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Advanced Frog Call Collection and Species Identification using Lightweight Acoustic Equipment and EfficientNet AI Model[1)]

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ABSTRACT

Accurate and efficient frog monitoring is essential. We have introduced a cutting-edge platform equipped with the latest hardware and software. Traditional recording tools are often expensive, heavy (over 1kg), and bulky, but our new device is a game changer. It weighs less than 400g, runs for over 450 hours, and features wireless data transfer. Its recording quality is exceptional, capturing even ultrasonic waves above 700kHz.

Using the EfficientNet AI model, we've developed a system that can automatically identify frog species based on their calls. We collected frog call data over two years from various regions, ensuring our model learned the nuances of different frog sounds. An added noise reduction feature enhances accuracy.

1) 경량 음향장비와 EfficientNet AI 모델을 이용한 첨단 개구리 울음소리 수집 및 종 식별

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Our system successfully identified 91.50% of approximately 20 Korean frog species by their calls. As more frog calls are input, the system's automatic recognition will improve. Our lightweight device, combined with our high-precision AI model, promises significant advancements in global biodiversity monitoring, addressing many of the limitations of traditional research methods.

Key words: Bioacoustic Analysis, Frog Monitoring Technology, Citizen Science in Herpetology, Ecological Surveys, EfficientNet AI Model

Ⅰ. INTRODUCTION

Frog monitoring is crucial for assessing biodiversity, evaluating environmental health, and identifying sensitive species. It aids in conservation awareness and research on frog populations (Xie et al., 2018). However, traditional frog monitoring methods face challenges such as high hardware costs, significant weight, large size, and limited sound quality, which impede data collection and efficiency (Huang et al., 2009). Additionally, classifying frog species by vocalizations requires specialized knowledge, adding complexity to the process (Xie et al., 2018).

1. Ecological Surveys and Technological Advances

Ecological surveys are vital for understanding frog distribution and ecosystem changes. Advances in machine learning and bioacoustics have improved frog species classification through vocalizations, offering more accurate data collection (Xie et al., 2018; Stowell, 2023).

2. Traditional vs. Modern Classification Methods

Traditional frog classification methods, such as point counts and transect surveys, are labor-intensive and require expert knowledge. In contrast, modern machine learning techniques automate and enhance classification accuracy. Studies have demonstrated the effectiveness of machine learning approaches, such as convolutional neural networks, in frog sound classification (Xie, 2018; Huang et al., 2009; Alabi, 2021).

3. Citizen Science in Frog Monitoring

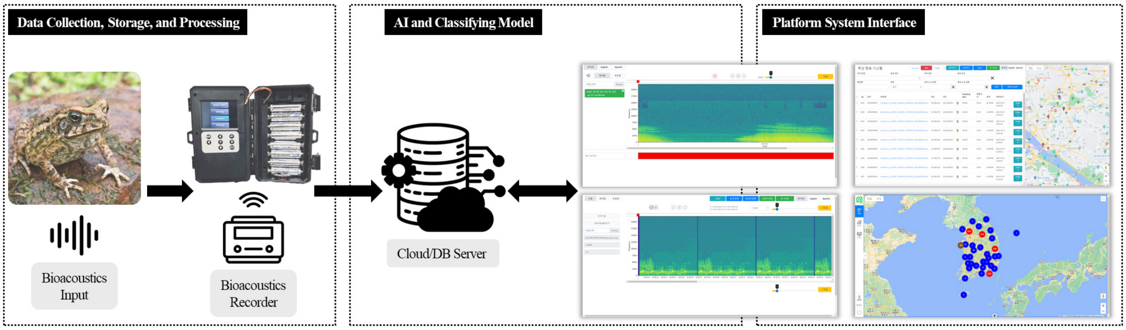
Citizen science plays a significant role in frog monitoring but faces challenges in volunteer recruitment and data quality (Klingbeil & Willig, 2015). Training can improve participant skills and data accuracy (Farr et al., 2023; Gorleri et al., 2023). Innovative approaches, such as combining citizen science data with remote sensing, have been proposed for species distribution modelling (Teng et al., 2023; Squires et al., 2021).

4. Research Aims and Objectives

Citizen science plays a significant role in frog monitoring but faces challenges in volunteer recruitment and data quality (Cruickshank et al., 2019; Callaghan et al., 2020). Training can improve participant skills and data accuracy (Cruickshank et al., 2019). Innovative approaches, such as combining citizen science data with remote sensing, have been proposed for species distribution modelling (Garrido-Priego et al., 2023; Teng et al., 2023).

II. MATERIALS AND METHODS

1. Linnaeus AI-Integrated Frog Call Classification Platform Overview



⟨Fig. 1⟩ Overview of the Linnaeus AI frog call classification platform, encompassing three main sections: Data collection, storage, and processing; AI and classifying model; and platform system interface.

The Linnaeus platform provides a state-of-the-art solution for identifying and classifying frog calls using artificial intelligence to process bioacoustic data. It captures bioacoustic inputs through advanced recorders, stores this data in cloud servers, and analyzes it with AI models to accurately identify frog species. The resulting data is accessible for in-depth herpetological study and taxonomy research via a user-friendly web and mobile interface.

2. Data Collection, Storage, and Processing

In the data collection phase, Shinhwa Engineering's bioacoustic recorders capture anuran sounds in high fidelity. These lightweight and resilient devices ensure reliable operation across diverse environmental conditions. Data is transmitted wirelessly to cloud servers, providing a secure and scalable data management solution.

3. Bioacoustic Recorder

The bioacoustic recorders developed by Shinhwa Engineering capture frog sounds in various environments. Their design is depicted in Fig. 2., highlighting their compactness and robust features such as IP54 rating, high-frequency recording capabilities, and long operational times. They are equipped with GPS and wireless transmission to send bioacoustic inputs to cloud servers.

〈Fig. 2〉 Shinhwa Engineering's bioacoustic recording device used for frog species monitoring.

〈Table 1〉 Specifications of the monitoring device, highlighting key features under three categories: Physical & build, power & operation, and audio & recording

PHYSICAL & BUILD		POWER & OPERATION		AUDIO & RECORDING	
SIZE	L 145mm × W 95mm × H 75mm	POWER	AA × 8 or external power	ULTRASOUND	up to 768KHz
WEIGHT	400g (sans battery)	SOLAR POWER	solar panel option with battery pack	MICROPHONE	captures bat sounds (ultrasonic sound)
DUST & WATER	IP54 rating	WIRELESS REMOTE	cellular-based wireless	FILE FORMAT	wav
RESISTANCE		TRANSMISSION	remote transmission		
SWITCH	8 key placement & normal operation	GPS	built-in	SPEAKER	1 – 2 watt output
LCD	2“ full color	OPERATING TEMPERATURE	-20℃ to 70℃	CONTINUOUS OPERATING TIME	450 hours (at 24KHz)
		OPERATING HUMIDITY	5% to 95%	OPERATING TIME SETTING	manual & wireless setting

4. Bioacoustic Input

Frog sounds, or bioacoustic inputs, are fundamental data for this platform. Their properties like amplitude, frequency, and timbre are crucial for classification. The amplitude represents the loudness of the sound, frequency pertains to the pitch, and timbre is the quality that makes the sound unique to each species. By analyzing these properties, the platform can distinguish between different frog species with high accuracy.

5. Data Cloud Servers

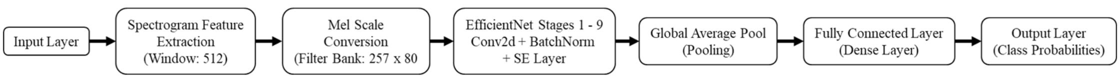
Primary cloud servers initially receive and organize recordings, attach metadata and perform preliminary preprocessing tasks. These servers are equipped with high-performance CPUs and GPUs to handle intensive processing, including applying the Fourier transform and running the EfficientNet-based AI model for species classification. The system ensures data security through encryption and compliance with protection regulations, while also offering scalability to accommodate increasing data volumes. Researchers access the data via a user-friendly interface, enabling efficient retrieval, analysis, and collaboration, thus enhancing the platform's effectiveness in frog species classification and biodiversity monitoring.

6. AI Classifying Model Section (Fig. 3)

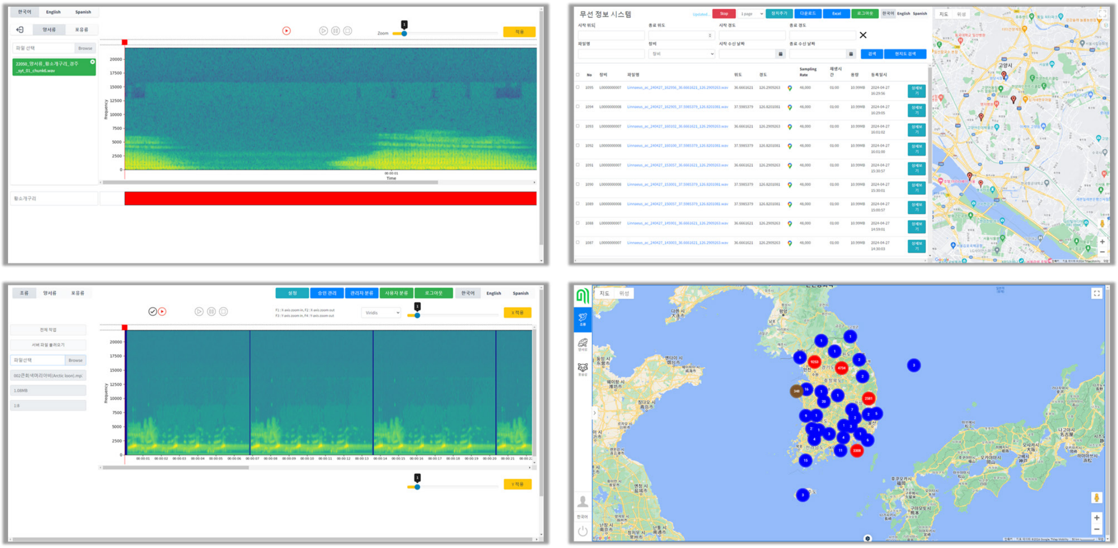
The AI model uses the EfficientNet architecture within the PyTorch framework, optimized for audio signal processing. It employs reflective padding, convolutional processes, and squeeze-and-excitation (SE) mechanisms to analyze and classify frog calls.

7. Platform System Interface Section (Fig. 4)

The Platform System Interface integrates the Species Identification System and the Monitoring & Wireless Information System into a sophisticated web-based application for frog monitoring. Featuring an AI classifier model utilizing the EfficientNet architecture, it processes audio files stored in the cloud database to accurately identify frog species in each recording, updating results in real-time on a user-friendly interface. This interface caters to both expert herpetologists and casual users, providing easy access to data and insights. Complementing this is the Sound Label System, which allows manual



〈Fig. 3〉 Architecture of the AI classifying model, showcasing the flow from raw audio input through spectrogram conversion and EfficientNet layers to the final species classification output.



〈Fig. 4〉 Components of the Platform System Interface, including audio spectrogram analysis, real-time device tracking, and geographical distribution mapping of frog species.

interaction with audio data for ongoing AI model training and refinement. Users can manually classify, label, and edit sound files, feeding back into the AI model to enhance its accuracy. Additionally, the Monitoring Information System enhances understanding of frog population dynamics and habitat use by integrating data from various sources, visualizing species distribution and movements through advanced tools. The Wireless Information System manages the operational aspects of bioacoustic and wildlife camera recorders, monitoring real-time location, device status, and generating alerts for maintenance, ensuring efficient functionality and minimal downtime of the monitoring equipment.

Ⅲ. RESULTS

This study evaluates the effectiveness of a deep neural network in automatically identifying 20 common frog species based on their vocalizations, using over 19 hours, 15 minutes, and 46 seconds of recorded frog calls. The model achieved an average accuracy of 91.50%, with the highest accuracy for *Xenopus laevis* (98.60%). It performed

〈Table 2〉 Accuracy of species identification for different frog species by the deep neural network model, shown in descending order of accuracy in (%)

SPECIES NAME	KOREAN NAME	ACCURACY (%)	SPECIES NAME	KOREAN NAME	ACCURACY (%)
Xenopus laevis	아프리카발톱개구리	98.60	*Rana coreana*	한국산개구리	91.54
Rhinella marinus	사탕수수두꺼비	96.60	*Fejervarya kawamurai*	히로시마늪개구리	91.24
Bufo japonicus formosus	동일본두꺼비	95.56	*Anaxyrus cognatus*	대평원두꺼비	89.76
Rana catesbeiana	황소개구리	93.80	*Epidalea calamita*	서유럽황갈색두꺼비	89.32
Pelophylax nigromaculata	참개구리	93.57	*Bufo japonicus japonicus*	서일본두꺼비	88.99
Duttaphrynus melanostictus	아시아검은안경두꺼비	93.23	*Anaxyrus punctatus*	붉은점박이두꺼비	88.87
Rana pipiens	북방표범개구리	93.23	*Bufo gargarizans*	두꺼비	87.00
Pelophylax chosenicus	금개구리	92.73	*Rana japonica*	일본산개구리	86.98
Hoplobatrachus tigerinus	인도황소개구리	92.50	*Rana lessonae*	유럽연못개구리	86.75
Pelophylax porosus	다루마개구리	92.10	*Rana grylio*	돼지개구리	86.66

well even for complex species, though the lowest accuracy was 86.66% for *Rana grylio*. Overall, the results confirm the model's capability for precise frog species identification from vocalizations, suggesting its suitability for bioacoustic monitoring systems, with potential for further refinement.

Ⅳ. DISCUSSION

The gap between anuran conservation research and its practical application, and how translational ecology can bridge this gap through collaboration among ecologists, stakeholders, and conservation managers. Frogs are ideal subjects for this approach due to their wide distribution, extensive research, and the need for coordinated conservation efforts. Technological advancements, particularly in satellite telemetry, have revolutionized our understanding of anuran migration, aiding conservation efforts against threats like habitat degradation.

Artificial intelligence, especially EfficientNet-based models, has enabled the automated classification of frog species from their vocalizations, achieving about 91.50% accuracy for 20 Korean frog species. Additionally, the development of a new, affordable, and efficient frog monitoring platform marks a significant advancement in biodiversity surveillance. These technological innovations, combined with collaborative conservation efforts, promise to enhance our understanding of biodiversity and support effective conservation strategies.

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