First Year Report on Research of image-based automatic pig pregnancy judgment and abnormal behavior detection technology(3)

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Ⅰ. Introduction

□ Within the domain of smart farming, a crucial aspect is the monitoring and management of livestock, particularly pigs. Monitoring pig's health by human is challenging and time-consuming task.

□ The sounds produced by pigs are rich source of information about their well-being, health, and environmental conditions. The classification of these vocalizations has emerged as a pertinent challenge in pursuing precision livestock farming.

□ The ability to distinguish between various vocalizations can provide valuable information, such as detecting signs of distress, assessing reproductive behaviors, and monitoring overall herd health.

□ This research arms to identify pig's health based on their vocalization using deep learning model. The pig vocalization classification problem involves identifying and interpreting different vocal signals emitted by pigs, aiming to extract meaningful insights about their physiological and behavioral states.

Ⅱ. Materials and Methods

□ Dataset Collection and Preparation

○ The experimental data were collected from April to August 2023 at three domestic pig farms in Wanju, Jeongeup, and Gimje, South Korea. Another pig farm in Iksan will be collected from January 2024 when a recording device is installed.

○ The experimental recording equipment was a microphone model PLCM-Q5 noise reduction, frequency range 20Hz~20Khz, and recorder device Raspberry Pi 4, model B Rev 1.5.

○ The microphone device is installed inside the pig pen at a height of 150 centimeters from the ground, and the recorder device is installed at the wall of the pig house.

○ The sound data was collected by recording the device 24 hours a day continuously at sample 44.1 Khz for one-channel audio and stored in .wav format in the device. A dataset of 4,000 audio files (2,000 vocalizations and 2,000 non-vocalizations), each with a duration of three-second intervals, was gathered from each pig farm.

◯ The collected pig sounds were classified by manual making through consultation with an advisor in the smart farm laboratory at the livestock environmental division.

Figure 1. Microphone device

Figure 2. Recorder device

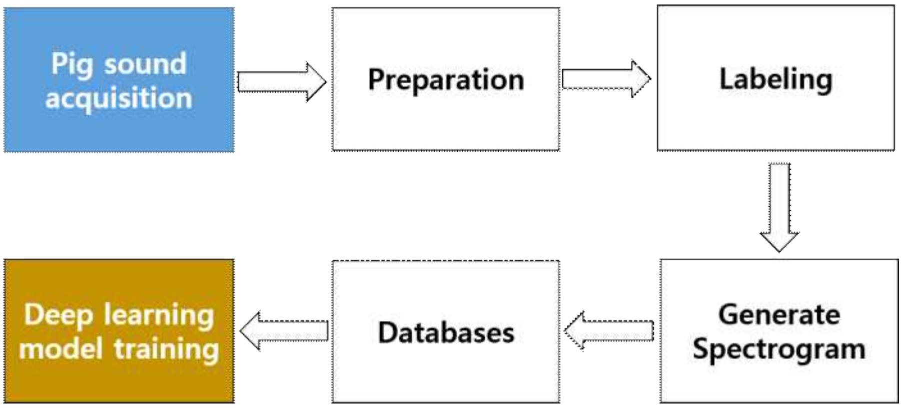


Figure 3. General structure diagram of pig vocalization classification method

Table 1. This table shows the amount of data samples in each pig farm.

Farm Location	Amount of Dataset	Vocalization	Non-vocalization
Wanju	4,000	2,000	2,000
Gimje	4,000	2,000	2,000
Jeongeup	4,000	2,000	2,000

☐ Feature Extracting Methods

◯ The audio classification task is assigned to predefined labels to audio data segments and has witnessed significant advancements in integrating deep learning models.

◯ A feature extraction step is required to facilitate the deep learning model's understanding of audio signals. Feature extraction is a crucial step in audio classification, as it involves the transformation of raw audio signals into a set of relevant and discrimination features that can be used as input for machine learning models.

- ◯ This research explores the application of a deep learning model for audio classification. The following feature extraction methods are employed:
  - Mel-spectrogram: this method visually represents the spectrum of frequencies over time. It is derived from the mel-frequency scale.
  - MFCC (Mel-Frequency Cepstral Coefficients): this method captures the characteristics of the audio signal. By representing the power spectrum in a manner inspired by the human auditory system, MFCCs are particularly effective for pig vocal classification tasks.
  - Chroma: this method highlights energy distribution in different pitch classes, enabling the model to recognize tonal patterns in the audio.
  - Tonnetz (Tonal Centroids Features): this method captures the tonal characteristic of audio signals by representing musical harmony and tonal relationships. This feature extraction method is particularly useful for harmonic analysis of pig vocalization.
  - Mixed-MMCT: this method is to improve pig vocalization classification accuracy by integrating Mel-spectrogram, MFCC, Chroma, and Tonnetz features.

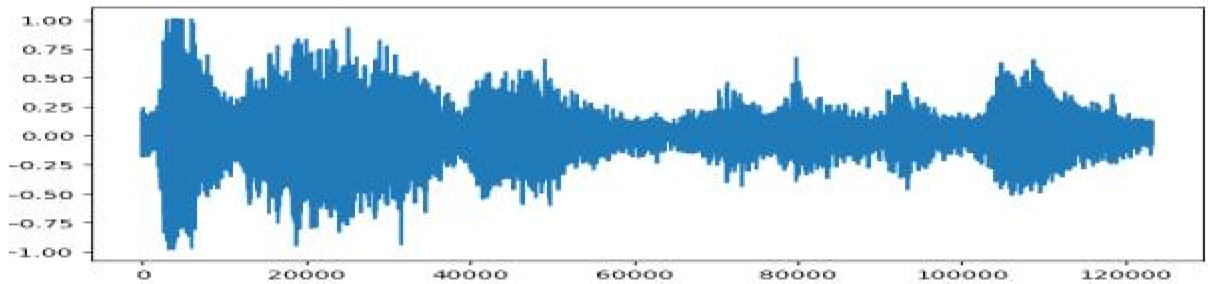


Figure 4. Waveform of pig vocalization

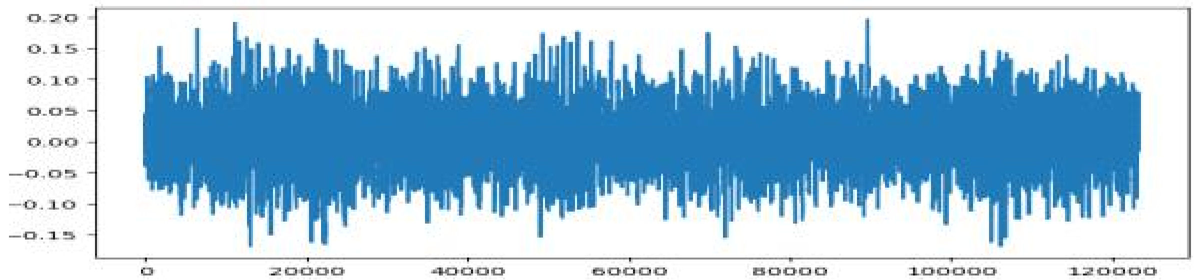


Figure 5. Waveform of pig non-vocalization

◯ In Figure 4, the pig vocalization waveform typically has discernible peaks and valleys corresponding to the individual phonemes, syllables, or notes produced during pig sound.

◯ In Figure 5, the pig non-vocalization waveform does not have as many discernible peaks and valleys as a vocalization waveform.

◯ It is important to note that while these general differences exist, there is a wide range of vocalization and non-vocalization sounds with varying characteristics. Additionally, the context and specific characteristics of the sound source can influence the appearance of the waveform.

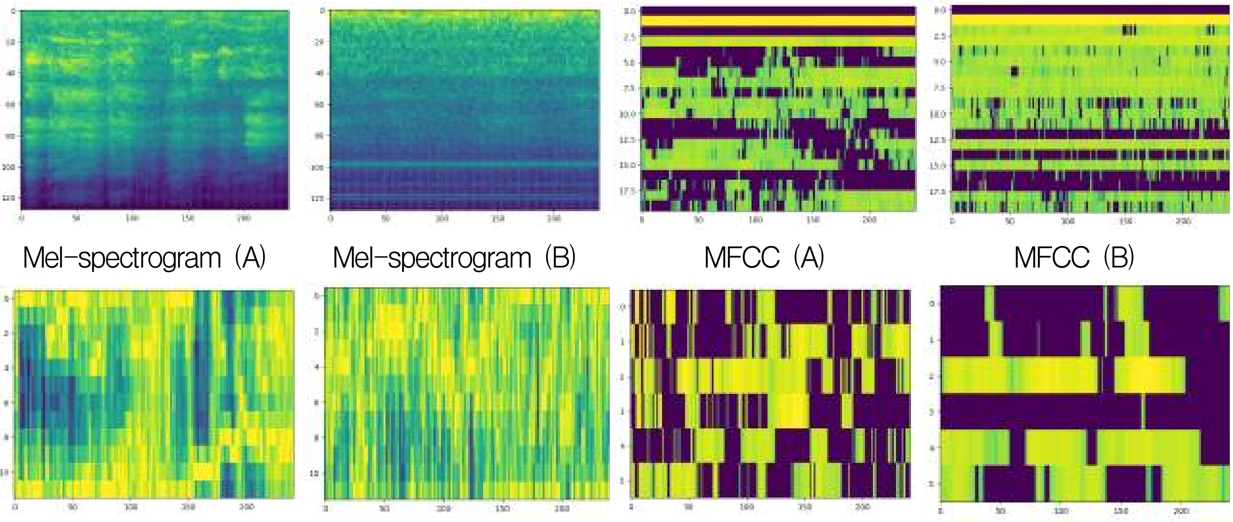


Figure 6. visualizes the feature extraction method. A and B represent the pig vocalization and non-vocalization, respectively.

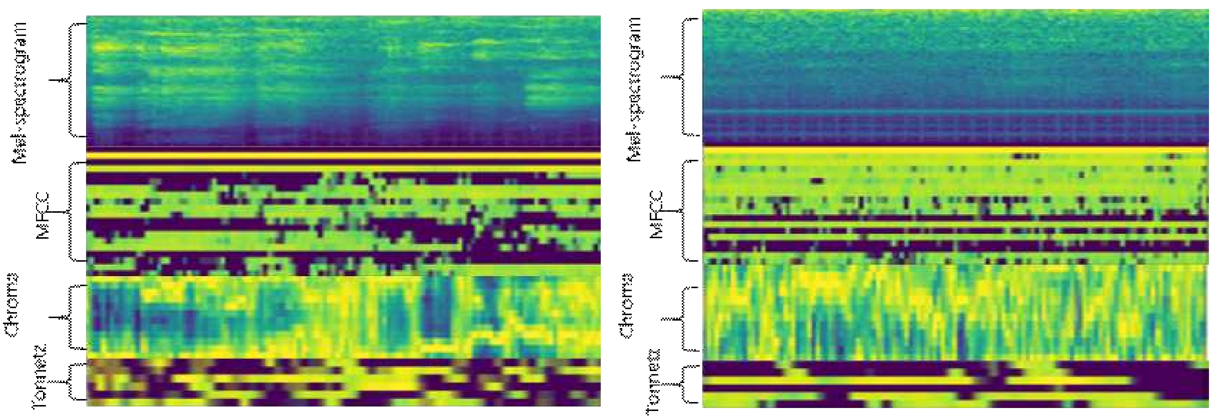


Figure 7. visualizes the proposed Mixed-MMCT feature extraction method.. A and B represent the pig vocalization and not vocalization, respectively.

□ Network Architecture

○ Figure 8 shows the overall of the network architecture diagram. The proposed network used a dataset produced from the feature extraction process with the size 166x130x1 (height, width, channel) as the input.

○ The network backbone architecture consists of three main convolutional layer blocks. The size of the feature maps in the first, second, and third are 166x130x16, 83x65x32, and 41x32x64 with max-pooling size 2x2 and kernel size 5x5, respectively.

○ The network calculates until the last convolutional block and the flattened and dense layer are applied to obtain 1,000 features. Then, the SoftMax function proceeds and contributes to the binary cross-entropy loss.

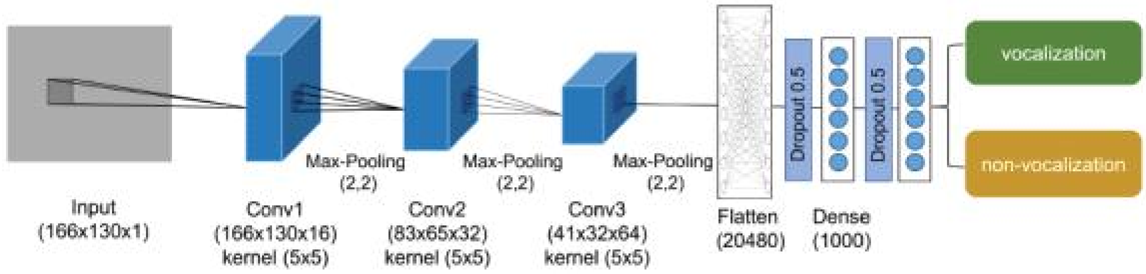


Figure 8. The overall structure of the proposed network architecture.

□ Evaluation Metrics

○ To assess the proposed method, four evaluation parameters, accuracy, precisio, recall, f1-score and confusion a matrix are adopted.

- Accuracy: the accuracy is an intuitive performance measure defined to describe the accuracy of the algorithm for pig vocal classification. It represents the ratio of the correctly predicted sample to the total sample, which can be computed as shown in Equation (1).

$$Accuracy = (TP + TN)/(TP + TN + FP + FN) \tag{1}$$

where TP, TN, FP, and FN are true positive, true negative, false positive, and false negative, respectively.

- Precision: precision is a metric that determines the number of accurate positive predictions. It is calculated as the ratio of correctly predicted positive samples divided by the predicted number of positive samples. Precision can be computed as defined in Equation (2).

$$Precision = TP/(TP + FP) \tag{2}$$

- Recall: The recall is a metric that measures the number of correct positive predictions made from positive predictions that could have been made. This is the opposite of precision, which only considers correct positive predictions out of all positive predictions. Recall can be computed as defined in Equation (3).

$$Recall = TP/(TP + FN) \tag{3}$$

- F1-score: the f1-score allows precisions and recalls to be combined into a single measure that captures both properties. It can express high precision with poor recall or, alternately, terrible precision with perfect recall. The f1-score can be computed as defined in Equation (4).

$$F1 - score = 2 \times (Precision \times Recall)/(Precision + Recall) \tag{4}$$

- Confusion matrix: It represents the accuracy of a classification model and displays the number of true positives, true negatives, false positives, and false negatives. This matrix aids in analyzing model performance, identifying misclassifications, and improving predictive accuracy. A confusion matrix is an NxN matrix used for evaluating the performance of a classification model, where N is the total number of target classes. The dataset has two classes, so the confusion matrix has a 2 x 2 matrix.

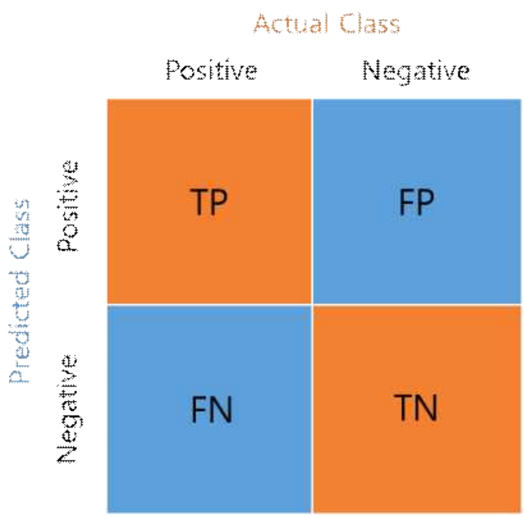


Figure 9. Confusion matrix

□ Experimental setup

○ Initially, the dataset was separated into training, validation, and test sets(Table 2).

○ Dropout is used to help avoid over-fitting and obtain better generalization feature classification. In the experiment, the dropout parameter was set to 0.5.

○ All experiments in this work were implemented using Python programming language and Keras open-source deep learning library. The batch size was 32, and the model was trained on NVIDIA RTX 2080 GPUs. The overall model architecture was trained up to 100 epochs, and the learning rate was 0.001. Lastly, stochastic gradient descent (SGD) was used as the optimizer, and momentum and weight decay were set as 0.9 and 1 x 10-6, respectively.

Table 2. Summary of datasets used for model training, validation and testing in each pig farm.

Farm Location	Amount	Training	Validation	Testing	Classes
Wanju	4,000	2,560	640	800	2
Gimje	4,000	2,560	640	800	2
Jeongeup	4,000	2,560	640	800	2

Ⅲ. Experimental Results

□ This research study performed experiments on all three pig farm datasets (Wanju, Jeongeup, Gimje).

□ By conducting rigorous experimentation, implementing these feature extraction methods, and classifying using a deep learning network, the classification accuracies of Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC are shown in this section.

□ Furthermore, the K-fold cross-validation (K=5) technique was used to evaluate the predictive model performance.

□ Tables 3, 4, and 5 show the report's measurements of the performance of the model in terms of accuracy, precision, recall, and f1-score metrics of the pig farm dataset in Wanju.

○ The classification accuracies of Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC were 98.38%, 92.50%, 91.00%, 82.12%, and 98.88% with validation dataset, and 96.72%, 90.00%, 87.97%, 79.69%, and 97.97% with test dataset, respectively.

○ The average accuracy of 5-fold cross-validation on the Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC reached rates 96.68%, 91.65%, 87.87%, 80.09%, and 97.71%, respectively. Figure 10 shows the confusion matrix results.

Table 3. This table shows the validation results of pig farm dataset in Wanju.

Validation Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9838	0.9838	0.9838	0.9838
MFCC	0.9250	0.9323	0.9250	0.9286
Chroma	0.9100	0.9117	0.9100	0.9108
Tonnetz	0.8212	0.8216	0.8213	0.8214
Mixed-MMTC	0.9888	0.9888	0.9888	0.9888

Table 4. This table shows the test results of pig farm dataset in Wanju.

Test Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9672	0.9674	0.9672	0.9673
MFCC	0.9000	0.9084	0.9000	0.9041
Chroma	0.8797	0.8817	0.8797	0.8807
Tonnetz	0.7969	0.7970	0.7969	0.7969
Mixed-MMTC	0.9797	0.9798	0.9797	0.9798

Table 5. This table shows the average results of the 5-fold cross-validation on test dataset of pig farm dataset in Wanju.

5-fold average test accuracy (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9668	0.9670	0.9668	0.9669
MFCC	0.9165	0.9220	0.9165	0.9192
Chroma	0.8787	0.8794	0.8787	0.8791
Tonnetz	0.8009	0.8024	0.8009	0.8016
Mixed-MMTC	0.9771	0.9774	0.9771	0.9773

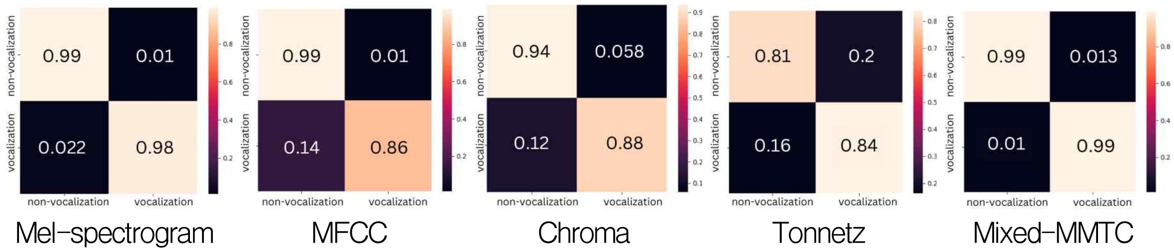


Figure 10. The confusion matrix results of each feature extraction method.

◯ Figure 10 shows the confusion matrix results, and Figure 11 illustrates the training, validation loss, and accuracy curves of the model. the training, validation loss, and accuracy curves of the model. The loss curve shows that the model is learning from data by trying to reach the minimum point, and the accuracy curve still slightly increases until the loss epoch.

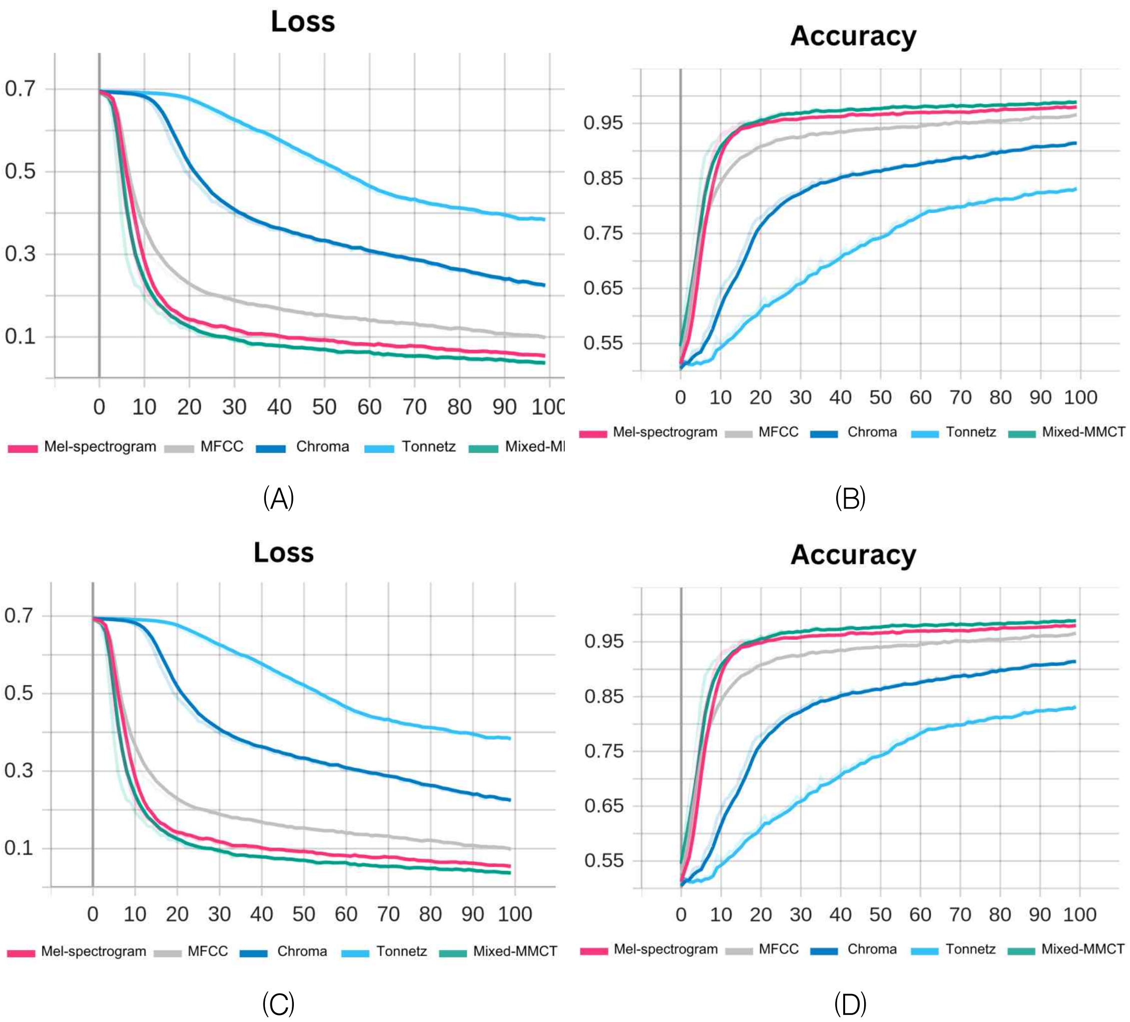


Figure 11. The training and validation curves. (A), (B) are training loss and accuracy curves. (C), (D) are validation loss and accuracy curves.

□ Tables 6, 7, and 8 show the report's measurements of the performance of the model in terms of accuracy, precision, recall, and f1-score metrics of the pig farm dataset in Jeongeup.

○ The classification using a deep learning network, the classification accuracies of Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC were 97.12%, 95.25%, 92.00%, 77.38%, and 98.00% with validation dataset, and 96.56%, 94.69%, 93.59%, 78.28%, and 97.66% with test dataset, respectively.

○ The average accuracy of 5-fold cross-validation on the Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC reached rates 95.81%, 94.84%, 91.53%, 78.06%, and 97.13%, respectively.

○ Figure 12 shows the confusion matrix results, and Figure 13 illustrates the model's training, validation loss, and accuracy curves. The loss curve shows that the model is learning from data by trying to reach the minimum point, and the accuracy curve still slightly increases.

Table 6. This table shows the validation results of pig farm dataset in Jeongeup.

Validation Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9712	0.9714	0.9712	0.9713
MFCC	0.9525	0.9525	0.9525	0.9525
Chroma	0.9200	0.9224	0.9200	0.9211
Tonnetz	0.7738	0.7776	0.7737	0.7756
Mixed-MMTC	0.9800	0.9804	0.9800	0.9802

Table 7. This table shows the test results of pig farm dataset in Jeongeup.

Test Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9656	0.9663	0.9656	0.9659
MFCC	0.9469	0.9469	0.9469	0.9469
Chroma	0.9359	0.9378	0.9359	0.9368
Tonnetz	0.7828	0.7885	0.7828	0.7856
Mixed-MMTC	0.9766	0.9771	0.9766	0.9768

Table 8. This table shows the average results of the 5-fold cross-validation on test dataset of pig farm dataset in Jeongeup.

5-fold average test accuracy (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9581	0.9592	0.9586	0.9589
MFCC	0.9484	0.9488	0.9484	0.9486
Chroma	0.9153	0.9168	0.9153	0.9160
Tonnetz	0.7806	0.7858	0.7806	0.7832
Mixed-MMTC	0.9713	0.9727	0.9722	0.9724

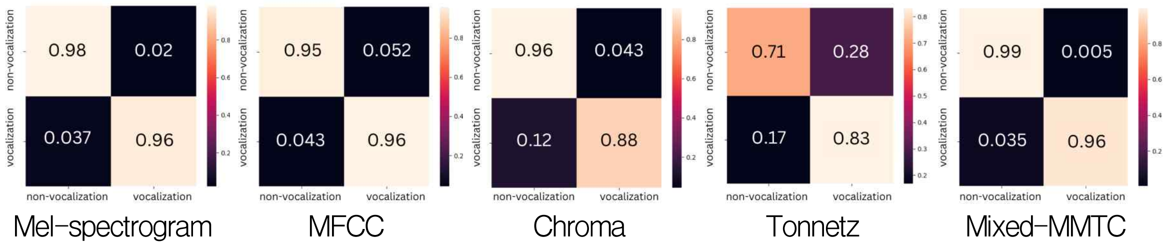


Figure 12. The confusion matrix results of each feature extraction method.

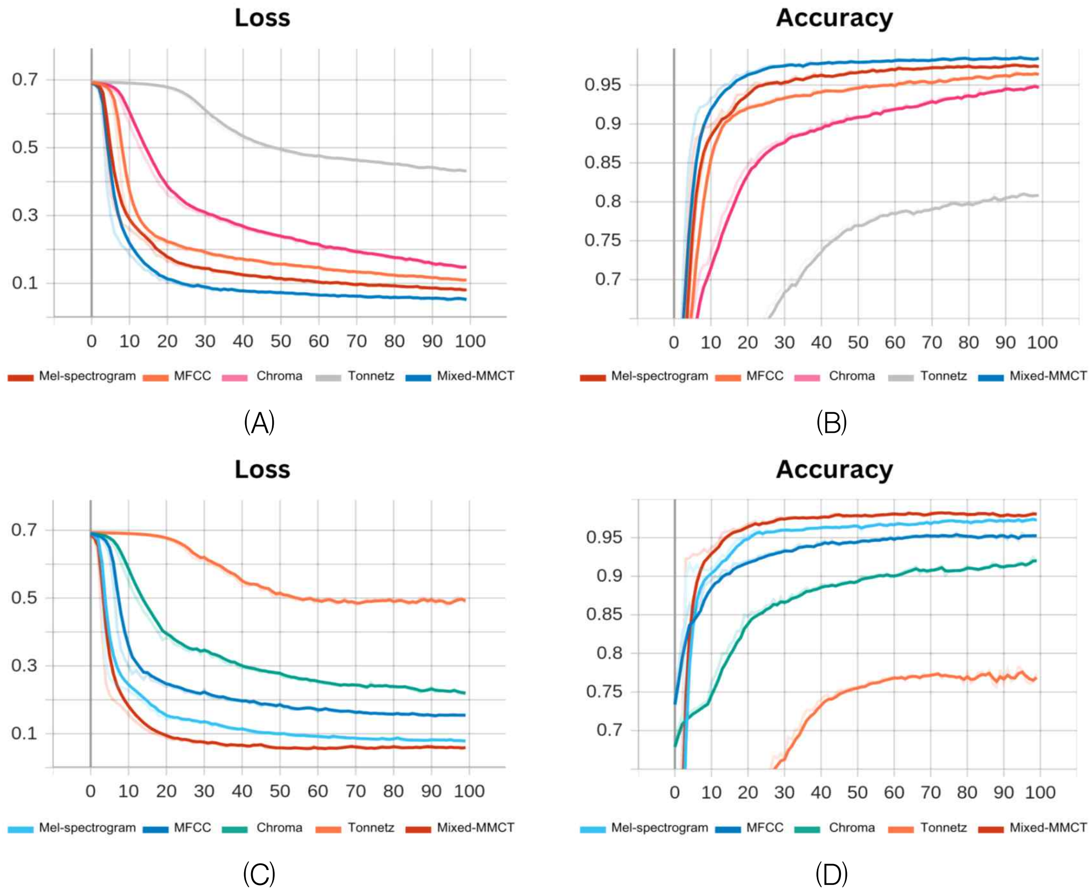


Figure 13. The training and validation curves. (A), (B) are training loss and accuracy curves. (C), (D) are validation loss and accuracy curves.

☐ Tables 9, 10, and 11 show the report's measurements of the performance of the model in terms of accuracy, precision, recall, and f1-score metrics of the pig farm dataset in Gimje.

○ The classifying using a deep learning network, the classification accuracies of Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC were 94.64%, 87.88%, 84.62%, 75.00%, and 96.50% with validation dataset, and 96.25%, 89.69%, 83.75%, 78.12%, and 97.97% with test dataset, respectively.

○ The average accuracy of 5-fold cross-validation on the Mel-spectrogram, MFCC, Chroma, Tonnetz, and Mixed-MMTC reached rates 95.96%, 90.53%, 83.22%, 76.81%, and 97.90%, respectively.

○ Figure 14 shows the confusion matrix results, and Figure 15 illustrates the model's training, validation loss, and accuracy curves. The loss curve shows that the model is learning from data by trying to reach the minimum point, and the accuracy curve still slightly increases until the loss epoch.

Table 9. This table shows the validation results of pig farm dataset in Gimje.

Validation Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9462	0.9466	0.9463	0.9464
MFCC	0.8788	0.8878	0.8787	0.8882
Chroma	0.8462	0.8524	0.8462	0.8492
Tonnetz	0.7500	0.7502	0.7500	0.7501
Mixed-MMTC	0.9650	0.9654	0.9650	0.9652

Table 10. This table shows the test results of pig farm dataset in Gimje.

Test Results (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9625	0.9625	0.9625	0.9625
MFCC	0.8969	0.9038	0.8969	0.9003
Chroma	0.8375	0.8414	0.8375	0.8394
Tonnetz	0.7812	0.7821	0.7812	0.7816
Mixed-MMTC	0.9797	0.9797	0.9797	0.9797

Table 11. This table shows the average results of the 5-fold cross-validation on test dataset of pig farm dataset in Gimje.

5-fold average test accuracy (%)				
Methods	Metrics			
	Accuracy	Precision	Recall	F1-score
Mel-spectrogram	0.9596	0.9598	0.9596	0.9597
MFCC	0.9053	0.9093	0.9053	0.9073
Chroma	0.8322	0.8350	0.8322	0.8336
Tonnetz	0.7681	0.7752	0.7681	0.7716
Mixed-MMTC	0.9790	0.9790	0.9790	0.9790

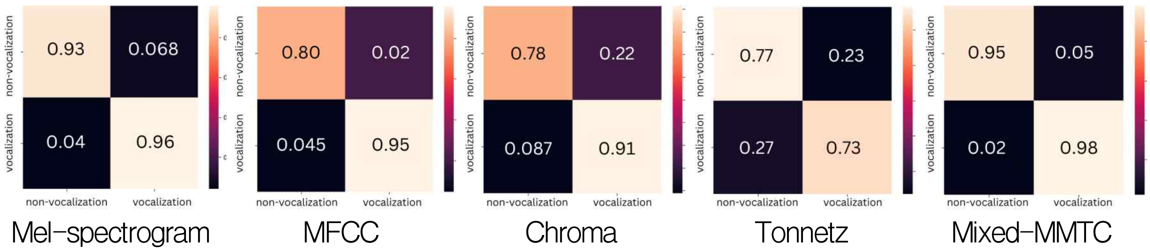


Figure 14. The confusion matrix results of each feature extraction method.

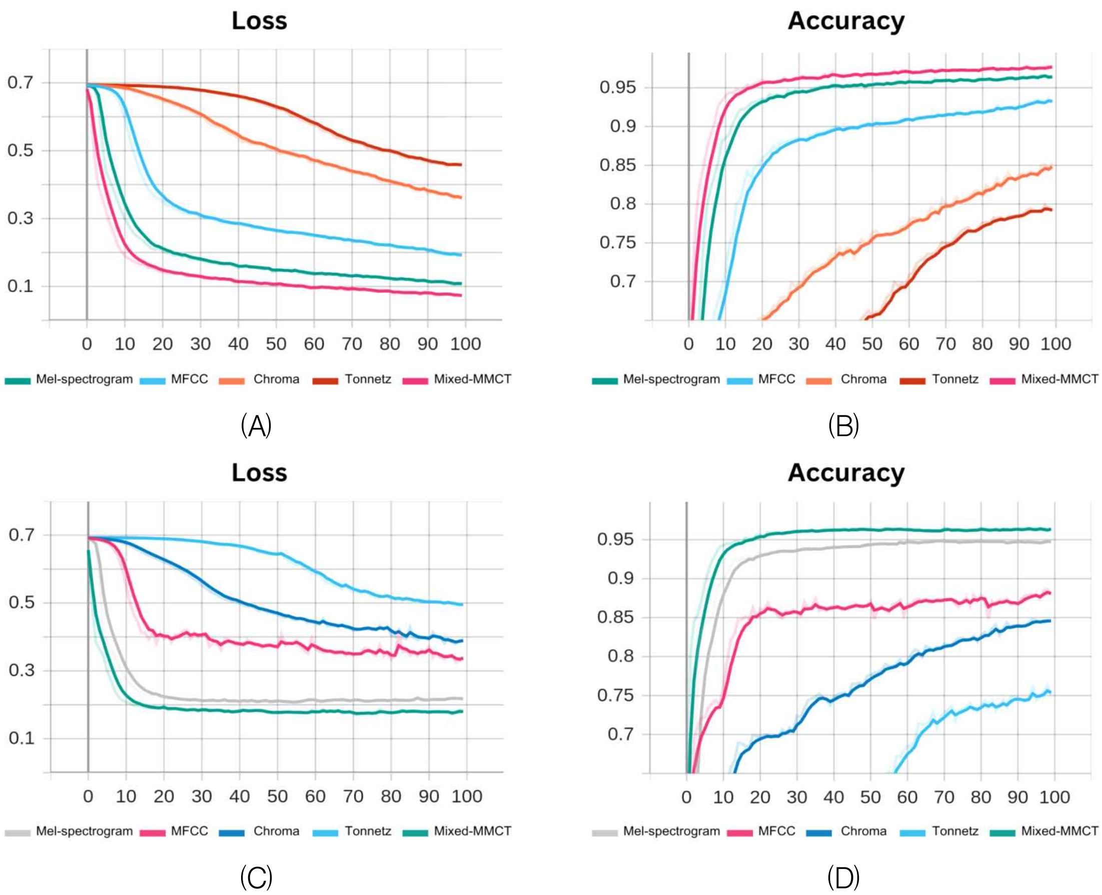


Figure 15. The training and validation curves. (A), (B) are training loss and accuracy curves. (C), (D) are validation loss and accuracy curves.

Ⅳ. Discussion

☐ Pig vocalization and non-vocalization classification problems are attracting research interest in machine learning and deep learning.

☐ The experimental results show the different performance in each feature extraction method. Chroma and Tonnetz methods perform poorly because of insufficient relevant features for the model. Mel-spectrogram and MFCC, however, achieve notable performance since these two methods provide rich information and relevant features for model learning.

☐ The proposed novel feature extraction method called Mixed-MMCT provides superior performance compared to others because integrating all feature methods together increases the reach of information and relevant features.

☐ The model can learn and discriminate features better than using feature extraction methods separately. All experimental results confirmed that the Mixed-MMCT feature extraction method outperforms other methods and improves pig vocalization classification.

Ⅴ. Conclusions and Future plan

☐ This research study presents various methods to solve the pig vocalization and non-vocalization classification problems using deep learning technology.

☐ Through the analysis of the experimental results, this study found that signal feature extraction methods play an important role in extracting features from audio to build an input dataset for a deep learning model.

☐ The various experiments, the following points summarize the findings of this research study:

○ The audio feature extraction method is important when working with deep learning model networks. It helps reduce the dimensionality of raw audio signal input data and the network's computational cost. In addition, it can extract the relevant features that improve the model generalization and provide the model with the most important information for the task at hand, such as identifying and recognizing pig vocalization and non-vocalization.

○ The comparable feature extraction methods and their advantages when using a deep learning network. According to the results, the Mel-spectrogram and MFCC perform better than Chroma and Tonnetz in this research dataset.

○ The proposed feature extraction method, Mixed-MMCT, improves the model performance of the pig vocalization classification. Since each feature extraction method has unique feature information, combining all features significantly increases the relevant features for model learning.

◯ Underscores the vital role of deep learning networks in advancing the field of smart livestock farming, with a specific focus on pig vocalization and non-vocalization classification.

☐ In the first year, the research study of pig vocalization and non-vocalization is conducted to improve the management and welfare of modern smart livestock farming. The following works are covered in the second-year research.

◯ Conduct more experiments to find the model robustness performance with all pig farms. This work will use each previous pre-trained model to test with other pig farm datasets. According to these experiments, the research will find the best methods and models to generalize for all pig farm environments..

◯ Label all pig vocalization types into four groups: grunt, squeal, scream, and cough.

◯ Improve the previous network architecture model or design a new one (if needed) to work with pig vocalization types of classification.

◯ Organize material and documentation in preparation for submitting a paper to the high-level journal.

VI. Recommendations

☐ Based on findings of this report, the following recommendations are made:

◯ Collecting and manually labeling pig vocalization types (grunt, squeal, scream, cough) are time-consuming tasks.

◯ Various pig sounds are in a pig farm, and some sounds are difficult to differentiate. To solve this problem and speed up the working flow, a person specializing in animal welfare, specifically pig feeding, who can understand the types of pig vocalization, is needed.

◯ Pig vocalization and non-vocalization research have a novelty that can be published in Korean academic journals or non-SCI, such as the Journal of the Korean Society of Agricultural Engineers or the Journal of the Korea Academia-Industrial.

◯ Using a currently designed model with pig vocalization types of classification tasks is a big challenge. A deeper network and attention mechanism techniques are recommended because deeper layers aid in extracting more abstract or higher-level features from the input data, and attention can be incorporated into a deep network model to focus on the most relevant parts of the audio input.

Research of image-based automatic pig pregnancy judgment and abnormal behavior detection technology(3)

□ 연구 배경

○ 양돈 농가의 규모가 점차 확대됨에 따라 돼지의 생산성 향상과 품질의 균일성 관리에 대한 필요성이 강조되고 있음

○ 비육돈의 호흡기질병은 양돈농가 생산성 저하의 주요 원인 중 하나이지만 인력을 통한 상시 모니터링은 불가능하기 때문에 호흡기질병의 조기발견이 어려워 지속적인 피해가 발생되고 있음

* 비육돈 주요사고 원인 : 호흡기질병(70%), 소화기질병(20%), 관절염·피부병(5%) 등

○ 따라서, 비육돈의 건강상태 모니터링을 위해 발성음 기반의 돼지 기침소리 수집 기술 개발과 수집된 데이터를 활용한 호흡기질병 발병 알림 기술이 필요함

□ 주요 연구성과

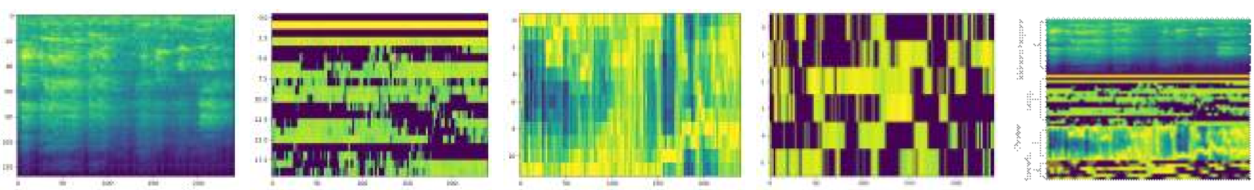
○ 국립축산과학원 내 환경조절돈사와 정읍시 및 김제시 소재 농장에서 소리수집 장치 설치 및 발성음 유/무 데이터세트 구축

농장 위치	데이터 수	음성 데이터 수	비음성 데이터 수
국립축산과학원	4,000	2,000	2,000
김제	4,000	2,000	2,000
정읍	4,000	2,000	2,000

<비육돈 발성음 데이터 세트>

○ 비육돈 발성음 분류를 위한 딥러닝 모델 개발

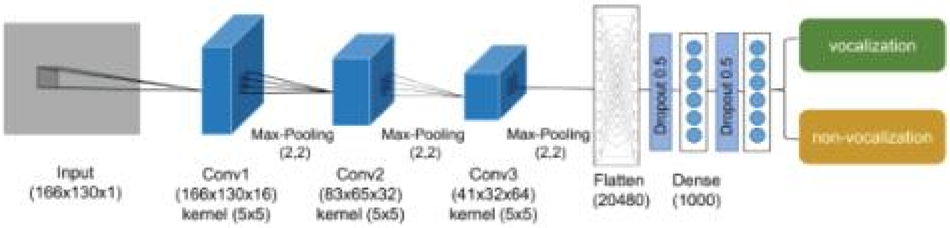
- Mel-spectorgam, MFCC, Chroma, Tonnetz을 이용한 발성음 데이터 특징 추출



Mel-spectrogram MFCC Chroma Tonnetz Mixed-MMTC

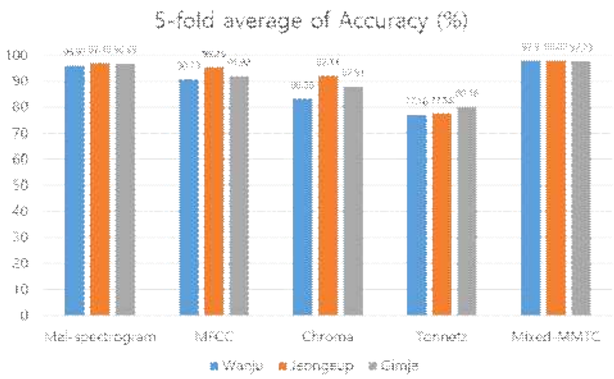
<발성음 데이터 특징 추출 결과>

- 발성음 특징 정보를 활용한 발성음 유/무 분류 딥러닝 모델 구축

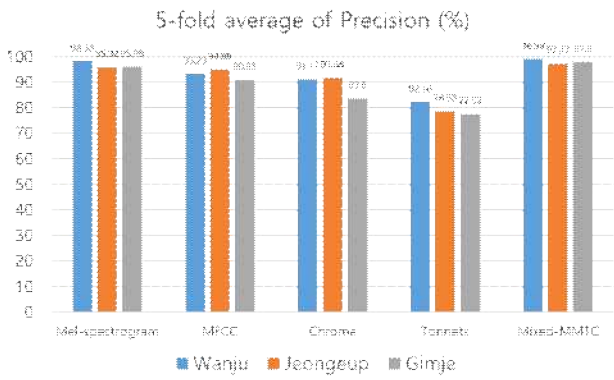


<발성음 분류 모델 구조>

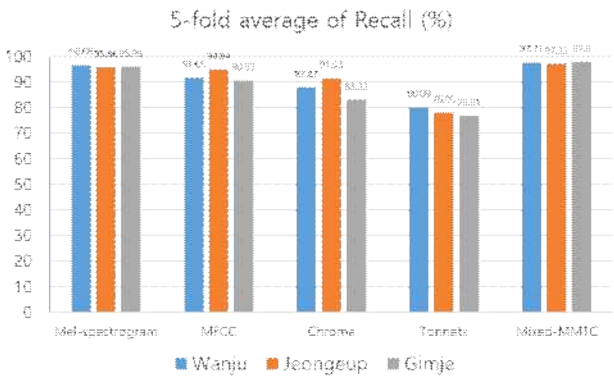
- 발성음 특징에 따른 발성음 유/무 분류 딥러닝 모델 성능 평가



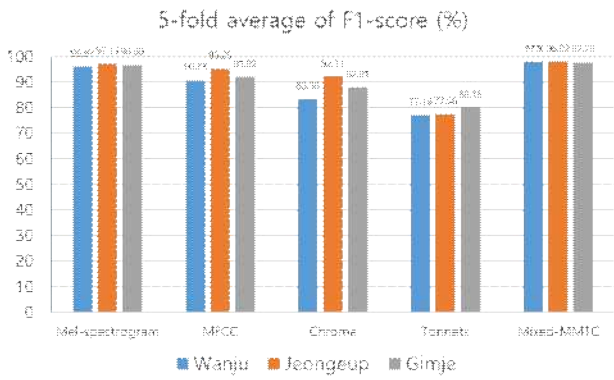
<Accuracy>



<Precision>



<Recall>



<F1-score>

☐ **파급효과**

○ 돈방 내 소리를 이용하여 돼지 발성음 유/무 모니터링 기반 마련

○ 향후 모델 고도화를 통한 돼지 기침소리 기반 호흡기질병 의심 조기알림에 대한 시스템이 농가에 보급될 수 있으며, 이를 바탕으로 육성·비육돈 정밀 관리가 가능할 것으로 기대

[별지 제12호 서식]

농촌진흥청 전문연구원 활용계획서

				분류번호 :	
석사후연구원	성 명	VANDET PANN	생년월일	1991.12.09	
	주 소	#101, 42-1, Geumam 6-gil, Deokjin-gu, Jeonju-si Jeollabuk-do			
연수책임자	성 명	김종복	소속	축산환경과	직급 / 농업연구관
연 수 기 간	2023. 3. 6 부터 2025. 12. 31 까지 (34 개월)				
연수과제명	디지털기반 돼지 임신여부 자동판정 및 이상행동 탐지 기술 연구(3공동)		참여형태	참여연구자	

<주요 연구분야>

○ 연수과제에 대한 연구목적, 범위 등 작성
- 비육돈 행동영상, 발서음 수집 및 인공지능 학습용 데이터 세트 구축
- 사료섭취행동, 활동량, 기침소리 모니터링 알고리즘 개발
- 행동영상, 발성음 정보 기반 이상개체 탐지 모델 개발

○ 연수과제 외에 참여과제에 대한 내용
- 2세대 가금 스마트 축산 모델 개발 및 실증
- 축사(양돈, 양계) 복합환경 센싱 및 국내 적합형 양돈·양계 표준 모델 개발

<활용계획>

○ (1년차) 비육돈 발성음 검출 알고리즘 개발 및 행동영상, 발성음 학습용 데이터 세트 구축

○ (2년차) 딥러닝 활용 비육돈 행동 및 기침소리 검출 알고리즘 개발

○ (3년차) 비육돈 행동 및 기침소리 검출 알고리즘 현장 적용 및 최적화

<연구성과 목표>

구분	논문게재		학술발표				정책자료 기관제출	영농기술·정보 기관제출	지식재산권	
	SCI	비SCI	구두		포스터					
			국제	국내	국제	국내			출원	등록
2023년(1년차)						1				
2024년(2년차)		1				1				
2025년(3년차)		1				1				
계		2				3				

2023 년 3 월 6 일

박사후연구원/석사후연구원 (인 또는 서명)

연수책임자 김종복 (인 또는 서명)

연수책임자 소속 부서장 유동조 (인 또는 서명)

1. 도출성과 건수

구분	평 가 사 항	번호
SCI급 논문	제1저자로서 SCI급 논문 게재승인	
	SCI급 공저자(교신저자 포함)	
학진등재 논문(KSCI)	제1저자로서 학진등재 논문 게재승인	
	비SCI급 공저자(교신저자 포함)	1
학술(구두)발표	제1저자로서 학술(구두)발표	
학술(포스터)발표	제1저자로서 학술(포스터)발표	2,3
정책자료 기관제출	주담당자로 정책자료 기관제출	
영농기술·정보 기관제출	주담당자로 영농기술·정보 기관제출	
산업재산권(특허)	출원 또는 등록(출원서 상 지분율이 있는 경우)	
저작권, 신지식재산권	출원 또는 등록(출원서 상 지분율이 있는 경우)	
전문서 등 저술활동	제1저자로서 전문서 발간	
	공동저자로서 전문서 발간	

2. 도출성과 세부내역

연번	구분	ATIS 적용년월	제 목	저널(학회)명	비고
1	논문 표준화된 영향력 지수(비SCIE)	2023.10.10	돈사 내 암모니아 농도가 육성·비육돈의 행동 변화에 미치는 영향	산학기술학회지	공저자
2	학술발표 (국내)	2023.07.26	Comparative Analysis of Audio Feature Extraction Methods for Pig Vocalization Classification using Deep Learning	한국축산학회	포스터 발표
3	학술발표 (국내)	2023.10.16	Improvement of Pig Vocal and Non-Vocal Classification in Smart Livestock Farming Using Deep Learning	한국축산학회	포스터 발표