

PROPOSAL >A new convolutional neural network architecture for the bird audio detection (BAD) problem >A divergence based information channel weighing strategy to achieve faster convergence and improved state-of-the-art performance DATA ➢Bird Audio Detection Challenge 2018 (Detection and **Classification of Acoustic Scenes and Events** Challenge, Task 3) development data set The audio clips are collected from 1) Field recordings around the world, gathered by the FreeSound project 2) Crowd-sourced smartphone audio recordings 3) Remote monitoring near Ithaca by the BirdVox project Each clip consists of a 10 second single-channel recording sampled at the 44.1 kHz sampling rate, non-equantised to 16-bit resolution and stored as a PCM file **APPROACH** >We first introduce a new DNN architecture addressing the BAD problem by extending the stateof-the-art system, bulbul [3], that has won the BAD Challenge 2017 The proposed architecture is named BirdNet \succ We then use a novel weighting strategy to learn the weights for the information channels of BirdNet Based on information divergence between the positive and negative pattern distributions observable at different convolutional layer channels This version of the BirdNet, aided by contextual channel weights, is named **BirdNet-D** CONTRIBUTIONS >BirdNet is demonstrated to outperform the bulbul system by 6.55%. \succ By employing BirdNet-D, it is possible to obtain a better accuracy than that of BirdNet in every epoch and converge to optimum performance much earlier

It is also possible to achieve a slight improvement in the performance

DIVERGENCE BASED WEIGHTING FOR INFORMATION CHANNELS IN DEEP CONVOLUTIONAL NEURAL NETWORKS FOR BIRD AUDIO DETECTION

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| METHODOLOGY 1) Feature Extraction | | | | 3) W | |
|---|--|---|--|------------|--|
| | | | | ► To | |
| The input signals are downsampled to 22.05 kHz and short-term Fourier transform spectra are calculated with a window size of 1024 and hop size of 220 | | | | Bir • | |
| samples | | | | Aft | |
| From the sp computed vi | ectra, logmel f ia a filter bank | frequency coeff of 80 triangula | r mel filters | the ana | |
| The coefficiency of the | ents are norm ividing by the s | alised by subtra standard deviat | acting the tion per | • | |
| inequency b | and | | | | |
| The size of t | the resulting fe | eature matrix fo | r an input clip | | |
| is 80x1000 (| (frequency by | time) | | | |
| | | | | rec | |
| 2) Network A | rchitectures | | | 120 | |
| BirdNot BirdNot-D | | | | | |
| Diranet | | Birunet-D | | | |
| Input | 80 x 1000 x 1 | Input | 80 x 1000 x 1 | | |
| Conv (5x5) | 80 x 1000 x 32 | Conv (5x5) | 80 x 1000 x 32 | | |
| Pool(2X2) | 40 x 500 x 32 | Pool(2X2) | 40 x 500 x 32 | | |
| $\frac{\text{Conv}(3X3)}{\text{Pool}(2x2)}$ | 40 x 500 x 64 | $\frac{\text{Conv}(3X3)}{\text{Pool}(2x2)}$ | 40 X 300 X 64 20 x 250 x 64 | + *** | |
| Conv (3x3) | 20 x 250 x 04 20 x 250 x 128 | Conv (3x3) | 20 x 250 x 04 20 x 250 x 128 | | |
| $\frac{\text{Conv}(3x3)}{\text{Pool}(2x2)}$ | 20 x 230 x 128 | $\frac{\text{Conv}(3x3)}{\text{Pool}(2x2)}$ | 20 x 230 x 128 | es | |
| Conv (3x3) | $10 \times 125 \times 120$ 10 x 125 x 128 | Conv (3x3) | $10 \times 125 \times 120$ 10 x 125 x 128 | US | |
| Pool t $(1x^2)$ | 10 x 62 x 120 | Pool t $(1x2)$ | 10 x 62 x 128 | • | |
| $Conv_t(1x3)$ | 10 x 62 x 128 | $Conv_t(1x3)$ | 10 x 62 x 128 | • | |
| Pool_t $(1x3)$ | 10 x 20 x 128 | Pool_t $(1x3)$ | 10 x 20 x 128 | | |
| $Conv_t(1x3)$ | 10 x 20 x 128 | $Conv_t(1x3)$ | 10 x 20 x 128 | | |
| Pool_t $(1x2)$ | 10 x 10 x 128 | Pool_t $(1x2)$ | 10 x 10 x 128 | | |
| $Conv_t(1x3)$ | 10 x 10 x 128 | $Conv_t(1x3)$ | 10 x 10 x 128 | | |
| Pool_t (1x10) | 10 x 1 x 128 | Pool_t (1x10) | 10 x 1 x 128 | | |
| | | Weight_f | 10 x 1 x 128 | | |
| $Pool_f(10x1)$ | 1 x 1 x 128 | Pool_f $(10x1)$ | 1 x 1 x 128 | | |
| Dropout (0.5) | | Dropout(0.5) | | | |
| Fully connected | 256 | Fully connected | 256 | | |
| Dropout (0.5) | 64 | Dropout (0.5) | 64 | | |
| Dropout (0.5) | 04 | Fully connected D | 04 | | |
| Diopout (0.5) | | Diopout (0.5) | | | |
| | | | | | |
| BirdNet-D aims faster convergence than BirdNet | | | | | |
| N Different frequences the second and the size second second | | | | | |
| Different frequency bands or their convolved | | | | | |
| representations are of different importance to the task | | | | | |
| of bird audic |) detection | | | | |
| Learning the weights that can act on each output | | | | | |
| channel is beneficial to underline their contributions to | | | | 🗸 Birc | |
| the predictic | n | | | ✓ Birc | |
| In RindNot D wa introduce a new lower (Mars-1-4 f) | | | | | |

 \succ In BirdNet-D, we introduce a new layer (Weight_f) which assigns a weight for each convolved frequency channel across all feature maps (128 maps)

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leight Initialisation

initialise the Weight_f layer, BirdNet-D requires rdNet to run on a small portion of the training data We select this to be 1/5th of the original training set

ter the convergence of BirdNet using the subset, e output of the Pool_f layer is recorded for further alysis

A matrix of size 10x1x128 is generated for each training pattern, where 10 is no. convolved frequency bands, and 128 is no. feature maps

r each frequency channel, PCA is applied for ducing the dimensionality of the feature maps from 28 to 4

Extracting the highest energy components while keeping the analysis tractable

he distributions of the positive and negative class aining samples in the 4D feature space are stimated, and the class separability is measured sing information divergence

Using symmetric Kullback-Leibler (KLS) divergence Let P(x) and Q(x) denote the probability distributions of the input data x in the positive and the negative classes

$$D_{KL}(P||Q) = \sum_{x} P(x) \log\left(\frac{P(x)}{Q(x)}\right)$$

$$D_{KLS} (P||Q) = D_{KL} (P||Q) + D_{KL} (Q||P)$$

If the distributions are similar, the measure tends to zero. A high value would indicate high discrepancy.

he KLS values computed for each frequency hannel are passed onto BirdNet-D as the starting oints of the Weight_f layer

High KLS value \rightarrow High separability between the positive and negative classes, high weighting for associated frequency bands

RESULTS

dNet achieves better than the state-of-the-art detection performance by 6.55%. dNet-D identifies frequencies that are more informative for the task of BAD, and initialise their weights accordingly. It exhibits much faster convergence and better accuracy compared to the rest of the networks, including BirdNet. KLS class separability measure is most effective in setting the layer weights. We show the effect of informed network design on the performance and the convergence rate of a detection system.



