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BELARUSIAN BIRD ACOUSTIC RECOGNITION: DATA PREPARATION AND MODEL TRAINING PROCESS

Abstract. The issue of substantial labor and time demands for monitoring bird species diversity and range changes, especially in developing countries, invites novel technological solutions. The recent advancements in machine learning (ML) have led to breakthroughs in AI-based data processing, including tools for automated passive acoustic monitoring (PAM) that utilize on-site bird vocalizations. Here we describe our preliminary results and difficulties encountered when developing an EfficientNetB3-based model for a PAM system to monitor bird diversity in the forested areas of interest in Belarus. A novel dataset of bird vocalizations from Eastern Europe, processed and converted into mel-spectrograms allowed us to achieve a respectable f1-scores (>0.9) in tests for certain species such as nightjar and nutcracker. However, the overall score (0.52) for the 116 species of interest was unacceptably low. Further testing with a more specialized dataset allowed us to determine that the problem lies with the peculiarities of species, and is not limited to species with complex vocalizations. We hypothesize that model overfitting to specific vocalization signals may be one of the main causes. Additionally, certain species require a thorough coverage of their vocalization diversity in the dataset.

Keywords: passive acoustic monitoring, avian vocalizations, machine learning

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ОПРЕДЕЛЕНИЕ ВИДОВ ПТИЦ БЕЛАРУСИ С ПОМОЩЬЮ НЕЙРОСЕТЕВОГО АНАЛИЗА ВОКАЛИЗАЦИЙ: ОСОБЕННОСТИ ПОДГОТОВКИ ДАННЫХ И ОБУЧЕНИЯ МОДЕЛИ

Аннотация. Проблема значительных трудовых и временных затрат для осуществления эффективного мониторинга диких популяций птиц требует современных технологических решений. Актуальные достижения в области машинного обучения обеспечили прорыв в возможностях анализа больших объемов данных с использованием нейросетей, и одним из перспективных методов применения этой технологии является ее использование в рамках пассивного акустического мониторинга (ПАМ) – перспективного подхода для наблюдения за птицами, основанного на автоматическом определении видов животных по их вокализациям на звукозаписях. В настоящей публикации описываются промежуточные результаты и достижения, полученные в ходе разработки средства для автоматического определения видов птиц в рамках ПАМ в Беларуси на основе нейросетевой модели EfficientNetB3. Применение упомянутой модели, обученной на новом наборе акустических данных птичьих вокализаций (29,6 ч), подготовленном по специализированному алгоритму, позволило нам достичь высоких показателей достоверности определения видов птиц по записям их вокализаций (точность, f1 > 0,9) для большинства видов, как, например, для козодоя и кедровки. Средний результат получен по полному перечню из 116 видов птиц. Углубленное тестирование позволило нам установить комплексную связь между видовыми особенностями вокализаций и точностью определения видов моделью на основе акустических данных. Мы предполагаем, что ключевыми факторами, снижающими показатели автоматизированного видового определения, являются оверфиттинг на конкретных акустических сигналах, а также неполное покрытие разнообразия вокализаций использованным в обучении набором данных.

Ключевые слова: пассивный акустический мониторинг, птичьи вокализации, машинное обучение
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Introduction. Bird vocalizations serve as a vital means of communication for a large part of the avifauna, with numerous characteristics that make species identification possible from acoustic data alone. This makes passive acoustic monitoring (PAM) a strong option for monitoring avian species diversity, migrations, and conservation. The use of PAM experiences significant growth due to the increasing availability and convenience of autonomous digital recording devices with the capacity for passive registration of animal vocalizations across areas of interest and obtaining huge volumes of acoustic data [1]. The massive amount of acoustic data, however, presents a challenge in terms of efficient processing and classification of species vocalizations present in the recordings [2, 3]. Solutions based on machine learning (ML) are currently seen as the most effective approaches to bird species identification in acoustic data [4] with numerous projects reaching good results with ML-based PAM systems [5–7]. ML solutions allow for automated classification of bird vocalizations in acoustic data, which drastically reduce labor requirements for monitoring efforts [3]. Such solutions can provide thorough and up-to-date monitoring of avian fauna diversity, migrations, and range changes for the purposes of conservation in areas that are not receiving sufficient attention.

The ML model (“the model” from here on) is aimed at providing PAM suited to local Belarusian avifauna, and meant to use natural acoustic data collected at monitoring stations across Belarus using passive recording equipment to reliably identify certain species for the purposes of monitoring and conservation. Here we describe our experience with implementing such model, focusing on the process, choice of the model architecture, data preparation, preliminary results, and encountered difficulties.

Materials and research methods. The Belarusian avifauna currently includes 342 species [8]. We set our goal at sufficiently reliable identification of 116 vocalizing species inhabiting woodland areas using acoustic data gathered on-site. To form the dataset for the model training we have taken acoustic recordings of bird vocalizations made in the field and the recordings from the open acoustic datasets, such as Xeno-Canto [9], that were made in Belarus or its surroundings, mostly from Eastern Europe. All field recordings used in this study were obtained in accordance with ABA Code of Birding Ethics. Each recording was checked and annotated manually by a qualified specialist with start and end timestamps for the vocalizations of foreground and background bird’s species and the noise sounds present at the recording. We used this approach to form an original dataset consisted of approximately 2300 audio records with approximately 41 000 labels of avian vocalizations. Additionally, we used the open database FSD50k [10] for our dataset to train the model’s capacity to recognize interfering noises.

To prepare the data for the model training the records in the dataset were broken into 2-second windows. Consecutive annotations with durations below 1 second were united into a single annotation if the pauses between them were below 0.5 seconds. Then the long annotations with duration more than 1 second were divided into 2-second windows with a 1.75 second shift, ensuring that each window contains at least 1 second of vocalization. Short vocalizations below 1-second length were taken in a 2-second context as a single window. We attributed each 2-second window with the main species present in it, as well as a separate list of any background species’ vocalizations present. Background species not present in the 116 species list were marked as “unknown”.

This approach allowed us to obtain a dataset of approximately 50 thousand 2-second windows with marked vocalizations of 116 species of interest. To prevent data leak, the dataset of 2 seconds windows was divided into train/test/validation datasets with approximate percentages 60 %–20 %–20 % so that each 2-second window produced from the same recording ended up in the same dataset. To balance the dataset between various species, we utilized various methods of data augmentation, including time shifting, noise and pitch shifting, and signal mixing, with the latter being implemented in the final dataset as the most effective approach.

In our earlier efforts [11], we changed the sample rate (sr) of the audio records to 22050 Hz, and converted them into mel-spectrograms with the Fast Fourier Transform window length (n_fft) of 1024, 512 samples between consecutive windows (hop_length) and 128 mel-filters (n_mels). The conversion process also removed frequencies below 1400 Hz, as target species (initially 50 species) do not use those frequencies much. This approach, however, displayed numerous issues, including the model trained this way severely struggling with identifying any *Columbiformes* and *Strigiformes* species. To counter this, we increased the acoustic range and adjusted the settings. The model described here was trained on mel-spectrograms that included the frequencies between 200 and 11025 Hz, with parameters sr = 22050, n_fft = 512, hop_length = 128, and n_mels = 128. Additionally, we compressed the acoustic signal according to μ-law compression after applying resampling and normalization, which served to "balance" the signal, making weak vocalizations more pronounced. We believe that this approach allowed us to extract the most acoustic information content into the spectrograms, improving the effectiveness of the obtained dataset for model training, and so these methods were the ones used to prepare data for model training and obtain the results discussed below.

The procedure of the model's recognition function is to divide the provided files into windows of certain length, detect recognizable acoustic signals (such as bird vocalizations), and classify them as one of the predetermined bird species, or interfering noise. We based the present model on a pre-trained convolutional neural network EfficientNetB3. While similar convolutional neural networks, such as ResNet [12] or Inception [13] were successfully used for similar goals, we chose EfficientNetB3 for its limited size and high performance characteristics [14, 15], as demonstrated in BirdCLEF-2023 challenge [16]. These are vital for use under conditions of limited computing power. We then added *Flatten*, *Dropout* and *Dense* layers to the model. Originally we used *softmax* as the activation function for the last layer, and *categorical cross entropy* as the loss function, but this approach introduced issues with identifying multiple species present at the same window. To address that, we switched the activator to *sigmoid*, and the loss function to *binary cross entropy*, allowing us to turn a multiclass classification task (one window – one prediction) into a multilabel classification task (one window – multiple predictions). We also used *Adam* optimizer.

The training process included 50 epochs with learning rate adjustment per *ReduceLROnPlateu*. To estimate the overall effectiveness of the model, we used the Precision, Recall and *F*1-score metrics obtained for the selection of the original dataset reserved for testing purposes.

Precision is a measure of the proportion of true positive predictions out of all positive predictions made by the model:

$$Precision = \frac{True\ positives}{True\ positives + False\ positives}.$$

Recall is the measure of the proportion of true positive predictions out of all the actual positive instances in the dataset:

$$Recall = \frac{True\ positives}{True\ positives + False\ negatives}.$$

*F*1-score is the harmonic mean of precision and recall, combining both metrics into a single score:

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision \times Recall}.$$

Additional model testing. The central principle of this in-depth test is evaluating the model's effectiveness when working with specific bird groups, recording quality and conditions. It is aimed at identifying the underlying issues that can be worked upon to improve the model's true positive rate, before moving on to decrease false positive and false negative rates.

For additional testing, we divided the 116 species into 5 groups according to their estimated vocalization complexity (Table 1). Then we picked 3 random species from each group to form the selection of 15 species: Common woodpigeon (*Columba palumbus*), Bohemian waxwing (*Bombycilla garrulus*), European turtle-dove (*Streptopelia turtur*), Hawfinch (*Coccothraustes coccothraustes*), Common cuckoo (*Cuculus canorus*), Hazel grouse (*Tetrastes bonasia*), Common raven (*Corvus corax*), Eurasian wren (*Troglodytes troglodytes*), Eurasian blackbird (*Turdus merula*), Tree pipit (*Anthus trivialis*), European robin (*Erithacus rubecula*), Blackcap (*Sylvia atricapilla*), Song thrush (*Turdus philomelos*), Great tit (*Parus major*), and Eurasian jay (*Garrulus glandarius*).

Table 1. **Estimated vocalization complexity groups of avian species used for additional model testing**

№	Characteristics	Species in the group
1	Structurally simple, monotypic vocalizations	Turtle dove, waxwing, common woodpigeon
2	Relatively simple vocalizations with no more than 2 highly prevalent signal types	Common cuckoo, hawfinch, hazel grouse
3	Intermediate complexity vocalizations	Common raven, Eurasian wren, Eurasian blackbird
4	Highly complex vocalizations including widely varying signals	Tree pipit, European robin, blackcap
5	Highly complex vocalizations including vocal mimicry of other species	Song thrush, great tit, Eurasian jay

The selected species were also represented by various amounts of annotated vocalization data within the training dataset, which allows us to estimate the effect that the amount of training data, used for individual species, has on the model's effectiveness. The number of annotated vocalizations for each selected species, as well as for each vocalization complexity group is given in Fig. 1.

To perform the test, we formed an additional set of 362 new natural acoustic recordings, divided into 7 classes according to their quality and composition, with class I including 20 recordings per bird species, the remaining classes each including 1 recording per species, plus 2 control recordings. The classes and their characteristics are given in Table 2.

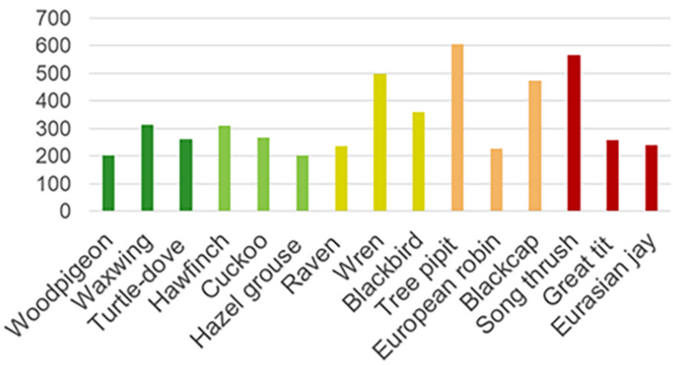

Fig. 1. The number of annotated vocalizations used to train the current iteration of the model, per species used for in-depth testing. Column color reflects the estimated vocalization complexity class of the species, from *1* (first three) to *5* (last three)

Table 2. **Classification of recordings used for the additional analysis of the model's true positive rate capabilities**

Type	Class	Contents
Test recordings	I (Typical) $n = 300$	A random selection of recordings of various quality with pronounced vocalizations of a single species, including or lacking interfering noises and background species vocalizations
	II (Clear) $n = 15$	High quality recordings with pronounced vocalizations of a single species, no noises or background vocalizations
	III (Noisy) $n = 15$	Recordings with pronounced vocalizations of a single species, rich in interfering noises, but without background vocalizations
	IV (Background) $n = 15$	Recordings with pronounced vocalizations of a single species, rich in background vocalizations of various species, but without interfering noises
	V (Noise and background) $n = 15$	Recordings with pronounced vocalizations of a single species, rich in both background vocalizations
Control recordings	VI (C1) $n = 1$	Files with no acoustic information present
	VII (C2) $n = 1$	Recordings possessing acoustic data without any bird vocalizations present

All test recordings were between 6 and 90 seconds in length. We ran the model on the abovementioned 362 records dataset and estimated the true positive rate with the criterion of at least one true positive result per recording counting as a success. We expected that the most consistently low success rate would point to the source of model's issues, be it classes of recordings, species, estimated vocalization difficulty or the amount of data used for training.

To estimate the baseline capacity of the model to identify bird vocalizations, we counted at least a single true positive result with the model's probability estimate at 0.4 or greater as a success, for the purpose of the additional test.

Results and discussion. The model testing on the 20 % test selection across the 116 target species displayed following average metrics: precision of 0.53, recall of 0.42 and $F1$-score of 0.52. The metrics for individual species are given in supplementary material 1. Results of additional testing are given in Table 3.

T a b l e 3. **Results for additional analysis of the model**

Species / Record class	Est. complexity	1 (Typical)	2 (Clear)	3 (Noisy)	4 (Background)	5 (Noise and background)
Woodpigeon	1	0.95	–	–	+	–
Waxwing		0.65	–	+	+	+
Turtle-dove		1	+	+	+	+
Hawfinch	2	0.2	–	–	–	–
Cuckoo		1	+	+	+	+
Hazel grouse		1	+	+	+	+
Raven	3	0.9	+	+	+	+
Wren		1	+	+	+	+
Blackbird		0.9	+	–	+	+
Tree pipit	4	0.9	+	+	+	–
European robin		0.35	+	+	–	–
Blackcap		0.6	–	–	–	+
Song thrush	5	0.25	–	–	–	–
Great tit		0.2	+	–	–	–
Eurasian jay		0	–	+	–	+
Controls		**K1 No sound data**			**K2 Pure noise recording**	
		+			–	

N o t e. For the column "1 (Typical)" the values indicate the ratio of recordings for which the model managed to achieve at least one true positive identification of that species out of 20 recordings. For the remaining columns a "+" indicates at least a successful true positive for the recording, and "–" a complete absence of true positive recordings. For the "Controls" row, "+" indicates absence of false positives, and "–" – at least a single false positive.

While the model's difficulties in obtaining any true positives for species with highly complex vocalizations (0.2 for great tit, 0 for Eurasian jay) was anticipated, the low values for certain species with relatively simple vocalizations (0.65 for waxwing, 0.2 for hawfinch) were unexpected. Another significant detail is the lack of correlations between true positive results and the presence of interfering noise or background vocalizations. We did not detect a significant correlation between the sheer volume of vocalization data and the true positive rate either (Fig. 2).

Conclusion. The testing of the current model iteration points us towards a few conclusions that might be useful for the development of similar PAM systems using ML and convolutional neural networks in particular. The major point would be the high effect of vocalization peculiarities of certain species on the system's performance, which can affect the model's effectiveness in identifying species with simple vocalizations as well as those with highly complex ones. We theorize that the low density of unique elements in certain simple vocalizations has negative effects on the effectiveness of model, particularly through pattern overfitting, which makes the model highly prone to false positive classification when faced with similar types of signals. Another possibility is the prevalence of high-frequency elements, or elements underrepresented in the training dataset among the species' vocalizations, which reduce the training effectiveness.

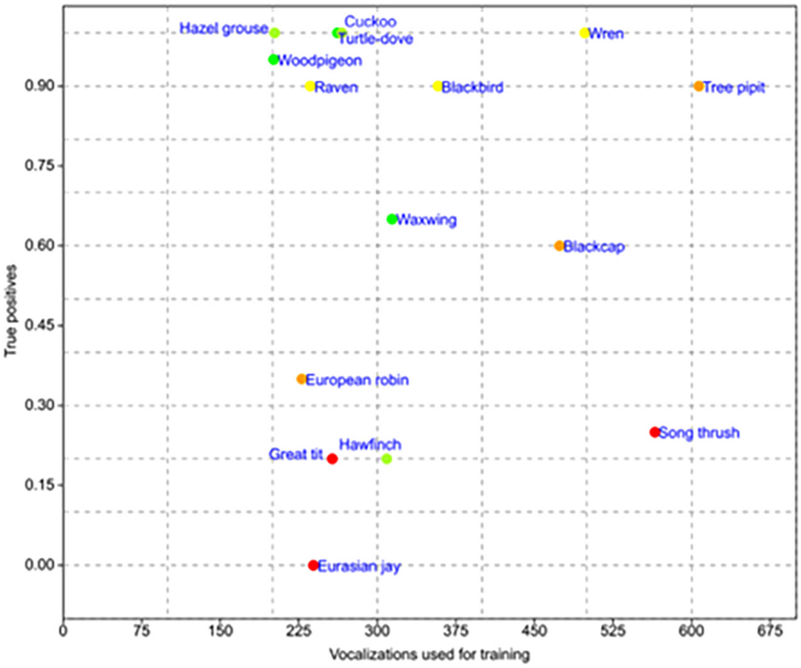

Fig. 2. The achieved true positives (Y-axis) per vocalization used for training (X-axis) for each species used in the additional analysis. The dot color represents the estimated vocalization difficulty for the species, colors identical to those in Fig. 1

The success of similar models for PAM indicates that the issue can be overcome with sufficient volume and diversity of data, and we believe that there are two key elements that deserve additional attention. Firstly, measures should be taken to ensure that the dataset includes all the possible vocal variations of any given species for the region of interest. Secondly, the problematic species must be detected empirically at the early stage of work, and the subsequent data gathering should aim to meet the necessary data volume and diversity thresholds for those species and their particular vocalizations.

Conflict of interest. The authors declare no conflict of interest.

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