scratch with negative log-likelihood loss. The model input is log-compressed Mel-filterbanks with a window size of 25ms, a hop size of 10ms, and $N = 64$ Mel-spaced frequency bins in the range $60\text{--}7800\text{Hz}$ for $T = 98$ frames, corresponding to 980ms. We use Adam [17] optimizer with a learning rate of 0.001 for training the model for 100 epochs and batch size of 128.

The penultimate layer’s feature dimension is 1024, where the nearest neighbor search is performed. We also explore the efficacy of our approach with other architecture for which we use EfficientNet-B0 [18], where the training configuration is the same as mentioned earlier, and the dimensionality of the penultimate features is 1280. For efficient nearest neighbors search, we use Faiss [9] with Euclidean distance and set $k = 5$ and $k = 100$ for in-domain MSWC (Micro-EN) and Vocalsound datasets, respectively.

Likewise, for other traditional non-parametric methods (see Table 3) we use scikit-learn [19] and PyOD [20]. Specifically, we use 100 base estimators for IForest [21], apply RBF kernel in OCSVM with $\nu = 0.25$ [22], 10 number of bins for LODA [23], $k = 20$ for LOF [24], and use 128 components in PCA [25].

### 3.3. Results and Analysis

In this section, we investigate the feasibility of $k$-nearest neighbors method for detecting out-of-distribution samples. We use MobileNet [8] models trained solely on in-distribution data to highlight the feasibility of our method, unless stated otherwise. In Table 1, we compare results with competitive methods leveraging output and even gradient space of the model. When using Vocalsound as ID data (test set accuracy of 90.75%), where the task involves human vocal sound recognition, the $k$NN improves FPR95 by 17% while being extremely efficient as compared to more sophisticated methods as ODIN and GradNorm, which are computationally intensive as they require computing per-sample gradients. Further, as $k$NN has an entire training set embeddings at its disposal, it works effectively than traditional methods as it compares distance of a test input to rest of the samples to determine the OOD status.

Likewise, when a keyword spotting model trained on MSWC (Micro-EN) (with test set accuracy of 90.05%) is used we notice ODIN performs relatively better but $k$NN provides better FPR with an improvement of 3%. We further provide distance distribution in Figure 2 of demonstrating clear separation of ID and OOD distributions. Based on these results, we notice that the nature of ID data has a strong impact on the performance of OOD detection. For instance, MSWC contains audio of spoken words in general of one second in length as compared to variable length audio in Vocalsound dataset. Hence, the high FPR we observe on SpeechCommands (also see distance overlap in Figure 2) and MSWC (Micro-ES), i.e., when ID and OOD datasets have similar task characteristics, OOD identification is more challenging.

We also evaluate $k$NN on an alternative neural network architecture, EfficientNet-B0 [18]. In Table 2, we report averaged evaluation metrics across datasets mentioned in Table 1 and follow same experimental setting. We see that non-parametric $k$NN is largely effective and outperforms existing techniques. Further, as we can see in Table 3, the proposed $k$NN-based method outperforms all the other classical techniques in terms of both AUROC and FPR95 by a significant margin, while using same embeddings used for training of these other classical models.

### 4. CONCLUSIONS

We present a robust technique for out-of-distribution detection in the audio domain with deep $k$-nearest neighbors. Our approach leverages a non-parametric nearest-neighbor distance without making strong distributional assumptions regarding the underlying embedding space of a pre-trained neural network model. We demonstrate the effectiveness of $k$NN in OOD detection for audio (and speech) across a wide variety of tasks and model architectures. Our approach has the potential to improve the safety of audio models deployed in real-world settings by reducing the risk of making overconfident predictions on inputs that are not related to the task at hand.
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