An Artificial Intelligence of Things based Method for Early Detection of Bark Beetle Infested Trees

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Abstract: Bark beetles, like the European Spruce Bark Beetle (Ips typographus), are inherent parts of a forest ecosystem. However, with favorable conditions, they can multiply quickly and infest vast amounts of trees and cause their extinction. Therefore, it is important for forest officials and rangers of e. g. a national park, to monitor the population of the beetles and the infested trees. There are several ways to approach this, but they are often costly and time-consuming. Therefore, we design and test a bark beetle early warning system with AI-based data analysis: Audio data, data on pheromones and information for a drought stress assessment of the affected trees are to be collected and used as a basis for the analysis. The aim is to devise a micro-controller-based sensor system that detects the infestation of a tree as early as possible and warns the forest officials, e. g. via a message on their cell phone.

Keywords: Soundscape Ecology; Bark beetle detection; IoT sensors; AIoT-based evaluation

Addresses Sustainable Development Goal 15: Life on land

1. Introduction

Soundscape ecology [Pi11] is an interdisciplinary, systemic science approach that connects, among others, biology, landscape ecology, conservation research, eco-acoustics, bio- acoustics, and computer science. The origins of this research concept date back to the 1970s. [Sc93] Bernie Krause [Kr13] categorized sounds in terms of their origin into geophones (sounds of the natural environment, e. g. wind and water noise), biophones (sounds produced by non-human creatures) and anthrophones (sounds produced by humans, e. g. speech, machine or traffic noise). The composition of such noises form a characteristic soundscape of a locality or region. A soundscape can be systematically recorded and analyzed similar to a fingerprint. The analysis enables conclusions to be drawn about the local ecological situation, e. g. with regards to the biodiversity rate. [FT14] Soundscapes are not static, but are in a continuous process of change. The dynamics are shaped by human behaviors of the respective land use. Thus, it is possible to gain insights to regionally specific changes in terms of land use, but also with regards to climate change and its consequences on the basis of long-term observations of the acoustic environment. [Fa14]

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The starting point of our research approach is that bark beetles, in particular the European Spruce Bark Beetle (*Ips typographus*), can be detected quickly as an invasive species with the help of soundscape ecology tools. Throughout their life cycle, these beetles destroy and feed on the phloem, a layer inside the bark of trees, especially regular spruces (*Picea abies*). [Sc17] This extends from adult male individuals, which burrow through the outer layers of the bark into the phloem and bore tunnels for reproduction, over female individuals, which create further tunnels in a fanned-out structure for oviposition, to larvae and pupae, which feed on the phloem when they grow. The principle of the audio-based detection is to record these activities in-situ and attribute them to the beetle. [VH15]

However, we do not only rely on audio data as indicator, but also transfer the idea of soundscapes to pheromones. Bark beetles use pheromones to communicate, making them essential for their reproduction. Species-specific pheromones can be divided into releaser and primer pheromones and are composed chemical components. Volitile aggregation pheromones that attract the beetles to a tree spread rapidly, even without strong air movement. The beetle's sensory hairs contain up to 80 receptors for the pheromones, allowing them to be perceived even in very low concentrations. Male beetles begin searching for suitable breeding sites after winter dormancy or as young beetles after maturation feeding as so-called pioneer beetles. The onset of swarming depends on weather conditions, for example, Ips typographus swarms in dry weather and temperatures above 16.5 °C. [Ga19] After the pioneer beetles found a tree, a mass infestation is triggered by the aggregation pheromones. The beetles produce these pheromones in their digestive tract, from Alpha-Pinen and Myrcene. The main pheromone is 2-methyl-3-buten-2-ol, supplemented by the long-range attractants (S)-cis-verbenol and ipsdienol, among others. [Zu94]
Thus, we cover two approaches: 1. With the help of audio monitoring, we detect feeding sounds of the larvae or the sound of beetles boring into the phloem. 2. With the help of an artificial nose (volatile organic compounds (VOC) sensor), we detect pheromones and resin odors of the trees, which are typical for a bark beetle infestation.

2. Problem statement

When bark beetles infect a tree, it is quickly no longer economically viable to use it for lumber production. In most cases, the only option is to dispose of it, resulting in reduced revenues up to total loss. [De18] If the infestation is discovered too late, the rest of the population in the surrounding area is also vulnerable. Therefore, especially on the part of the forestry, the early detection of infestations or of the danger of an infestation is highly relevant. The changes in temperature due to climate change allow bark beetles to be active earlier in the year and thus they can even develop more generations than before. [WS98, TP08]
Currently, there are various ways to detect a bark beetle infestation. A ranger can suspect an infestation based on borings on the ground or strong resin odors in the air, and confirm it after removing tree bark and looking for burrows or nuptial chambers. [Hö16] However, this requires an experienced ranger. In addition, rain or wind may obliterate the borings or

suppress the odor. Areas that are difficult to reach may not be checked regularly enough, if at all. Many forest areas do not have a forester or ranger in charge. There is also already some work done on the (semi-)automated detection of bark beetles, such as the assessment of airplane- or drone images [He15, DD00], but they are costly and often quite inaccurate. At present, probably the most accurate method are trained dogs, which can unerringly "sniff out" a bark beetle infestation. [JBS19] However, the dogs need frequent breaks after 20 to 30 minutes and the number of trained dogs also does not suffice to ensure a comprehensive examination. Researchers at the Rottenburg University of Applied Sciences and the Universities of Göttingen and Freiburg are working on bark beetle detection from the air with the help of drones. [He20] With the help of a long nozzle below the drone, they also want to detect the resin odors caused by a bark beetle infection. Here, the flying skills of the drone pilot are a decisive factor. They must approach the forest canopy closely from above in order to be able to measure sufficient data. This method is well suited to assess forest sites that are difficult to reach. However, it is also quite personnel-intensive. In addition, strong winds and rain can make the flights difficult or impossible.

3. Proposed Method

To approach the automated detection of a bark beetle infestation in a cost- and energy efficient way, we focus our work on the design and evaluation of an Artificial intelligence of things (AIoT) based micro-controller sensor system. We use existing, open source IoT devices such as Espressif Systems on a Chip (SoC)[2] and Raspberry Pis as well as cheap sensor modules, like BME680[3] and piezoelectric contact pickups.

Currently, the data is analyzed with a TensorFlow model on a PC, but the goal is to transfer the trained model to tinyML, so that the sensor data can be classified directly on the IoT device and only the classification results from several sensor nodes are transferred to a Raspberry Pi-based central processing unit via a WiFi or LoRaWAN network. It would then relay the warnings to the forest owner. That way, we hope to reduce the energy consumption of the system, so that it can be deployed in remote areas without electrical connection.

Data for training the classification algorithms are taken from various sources. On the one hand, we obtained data recorded with experimental setups on deadwood in the lab and in the forest, on the other hand, data was provided by associated researchers, who investigate the bark beetle with the help of audio data [Du07], e. g. to observe its life cycle.

3.1 Audio-based detection

To detect the presence of European Spruce Bark Beetles in the trees bark, we designed a

[2] https://www.espressif.com/en/products/socs [2022-04-25]
[3] https://www.bosch-sensortec.com/products/environmental-sensors/gas-sensors/bme680/ [2022-04-25]

prototype to pick up structure borne sound from inside the phloem on the basis of a vibration transducer as described in [Du07]. For the main component, we use a piezoelectric element in form of a round disc, normally intended for DIX-electronics as an acoustic guitar-pickup[4], which we encase in a 3D-printed housing to shield it from environmental influences. We then screw a flat-head, woodworking screw into the bark of the tree that is to be monitored.

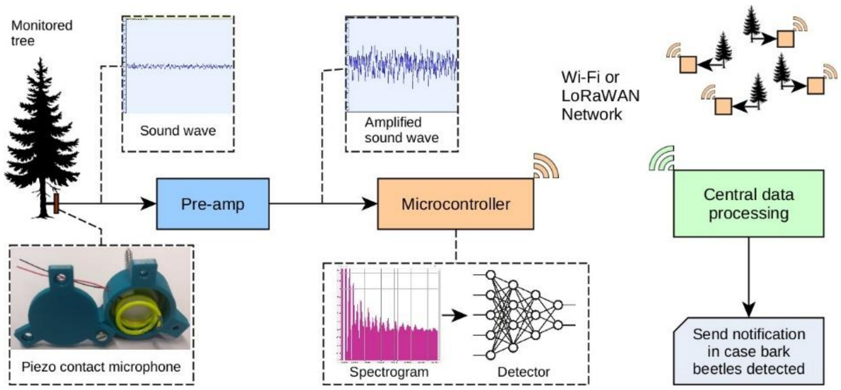

Fig. 1: Audio-based detection

In the housing, we incorporate a slot for the screw and an opposing spring, so that the piezoelectric pickup is firmly pressed against the screw. The sounds from inside the tree's bark are transmitted over the spring to the pickup which converts them into an electric signal, functioning as transducer. We fitted a standard 6.35mm stereo jack to the two wires that are soldered to the functional materials of the piezoelectric element. The signal is then passed through an amplifier and, at present, recorded with a professional handheld recorder as waveform audio format. In the envisioned final setup the amplification and audio jack will be connected directly to the microprocessor as shown in Fig. 1.

3.2 Pheromone-based detection

To detect the pheromones, we use an array of BME680 VOC sensors connected to a SoC to generate the data. The sensor generates relative resistance values as a function of ambient air VOC, which we use to explore whether the presence of bark beetles can be detected. We evaluate the data using algorithms from [Dz19], where we used a similar setup with one VOC-sensor to classify liquids using a support vector machine. The results show that this method is feasible, so we plan to use it for the classification of bark beetles as well. The sensors are attached to infested and not infested trees in similar environments. In the learning phase, we first perform extensive measurements of the ambient air. A small, heatable plate inside the sensor generates a temperature-dependent graph (similar to Fig. 5), whose characteristics allow detecting the concentration of many VOCs that

[4] https://robu.in/interfacing-of-piezoelectric-sensor-with-arduino/[2022-05-02]

evaporate at different temperatures. This data is analyzed, for example, with principal component analysis (PCA) and classification algorithms to estimate the causes of this air composition. Since the heating plate of the sensor is very small, the temperatures are reached within milliseconds and the required energy per measurement is very low. More concrete energy consumption measurements are planned as soon as the functionality is confirmed. Fig. 2 depicts the setup, again with several sensor nodes reporting to one central unit.

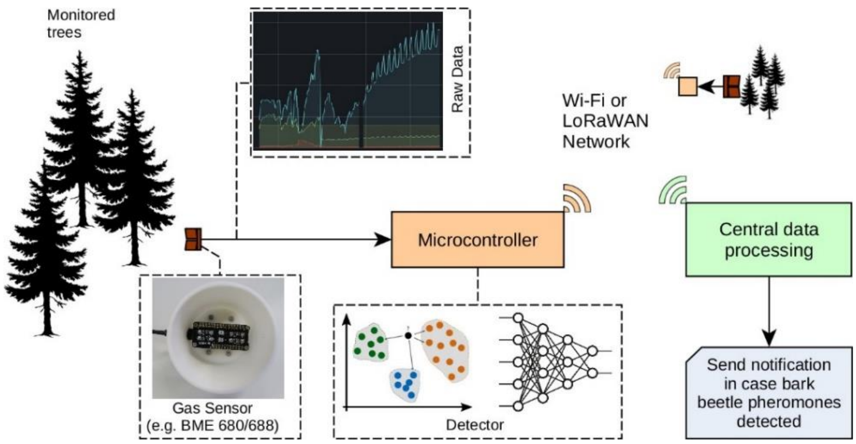

Fig. 2: Pheromone-based detection

4. Preliminary Results

As a proof-of-concept, we designed evaluation approaches for the sound-based and pheromone-based detection, which we describe here.

4.1 Sound-based classification

As a first approach for training the sound-based model, we used data collected through recordings in the Hunsrück-Hochwald National Park. We separated the sounds in two classes ”bark beetle“ and ”no bark beetle“. The second class consists of other noises, like animal sounds. In total, 47 sound files of different length ($< 20s$) were used. Since the training set is small and as such bears the risk of overfitting, we only split the data into a training and a test set. We plan on acquiring more beetle data during the summer of 2022 to extend the training process.

We trained two Keras[5]-models for classification, also making use of the python library

[5] https://keras.io/[2022-04-01]

librosa[6] for pre-processing. One model was trained with spectral features of the data (numerical data), the other with spectrograms (image data).

As training base for model 1, we used Mel Frequency Cepstral Coefficients (MFCC) which find usage in machine learning primarily for speech recognition (e. g. [Ko15]), but have also recently been used in animal sound classification [TH21]. We trained model 1 on the values of the first 13 coefficients. For the calculation, we split each sound file into snippets of 0.33 second length, from which we calculated the MFCCs. To further enlarge the small data set, we augmented the data from each snippet: Based on the positive results in [Ko15] for speech recognition, we changed the speed of the files arbitrarily between 90 and 110 %. We trained model 2 on mel-spectrograms, which are a common tool in audio classification and have also been used in animal sound recognition before (e. g. [Si20, NMP19]). Since our data already contained a lot of noise (e. g. wind), we did not use any other type of augmentation, like adding random noise, yet.

Analogous to model 1, we split the sounds into 1 second snippets and for each snippet derived the mel-spectrogram with librosa. We plotted the spectrogram without axes and saved them as image files. Spectrograms don't allow for a lot of possibilities when it comes to augmentation, since e. g. rotating or flipping them would alter the data too much. As mentioned in [NMP19], the best options are masks in the frequency and time domain. To increase the data, the spectrograms were augmented on these domains and saved respectively.

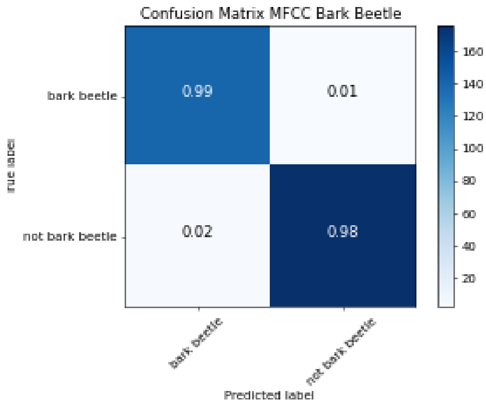

Fig. 3: Confusion Matrix for model 1

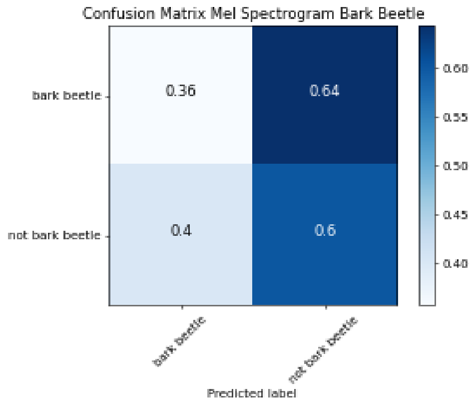

Fig. 4: Confusion Matrix for model 2

We trained both models for 110 epochs, using the sigmoid activation function and the adam optimizer. Not only are the models to be compared in their accuracy, but also in their energy efficiency, since we potentially want to deploy the detector on battery- or solar-powered devices. Considering the confusion matrices (Fig. 3 and 4), model 1 outperforms model 2, which presents a considerably higher false negative/positive rate ($40 - 64\%$ compared to

[6] https://librosa.org/[2022-05-02]

< 0.5 %).

The required storage space for the pre-processed training data needed is smaller for model 1 (around 3 mb) than model 2 (around 6 mb), which will be more significant with bigger data sets. Furthermore, model 1 itself needs considerably less storage space (356 kb) than model 2 (150 mb). We also noticed differences in power consumption. Model 2 consumes over three times the energy of model 1 (1.82 vs. 0.59 watthours) in pre-processing and training. model 2 also needed more time than model 1.

4.2 Pheromone-based classification

So far, we base our assumption that the pheromones can be detected upon measurement results (see Fig. 5) obtained in a lab-setup with the pheromones mentioned in section 1. To produce reliable results for the pheromone-based detection, we are currently in the field to record more data in this years' swarming season using a setup with the VOC-Sensor as described above. To conduct the measurements, we heat the sensor to 30 °C and increase the temperature by one degree every 0.1 seconds until it has reached 400 °C. After each of these 371 steps, the sensor measures the relative resistance of its gas sensitive layer. Since such a measurement takes about two minutes, we use PCA, which provides us with the three most valuable features out of these 371, to be able to perform a much more energy-efficient and fast (about three seconds) measurement after the learning phase. Once this methodology proves successful for this use case, we plan to use the algorithms from [Ma20] to simplify the learning process in the presence of frequently changing forest air conditions or species specificity through an adaptive application.

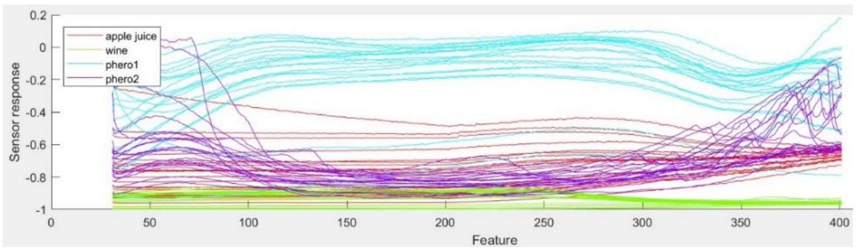

Fig. 5: Data visualization from the VOC sensor detecting bark beetle pheromones

4.3 Threats to the approach

In this section, we discuss the threats that could render the approach unsuitable for the intended usage, based on preliminary assessments of its viability. Although bark beetles as pest for the timber industry are not a new phenomenon, there are still many unanswered questions regarding their biology, like the exact time intervals and climate conditions favorable to their life cycle or determining which life stages (larvae, pupae, imago) represent which sounds and which part of the tree (trunk or at or directly under the crown) the pioneer beetles fly to. These questions obviously have implications for our sensors and the data they collect. We need to identify the right place to attach the sensors to or discern the beetle's sounds over its life stages, since we want to detect the beetles as early as possible. Furthermore, we need the data from the field to ascertain that the sounds can be unequivocally linked to the beetles and that similar sound – like those from other insects in the tree – can be distinguished.

Biology aside, there are also technical challenges that need to be overcome. As we apply tried and tested algorithms and hardware to the area of bark beetle detection, we focus on the major threats to our AI-setup: classification accuracy, the potential capability of the hardware as AIoT device, the energy consumption of the devices for its application in the field, and the sensors and data. Regarding the models for the audio-based detection, we need a bigger data set to build a more robust model. Furthermore, the data needs to be more suited to the given problem, i. e. data regarding healthy trees and trees with bark beetles for anomaly detection instead of comparing the existing bark beetle recordings with other random sounds. Because of the small data set, the current models were also not tested against unknown data, so the actual performance is to be determined in the future. An economically viable system must not only be inexpensive, but also have a long run-time. Therefore, we want to use SoCs. However, modern power banks switch off automatically when the load is too low, so we need to use a more tailored battery setup.

5. Conclusion and outlook

The approach to gather sound- and pheromone data with cheap and efficient IoT hardware and assess them with off-the-shelf algorithms seems promising. As a proof of concept, we showed that we can detect bark beetles by analyzing audio data, and a visual analysis of VOC data from the lab also looks promising. We currently test the sensor prototypes in the field. For this purpose, the Hunsrück-Hochwald National Park Authority has provided us with various forest areas with indisputable infestation status. We will then evaluate the data we obtain here further and expand the training of the models.

In the future, we plan on supplementing the existing sensors by further environmental sensors, e. g. for recording temperature or soil and air humidity. We argue that trees suffering from drought stress – i. e. the supply of water is too low – are more susceptible to the bark beetle. Not only are they able to produce less resin for defense [Ba21, p. 24], but we also assume that the bark beetle is able to explicitly target such trees. For this purpose, it will be necessary to define drought stress and gather resilient measurements for it. How the transmission of information to the responsible person regarding the infestation can be technically implemented still needs to be clarified. To avoid the problem of lacking network coverage, we plan on testing solutions like LoRaWan and adapt our detection setup if necessary. For the classification, we plan on considering anomaly detection e. g. through kNN and SVM which is also capable of running on SoCs.

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Bibliography

[Ba21] Bachlehner, Albert: Physiologische und hydrologische Parameter im Zusammenhang mit der Attraktivität trocken-gestresster Fichten (Picea Abies) für den Buchdrucker (Ips Typographus). Master's thesis, 2021. https://abstracts.boku.ac.at/download.php?dataset_id=19993&property_id=107 [2022-05-11].

[DD00] Dubayah, Ralph O.; Drake, Jason B.: Lidar Remote Sensing for Forestry. Journal of Forestry, 98(6):44–46, 06 2000.

[De18] Deter, Alfons: Bis zu zwei Milliarden Euro Schaden am deutschen Wald, 2018. https://www.topagrar.com/management-und-politik/news/bis-zu-zwei-milliarden-euro-schaden-am-deutschen-wald-9840658.html [2022-05-03].

[Du07] Dunn, David: Microphones, Hydrophones, Vibration Transducers: Rolling Your Own, 2007. https://www.zachpoff.com/site/wp-content/uploads/David-Dunn-Microphones_Hydrophones_Vibration-Transducers Rolling_Your_Own Dunn2007.pdf [2022-04-25].

[Dz19] Dziubany, Matthias; Garling, Marcel; Schmeink, Anke; Burger, Guido; Dartmann, Guido; Naumann, Stefan; Gollmer, Klaus-Uwe: Machine learning-based artificial nose on a low-cost iot-hardware. In: Big Data Analytics for Cyber-Physical Systems, pp. 239–257. Elsevier, 2019.

[Fa14] Farina, Almo: Soundscape Ecology. Springer Netherlands, 2014.

[FT14] Frommolt, Karl-Heinz; Tauchert, Klaus-Henry: Applying bioacoustic methods for long-term monitoring of a nocturnal wetland bird. Ecological Informatics, 21, 2014.

[Ga19] Gabriel, Oliver: Kleines Einmaleins des Borkenkäfers, March 2019. https://www.forstpraxis.de/kleines-einmaleins-des-borkenkaefers/ [2022-05-11].

[He15] Heurich, Marco; Krzystek, Peter; Polakowski, Fabian; Latifi, Hooman; Krauss, Andreas; Müller, Jörg: Erste Waldinventur auf Basis von Lidardaten unddigitalen Luftbildern im Nationalpark Bayerischer Wald. Forstliche Forschungsberichte München, 214:101–113, 2015.

[He20] Henning, Hete: Borkenkäfer-Früherkennung aus der Luft, 2020. https://www.uni-goettingen.de/de/document/download/efe458ff383b9ef8e472a48024f580f6.pdf/Rottenburger%20Post%202020.pdf [2022-05-03].

[Hö16] Höbarth, M.; Leitner, T.; Perny, B.; Reh, M.; Wöhrle, M.; Zobl, A.: Borkenkäfer - Vorbeugung und Bekämpfung. Technical report, LFI Österreich, Waldverband

Österreich, Vienna, Austria, 2016. https://de.readkong.com/page/borkenk-fer-vorbeugung-und- bek-mpfung-5680852 [2022-05-11].

[JBS19] Johansson, Annette; Birgersson, Göran; Schlyter, Fredrik: Using synthetic semiochemicals to train canines to detect bark beetle–infested trees. Annals of Forest Science, 76(2), 2019.

[Ko15] Ko, Tom; Peddinti, Vijayaditya; Povey, Daniel; Khudanpur, Sanjeev: Audio augmentation for speech recognition. In: INTERSPEECH. 2015.

[Kr13] Krause, Bernie: Das große Orchester der Tiere. Kunstmann Antje GmbH, September 2013.

[Ma20] Machhamer, Rüdiger; Garling, Marcel; Czenkusch, Levin; Ueding, Kristof; Guldner, Achim; Schneider, Jens; Latif, Azhar; Schmeink, Anke; Naumann, Stefan; Gollmer, Klaus- Uwe; Dartmann, Guido: Development of Edge Runtime Learning Systems for an Artificial Nose Classifying Drinks. In: 9. Medit. Conf. on Embedded Computing (MECO). 2020.

[NMP19] Nanni, Loris; Maguolo, Gianluca; Paci, Michelangelo: Data augmentation approaches for improving animal audio classification, 2019. https://arxiv.org/abs/1912.07756 [2022-04-01].

[Pi11] Pijanowski, Bryan C.; Farina, Almo; Gage, Stuart H.; Dumyahn, Sarah L.; Krause, Bernie L.: What is soundscape ecology? An introduction and overview of an emerging new science. Landscape Ecology, 26(9):1213–1232, 2011.

[Sc93] Schafer, R. Murray: The Soundscape: Our Sonic Environment and the Tuning of the World. INNER TRADITIONS, 1993.

[Sc17] Schebeck, Martin; Hansen, E. Matthew; Schopf, Axel; Ragland, Gregory J.; Stauffer, Christian; Bentz, Barbara J.: Diapause and overwintering of two spruce bark beetle species. Physiological Entomology, 42(3):200–210, 2017.

[Si20] Singh, Neha: Classification of Animal Sound Using Convolution Neural Network. Master's thesis, Technological University Dublin, 2020.

[TH21] Trouvain, Nathan; Hinaut, Xavier: Canary Song Decoder: Transduction and Implicit Segmentation with ESNs and LTSMs. In: Artificial Neural Networks and Machine Learning – ICANN 2021. Springer International Publishing, Cham, pp. 71–82, 2021.

[TP08] Tomiczek, C.; Pfister, A.: Was bedeutet der Klimawandel für die Borkenkäfer?,2008.https://www.waldwissen.net/de/waldwirtschaft/schadensmanagement/insekten/klimawandel-und-borkenkaefer [2022-05-18].

[VH15] Vega, Fernando E.; Hofstetter, Richard W.: Bark Beetles: Biology and Ecology of Native and Invasive Species. ACADEMIC PR INC, January 2015.

[WS98] Wermelinger, B.; Seifert, M.: Analysis of the temperature dependent development of the spruce bark beetle Ips typographus (L) (Col., Scolytidae). Journal of Applied Entomology, 122(1-5):185–191, 1998.

[Zu94] Zuber, Markus: Ökologie der Borkenkäfer. Biologie in unserer Zeit, 24(3):144–152, 1994.