Forest quality assessment based on bird sound recognition using convolutional neural networks

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ABSTRACT

Deforestation in Indonesia is in a status that is quite alarming. From year to year, deforestation is still happening. The decline in fauna and the diminishing biodiversity are greatly affected by deforestation. This paper proposes a bioacoustics-based forest quality assessment tool using Nvidia Jetson Nano and convolutional neural networks (CNN). The device, named GamaDet, is a portable physical product based on the microprocessor and equipped with a microphone to record the sounds of birds in the forest and display the results of their analysis. In addition, a Google Collaboratory-based GamaNet digital product is also proposed. GamaNet requires forest recording audio files to be further analyzed into a forest quality index. Testing the forest recording for 60 seconds at an arboretum forest showed that both products could work well. The GamaDet takes 370 seconds, while the GamaNet takes 70 seconds to process the audio data into a forest quality index and a list of detected birds.

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1. INTRODUCTION

A tropical forest is an ecosystem unit in the tropics in a stretch of land containing biological natural resources dominated by trees in their natural environment. This forest is needed, among others, to slow or prevent climate change. The forest quality tends to decrease due to natural and human factors, dominated by human activity. During the last five years, the average annual area of deforestation is estimated at 10 million hectares worldwide. There needs to be a balance between human greed, today’s human needs, and the need to provide a healthy environment for living things and be sustainable for future generations. Tropical forests need to be protected from damage, especially those caused by human activities. The woods need to be monitored and assessed to maintain the sustainability of forest ecosystems. Forest quality assessment aims to know the current forest condition, changes, and trends that may occur [1], [2].

Forest quality has a close relationship with the health of the ecosystem. A good ecosystem is an ecosystem that has balanced components, where each piece interacts and fulfills each other’s needs. The bioacoustic index is one way to identify the quality of the ecosystem in a place by monitoring the status and trends of bird diversity in a particular location [3].

Birds can be used as indicators of ecosystem changes in a forest. Many birds live in a forest habitat and have a high and dynamic level of mobility to quickly respond to changes in their environment [4], [5]. Overall, birds can function as the guard and superior species so that birds are suitable to be used as indicators of a forest ecosystem. In this case, indicators are defined as organisms closely related to specific environmental conditions so that changes in the environment will change the nature or existence of the organisms [2].

Based on [2], there are at least four things that state birds as environmental indicator species, namely: i) distribution, ecology, biology, and life history of birds are well known compared to other fauna; ii) poultry in the feed chain occupies high enough position so that they are sensitive to changes in environmental pollution; iii) the bird survey technique is simpler; and iv) to monitor them is relatively cheaper than monitor other faunas such as reptiles and mammals.

Traditionally, bird diversity was monitored using point counts. This method requires a particular expert to visually and aurally identify and count birds in the field at 5-10-minute intervals at the sampling site. The count's accuracy at these identification points is negatively affected by the detection variability between species and sites and weather conditions that cause bird movement and activity. Another drawback of this method is that monitoring large areas with high temporal resolution is usually more challenging due to logistical and financial constraints. The results of this survey may also be biased by the observer's level of experience [6], [7].

In contrast, passive acoustic monitoring using an automatic recording unit to monitor the acoustic environment can be carried out continuously with adjustable periods. Data collection using this method is more cost-effective and flexible and has been widely used for ecological monitoring over the past decade. Acoustic data set recorded into a permanent record with higher temporal resolution than point calculation [7], [8]. It allows the researcher to revisit the data to perform additional analyses or manually verify the detected signals automatically, reducing bias and uncertainty associated with extracted observations.

Several artificial intelligence methods have been applied to various applications [9]–[12]. One application of artificial intelligence is to recognize and classify acoustic signals is convolutional neural networks (CNN). CNN can outperform traditional techniques in bioacoustic classification and detection [13], [14]. This paper proposes a CNN-based artificial intelligence model to classify bird species based on sound recordings [15], [16]. The system is given additional capabilities in bioacoustic analysis that can assess the quality and diversity of forest ecosystems based on the recognition of birds' voices in the forest [17], [18].

2. RESEARCH METHOD

2.1. Tropical forest quality assessment tool

The concept of the design of the tropical forest quality assessment tool is portable, inexpensive, and easy to use. Therefore, the product is designed using components that can meet these aspects. The Nvidia Jetson Nano was chosen as the microprocessor of the system called as GamaDet. The Rode VideoMic Go mini-shotgun microphone was used to acquire and record forest sounds and had a frequency range of 2-8 kHz. Other components such as wifi dongle, sound card, and tripod were chosen by considering the aspects of optimality and functionality of the design. In GamaNet, Google Collaboratory was selected as the online computing framework. The library used in the design of GamaNet is an open source that can be developed further.

The assessment system of the forest quality index was designed using a python programming language. The system processes the bioacoustics of bird sounds. Four parameters of the bioacoustic index are used as forest quality parameters, namely: acoustic evenness index (AEI), bioacoustic index (BIO), normalized difference soundscape index (NDSI), entropy (H). AEI assumes that each biotic component species in a natural ecosystem has a unique frequency and active time that differ from one another [19], [20].

This approach method can be used as material for spatiotemporal comparison. BIO is used to measure the frequency spectrum range of bird sounds in the range of 2-8 kHz: the more significant the BIO, the more dominant the biotic components in the environment. H index is used to measure one animal species and all the biotic components of an ecosystem. The greater the H index, the more diverse is the ecosystem. The last acoustic index, NDSI, compares the frequencies between anthrophony in 1-2 kHz with biophony in 2-8 kHz. So that by using NDSI, it can be seen the dominance of human presence in an ecosystem [19].

The proposed tropical forest quality assessment tool is shown in Figure 1. The device has two main features: analyzing forest quality based on the bioacoustic parameters of bird sounds and the diversity of birds in a place [21], [22]. The two are combined to gain new insights regarding ecological quality. We used python programming and several libraries such as matplotlib, librosa, and pandas as the basis in the system's coding. In the deployment stage, GamaNet is installed into the Nvidia Jetson Nano [23], [24]. The result of this step is that the user can use the functions of the GamaDet tool. These functions include recording sound, data processing, and displaying visualization and can be online accessed from the user's device. Details of the prototype specifications are described in Table 1. GamaNet is also installed in a web-based environment, namely on the Google Collaboratory [25]. The deployed GamaNet can be accessed by users using a specific internet address.

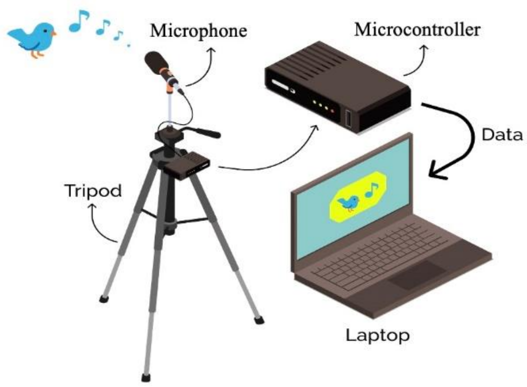

Figure 1. Tropical forest quality assessment tool using Nvidia Jetson Nano and CNN

Table 1. GamaDet spesification

No	Parameter	Specification
1	Length×width×height	11.5×9.5×5 cm (without tripod) 60×60×120 cm (with tripod)
2	Data processor	Quad-core ARM Cortex-A57 CPU, 4 GB RAM, 128-Core Nvidia Maxwell GPU
3	Operating System	Jetpack 4.6 basis Linux Ubuntu 18.04
4	Microphone	Supercardioid Rode VideoMic Go
5	Power Supply	Power Bank Redmi 20.000 mAh
6	Connectivity	Wifi TP-Link WN725N 150 Mbps

2.2. Bird sound data collection

The birds sound dataset consists of two parts. The first dataset is a large dataset consisting of bird records from around the world consisting of 984 bird species. Meanwhile, the second dataset consists of recordings of birds' endemic in Java Island. The primary dataset was collected from the Kaggle site, while the second dataset was collected from the Xeno-Canto site.

2.3. Signal processing and machine learning

We design the machine learning model based on a CNN [26]. CNN-based models are widely used in the field of image processing. In this paper, the system firstly processes the audio data into a spectrogram. The model with time-domain spectrogram data is then converted to the form of mel-frequency cepstral coefficients (MFCC) [27] or mel-spectrogram via the Fourier transform [28], as shown in Figure 2.

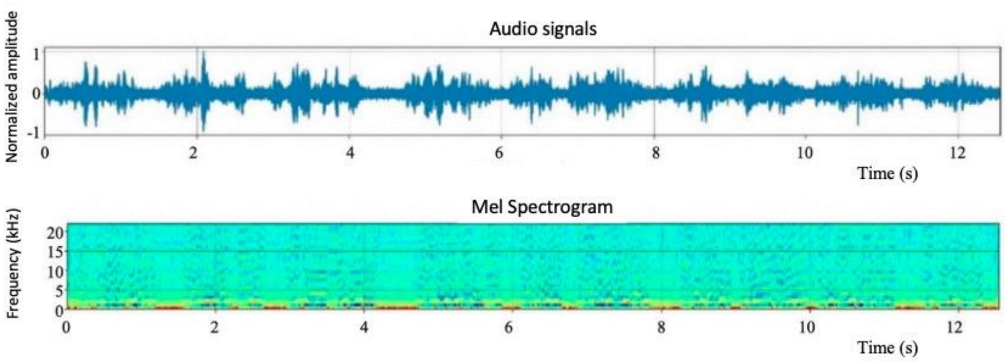

Figure 2. Comparison of spectrogram with mel-spectrogram [27]

One of the CNN models with good performance is the Wide-ResNet model [7]. The model has a shallow characteristic so that the model training time becomes shorter without sacrificing the accuracy of the standard ResNet model [29]. The architecture of the ResNet model used in this paper is shown in Table 2. The training flowchart of the proposed machine learning model is shown in Figure 3.

Table 2. BirdNet architecture [7]

Group	Name	Input shape	Output shape
Pre-processing	5x5 Conv+BN+ReLU	(1×64×384)	(32×64×384)
	Max Pooling	(32×64×384)	(32×64×192)
ResStack 1	Downsampling block	(32×64×192)	(64×32×96)
	2 ×ResBlock	(64×32×96)	(64×32×96)
ResStack 2	Downsampling block	(64×32×96)	(128×16×48)
	2 ×ResBlock	(128×16×48)	(128×16×48)
ResStack 3	Downsampling block	(128×16×48)	(256×8×24)
	2 ×ResBlock	(256×8×24)	(256×8×24)
ResStack 4	Downsampling block	(256×8×24)	(512×4×12)
	2 ×ResBlock	(512×4×12)	(512×4×12)
Classification	4×10 Conv+BN + ReLU +DO	(512×4×12)	(512×1×3)
	1×1 Conv+BN + ReLU + DO	(512×1×3)	(1024×1×3)
	1×1 Conv+BN + DO	(1024×1×3)	(987×1×3)
	Global LME Pooling	(987×1×3)	(987×1)
	Sigmoid activation	(987×1)	(987×1)

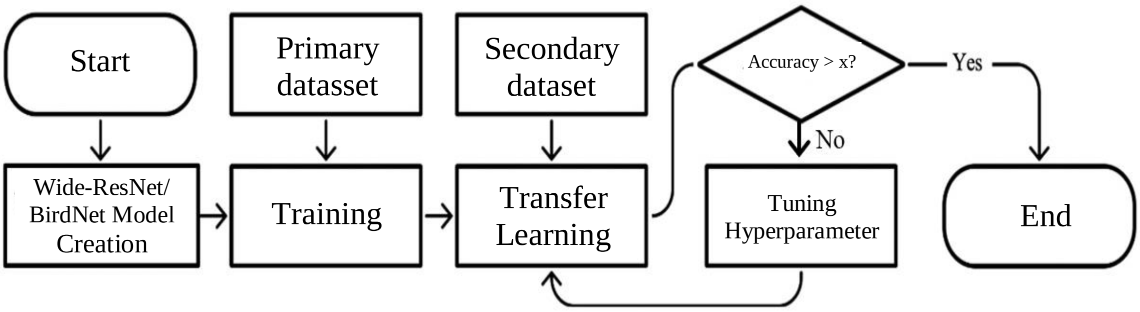

Figure 3. Flowchart of the training of the machine learning

2.4. Machine learning evaluation

The evaluation phase of this product consists of two stages. At first, the test used validation data. Validation data contains ground truth labels to compare the differences in test results with validation data. The machine learning model validation data was obtained from [7], while the data for the validation of the forest quality index was obtained from [19]. At five points, the second test was carried out directly on the arboretum forest of the Faculty of Forestry, Universitas Gadjah Mada (UGM).

3. RESULTS AND DISCUSSION

3.1. GamaDet

GamaDet is an integrated device that can record, store, and process bird sound data and display forest quality index. The GamaDet is designed based on a microcontroller connected to a microphone to record forest sounds. GamaDet is equipped with a tripod to increase portability so that measuring points in the forest can be easily reached. In terms of connectivity, GamaDet is fitted with a wifi network to simply access the user interface by connecting the user’s device (laptop or smartphone) to GamaDet’s IP address.

GamaDet starts to work by recording environmental sounds from a certain point of view through a microphone. The recordings are stored in a secure digital (SD) card for further processing. The microprocessor will process the recording through a trained machine learning model when the recording is complete. The recordings are converted into a mel-spectrogram used by the model to identify forest quality and bird sounds. If the identification probability of a bird’s voice exceeds a specific limit, the identification result will be stored on the user’s computer. The analysis results are sent to the user’s computer via a wifi network. In the analysis results, both forest quality bioacoustic parameters and bird species are visualized on the user’s screen.

3.2. GamaNet software

We also proposed GamaNet's digital product based on Jupyter notebook, which can be accessed online on a cloud computing engine. Sound data recorded in the forest environment is used as the input. Then, a dashboard of forest quality index and detected bird species are displayed. The user interface of GamaNet is shown in Figure 4. GamaNet was created to make the tool more flexible to record other standard-compliant devices.

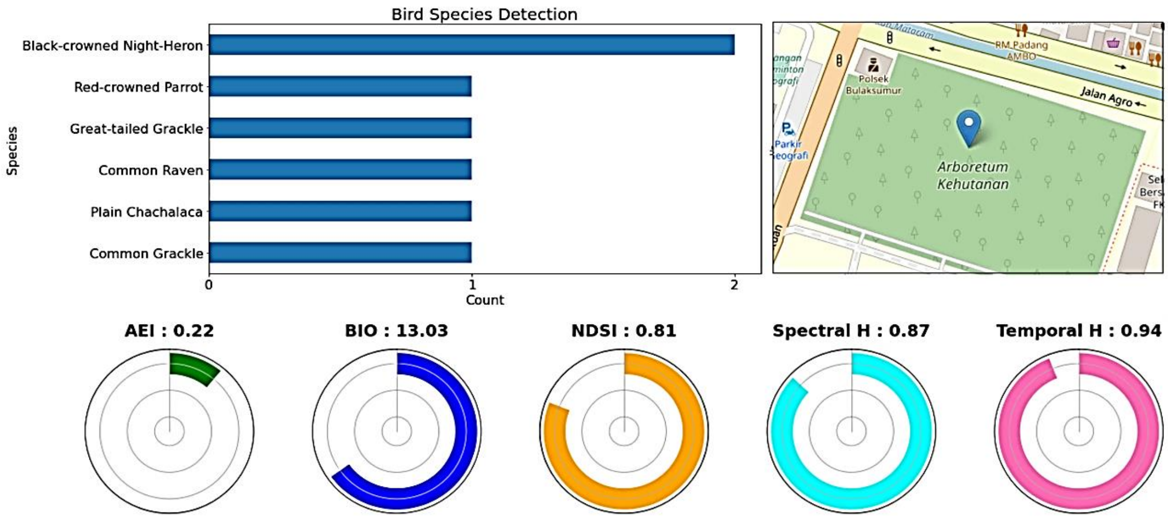

Figure 4. The user interface of GamaNet

To use GamaNet, users need to prepare audio data recorded in the forest environment as input. GamaNet processes the audio recording based on the model that has been created. The model's output is a comma-separated values (CSV) file that can be visualized easily. The processing results are displayed on the dashboard containing the forest quality index and the detected bird species.

Data processing tools were tested using audio-recorded data from the forest arboretum, Faculty of Forestry, UGM, in October every hour for 60 seconds from 07:00 to 17:00. The test results show that GamaDet processes the 60 seconds recording data for 370 seconds to produce a forest quality index output. The results of the web version of GamaNet testing take a shorter time, i.e., only 70 seconds, to create the work in the form of a forest quality index. GamaNet can process data faster because GamaNet uses Google Collaboratory as a data processing server where the computational performance is faster than using the Nvidia Jetson Nano.

The test of data processing sub-system used recorded audio data from the arboretum of the Faculty of Forestry UGM. The test results show that the recording has a time of 60 seconds when processed by GamaDet for 370 seconds to produce an output in the forest quality index. Meanwhile, the results of testing and processing using the GamaNet with the same data show the same results but need a shorter time. GamaNet needs only 70 seconds to produce the forest quality index.

We conducted two data analyses, namely bioacoustic indices and sound analysis for bird identification. Figure 5 shows the bioacoustics indices and sound analysis results at the UGM arboretum. Figures 5(a) and 5(b) offer the AEI in a range of 0.142-0.531 and the BIO of the sound data [20], [30]. The system detected several animal/biophony sounds from 5.083 to 9.996. BIO can also indicate dawn and dusk singing times. H index can predict an animal's appearance with a specific schedule. Figure 5(c) shows the H index and suggests that animals in the ecosystem do not have a particular schedule of appearances. An H index value above 0.5 indicates the occurrence of several animals quite often. Figure 5(d) shows the NDSI in a range of -0.610 to 0.207. A zero NDSI means that biophony has a value proportional to anthrophony. A negative NDSI indicates that biophony has a lower value than anthrophony. Overall, the arboretum has a diverse frequency of bird sounds. The bird identification is conducted based on the bird sounds recorded on the device. The device detected thirty-four bird sounds. This identification method has been successful and appropriate in identifying bird sounds.

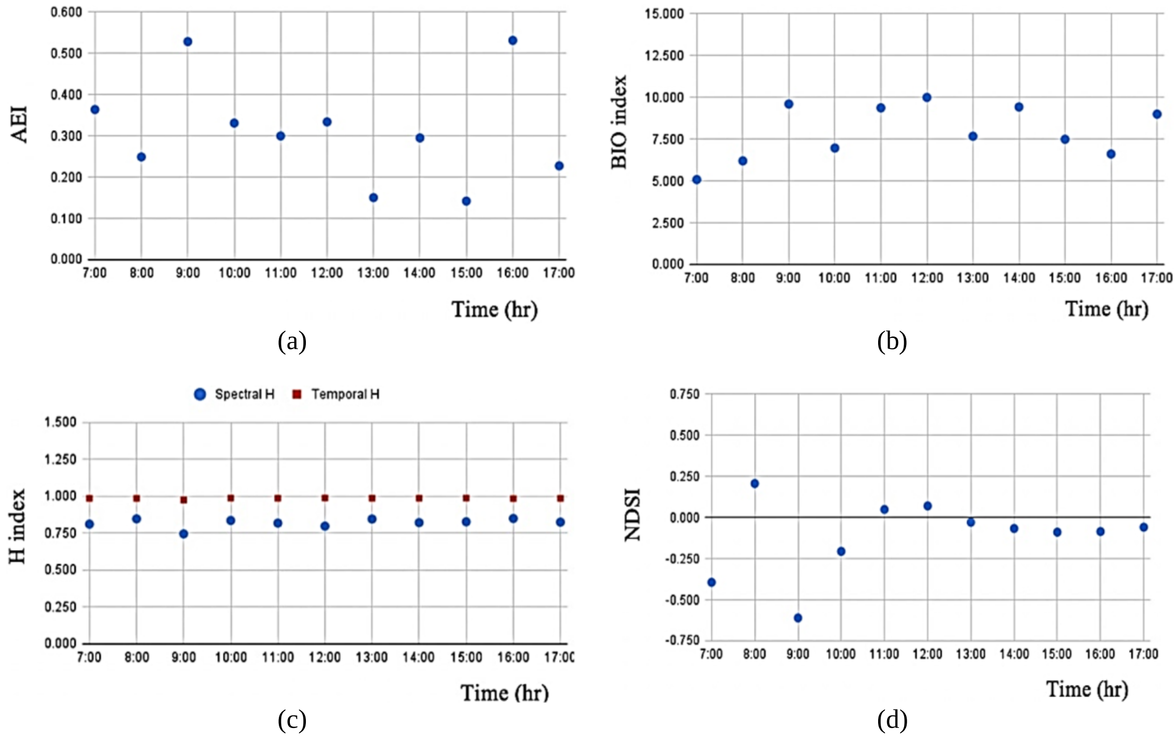

Figure 5. The results of (a) AEI, (b) BIO, (c) H index, and (d) NDSI measurement at UGM arboretum

4. CONCLUSION

We successfully design a tropical forest quality assessment tool by recognizing the sound of birds in the forest. This tool consists of GamaDet and GamaNet. GamaDet is designed based on Nvidia Jetson Nano to acquire and record the forest environment's sound, identify bird sounds, and assess forest quality index. The system needs 370 seconds to process the data with 60 seconds of audio data. Meanwhile, GamaNet is based on Google Collaboratory, succeeded in identifying bird sounds and assessing the quality of the audio recording provided with a processing time of 70 seconds on 60 seconds of audio data.

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