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Grasshopper sound acoustic signal analysis using FFT and Butterworth filter

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ABSTRACT

Grasshoppers are among the most destructive agricultural pests, making early detection essential to reduce crop losses while limiting excessive pesticide use. Acoustic monitoring provides a non-invasive and environmentally friendly approach for pest detection; however, its effectiveness is often constrained by strong environmental noise in open-field conditions. This study proposes a structured acoustic signal analysis framework for grasshopper detection based on fast fourier transform (FFT) and Butterworth bandpass filtering. Grasshopper sound recordings were collected in rice field environments and pre-processed using Butterworth filters with empirically determined cutoff frequencies to suppress out-of-band noise. FFT was applied to extract dominant spectral features, and signal quality was evaluated using both direct signal-to-noise ratio (SNR) and power spectral density (PSD)-based SNR estimated via the Welch method. Results indicate that grasshopper acoustic energy is consistently concentrated within the frequency range of approximately 5.8–9 kHz. Although direct time-domain SNR slightly decreases after filtering due to attenuation of out-of-band components, PSD-based SNR improves significantly, reaching 25–28 dB, demonstrating effective spectral concentration and noise suppression. The proposed approach is computationally efficient, interpretable, and suitable as a foundational module for low-cost, real-time acoustic pest detection systems in precision agriculture.

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1. INTRODUCTION

In the era of modern agriculture and smart farming, early pest detection is crucial for maintaining crop productivity without excessive reliance on pesticides [1], [2]. Grasshoppers are a major pest in various agricultural commodities, causing significant damage and reducing crop productivity [3], [4]. Early identification of grasshoppers is crucial for control measures to be implemented before populations become widespread. Conventional detection methods, such as visual observation or pheromone traps, require significant time, effort, and expense, and are often hampered by large and noisy field conditions [2]. Furthermore, grasshoppers produce distinctive acoustic sounds through the friction of their wings or legs, making these sounds potentially useful as non-invasive indicators of pest presence [1], [4]. By recording acoustic signals in agricultural environments and digitally processing them, grasshoppers can be detected automatically and in real time.

Although grasshopper calls can be detected acoustically, a major challenge lies in the presence of environmental noise, such as wind, water movement, or other insect sounds with adjacent frequency characteristics [5], [6]. While previous bioacoustic research has extensively investigated insects such as mosquitoes, crickets, and other model species, studies focusing on the acoustic and spectral characteristics of grasshopper calls, particularly under natural field conditions, remain relatively limited [7], [8]. In addition, inappropriate digital filter design may lead to distortion or loss of important spectral components, thereby degrading biologically relevant information [6], [9].

Several studies have demonstrated that fast fourier transform (FFT)–based signal analysis is effective for extracting dominant frequency information from insect sounds, including crickets and mosquitoes [7], [10]–[12]. Other studies have reported that digital filtering can significantly improve the signal-to-noise ratio (SNR), resulting in clearer spectral patterns [6]. Among various filter types, Butterworth filters are well known for their smooth passband response without ripple, making them suitable for biological applications that require preservation of spectral integrity [11], [13]. However, the combined application of FFT and Butterworth bandpass filtering specifically for grasshopper acoustic signals in tropical agricultural environments has rarely been reported, highlighting a research gap identified in orthoptera bioacoustics studies [8].

Bioacoustics has become an important approach for monitoring insect presence and activity, as well as for species detection and identification, in both natural and agricultural environments using acoustic signal analysis [7], [14], [15]. Acoustic signal analysis enables the identification of insect species through characteristic spectral and frequency features derived from wingbeat sounds, vibrations, and acoustic calls [2], [7], [15]–[17]. In agricultural contexts, early detection of grasshopper populations is strategically important because it enables timely monitoring and intervention measures, thereby reducing the risk of widespread crop damage and economic losses [18].

FFT methods are widely applied due to their ability to transform time-domain signals into the frequency domain, enabling the identification of characteristic frequency features of insect sounds [2], [7], [15], [16]. International studies have demonstrated the effectiveness of spectral analysis in characterizing acoustic signals from insects such as mosquitoes, cicadas, and other species [1], [3], [15]. In parallel, Butterworth bandpass filters are commonly used as a preprocessing technique to suppress out-of-band noise while maintaining a maximally flat frequency response [6], [11], [19]. Furthermore, acoustic monitoring and classification studies have employed Butterworth filtering to reduce environmental noise prior to spectral analysis and feature extraction, thereby improving the quality of bioacoustic signals [6], [19].

Studies conducted in Indonesia exhibit a similar trend. Local bioacoustic research has applied spectral analysis techniques, including FFT-based approaches, to bird vocalizations and frog calls for species identification and acoustic characterization [20], [21]. In addition, signal processing and denoising methods have been employed to enhance animal acoustic signals prior to classification [22]. These findings indicate that dedicated grasshopper acoustic modeling under Indonesian agricultural conditions remains limited and represents an important research gap. To address this gap, the present study analyzes grasshopper acoustic signals using a combination of FFT and a Butterworth bandpass filter. FFT is employed to transform time-domain signals into the frequency domain for dominant frequency identification [10], while the Butterworth bandpass filter is applied as a preprocessing step to retain frequency components characteristic of grasshopper calls and suppress environmental noise [5], [6], [11]. The proposed framework is implemented in MATLAB, enabling efficient and scalable frequency feature extraction. Signal quality is evaluated using the SNR, with enhancement assessed through power spectral density (PSD) estimation based on the Welch method [23].

The main contribution of this research is the modeling of grasshopper acoustic spectral characteristics under rice field conditions in Indonesia, derived from FFT analysis after bandpass filtering. The extracted dominant frequency features provide a scientific basis for the development of an automatic, acoustic-based grasshopper pest detection system that is low-cost, fast, and environmentally friendly, thereby supporting smart farming applications [7], [18], [23].

Recent advances in insect bioacoustics increasingly employ machine learning and deep learning techniques, such as convolutional neural networks applied to spectrogram representations and acoustic signal classification for insect monitoring systems [3], [4], [15], [19]. While these approaches demonstrate high classification accuracy, they often require large labeled datasets and substantial computational resources. In contrast, the present study emphasizes signal processing–based feature modeling as a lightweight, transparent, and interpretable alternative, particularly suitable for early-stage detection systems and resource-constrained agricultural environments [13], [18], [24].

2. METHOD

The research method is designed to systematically analyze the acoustic signals of grasshopper sounds by utilizing a digital signal processing approach based on FFT and Butterworth bandpass filters. The research stages include the process of acquiring grasshopper sound data in the field, signal pre-processing to

reduce environmental noise, applying a Butterworth filter to extract the target frequency range, and FFT transformation to obtain a representation of the dominant frequency spectrum. Furthermore, the spectrum results are analyzed to identify the characteristics of grasshopper sounds and distinguish them from other sound sources, so that they can support more accurate and efficient acoustic-based pest detection modeling. Signal analysis, visualization, and parameter calculations use Matlab software. The research method steps are shown in Figure 1.

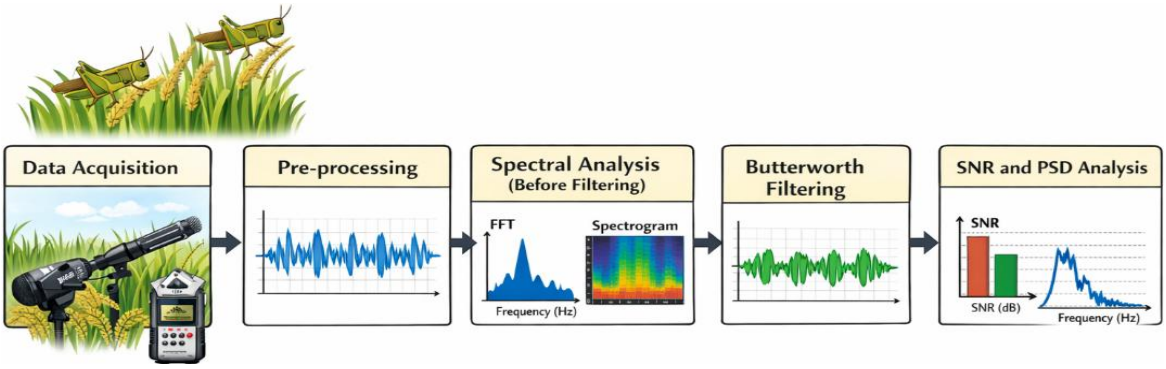

Figure 1. Flowchart of the research method steps

2.1. Data acquisition

Grasshopper sounds were recorded in rice fields using a condenser microphone and a portable recorder with a sampling rate of 44.1 kHz. The selection of open locations refers to established practices in insect acoustic surveys reported in international studies and Orthoptera-specific acoustic profiling, as well as insect monitoring methodologies in field environments [8], [10], [14]. The recordings were in MP3 format and first converted to WAV format.

Figure 2 illustrates the raw grasshopper acoustic signal recorded continuously for 120 seconds in an open rice field environment. The waveform shows irregular amplitude fluctuations caused by a combination of grasshopper wingbeat sounds and environmental noise such as wind, water movement, and other insects. This long-duration signal provides an overview of real field recording conditions and highlights the challenge of distinguishing biologically relevant grasshopper sounds from background noise prior to signal preprocessing.

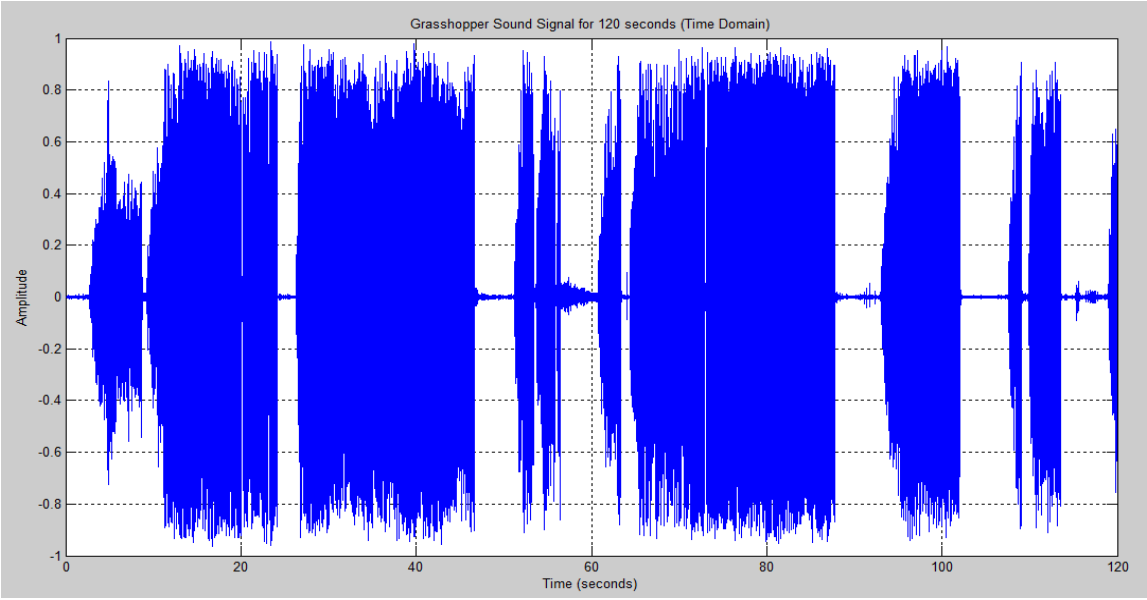

Figure 2. Grasshopper sound signal for 120 seconds

2.2. Pre-processing

The recorded signal was first normalized and segmented into 10-second intervals. To reduce environmental noise, a 4th–8th order Butterworth bandpass filter was applied, a commonly used approach in bioacoustic signal preprocessing and digital filter design [25]. Similar preprocessing strategies have been widely employed in insect acoustic analysis and classification studies [1], [26].

Figure 3 presents a 10-second segment extracted from the original 120-second grasshopper sound recording. This segmentation step is necessary to standardize signal length and facilitate consistent spectral analysis across multiple samples. The waveform still exhibits noise contamination, emphasizing the need for further preprocessing and filtering to isolate the grasshopper acoustic components.

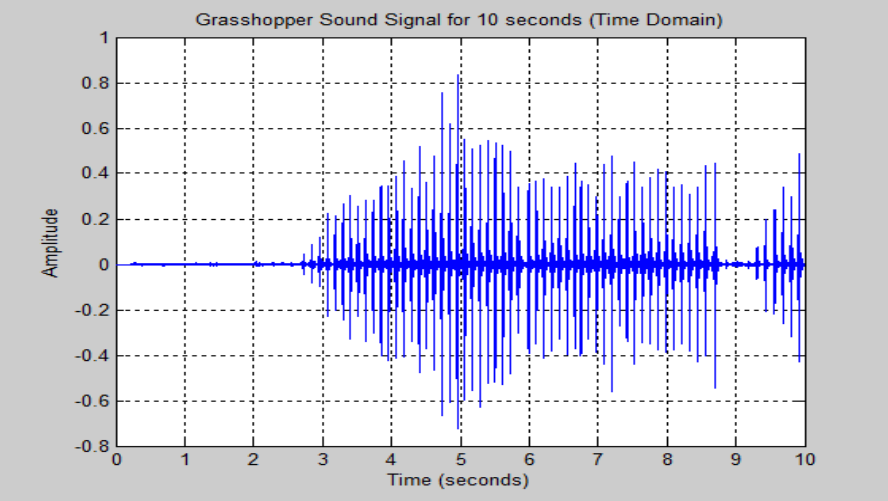

Figure 3. Grasshopper sound signal for 10 seconds

2.3. Spectral analysis (before filtering)

Each segment was analyzed using the FFT to obtain a frequency spectrum [10], [16]. Dominant frequency peaks and harmonic patterns were examined to distinguish grasshopper calls from environmental sounds [17]. This approach is consistent with established acoustic signal analysis methods applied in insect and environmental sound classification studies [7], [15], [19]. The five highest frequency peaks were identified to estimate the characteristic frequency range of the grasshopper calls. In addition, the time–frequency relationship was analyzed using a spectrogram to monitor signal dynamics.

Figure 4 shows the frequency-domain spectrum (left) and spectrogram (right) of the grasshopper sound signal before filtering. The spectrum reveals multiple frequency components spread across a wide bandwidth, while the spectrogram illustrates temporal variations of energy distribution over time. Although dominant peaks begin to emerge in the higher frequency region, significant noise remains present, making direct identification of grasshopper acoustic characteristics challenging.

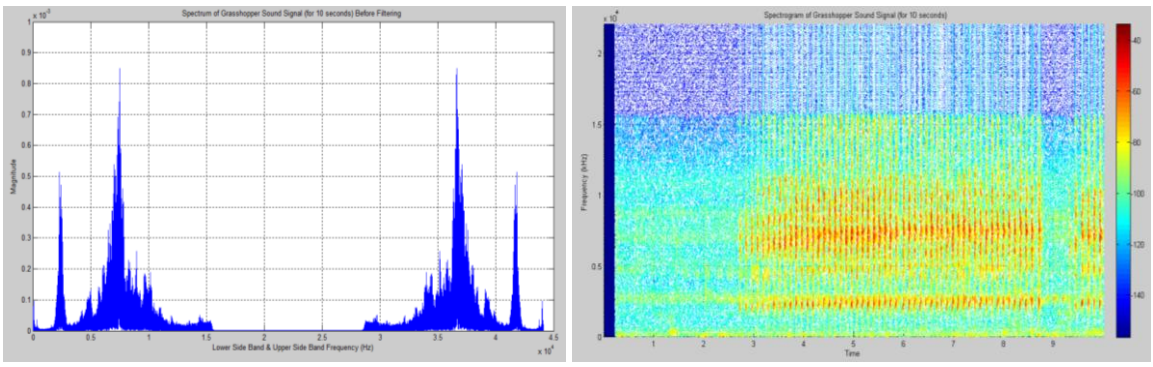

Figure 4. (Left) spectrum and (Right) Spectogram of grasshopper sound signal before filtering

2.4. Determining filter parameters

The Butterworth filter was selected due to its maximally flat magnitude response in the passband, which minimizes amplitude distortion of biologically relevant acoustic signals [11]. Unlike Chebyshev or elliptic filters, which introduce passband ripple and phase irregularities, Butterworth filters provide smoother spectral preservation, making them more suitable for bioacoustic signal analysis where waveform integrity is important [25]. Therefore, the Butterworth filter represents a balanced trade-off between spectral accuracy, computational efficiency, and implementation simplicity for practical bioacoustic applications [11], [25].

The Butterworth filter parameters were calculated and implemented using Matlab software. The design parameters include the bandpass frequency range, defined by the lower-side and upper-side cutoff frequencies, and the filter order. The frequency range was determined based on the dominant spectral peak obtained from FFT analysis [10], with an additional ±20% margin to define the passband limits. The filter was designed with order variations ranging from 4 to 8 to evaluate the trade-off between noise suppression performance and computational complexity [11], [25].

The ±20% margin around the dominant frequency peaks was determined empirically based on repeated FFT observations across multiple recording segments. This margin accommodates natural frequency variability caused by insect movement, wingbeat intensity, and environmental conditions. Similar variability in insect acoustic frequency characteristics has been reported in bioacoustic studies [12].

2.5. Filtering process

Figure 5 compares the grasshopper sound signal before and after Butterworth bandpass filtering in both the time domain (left) and frequency domain (right). After filtering, the time-domain signal exhibits reduced amplitude variability, while the frequency-domain representation shows clearer spectral concentration within the target band. This comparison demonstrates the effectiveness of the Butterworth filter in suppressing out-of-band noise while preserving relevant signal components.

- Apply a Butterworth filter by entering the previously calculated parameter values, namely the upper-side frequency, lower-side frequency, and filter order.
- Visualization of the filtered signal is plotted in the time domain to see the difference in amplitude.
- Visualization of the filtered signal spectrum is plotted to assess the success of noise attenuation.

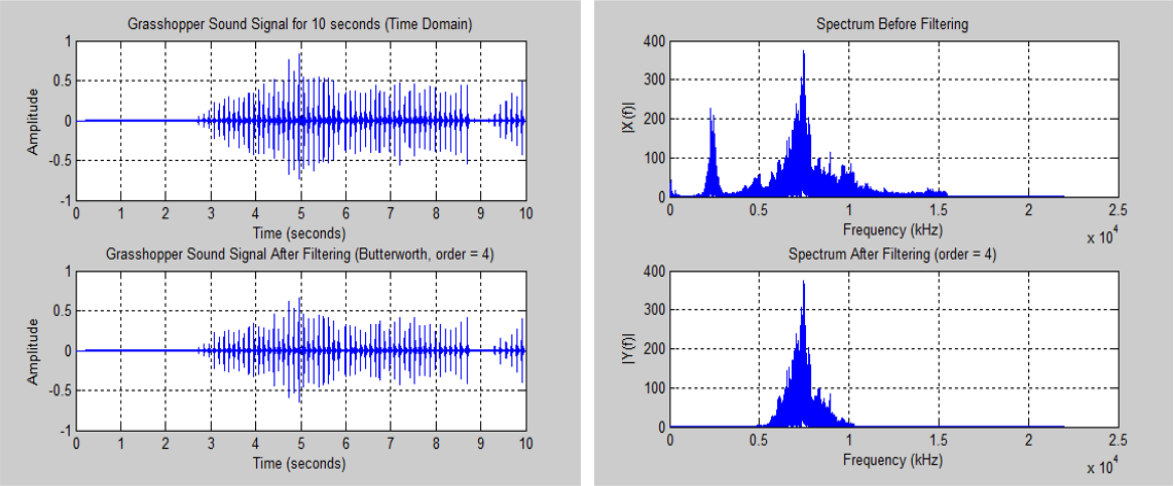

Figure 5. Grasshopper sound signal before and after filtering (left) time domain (right) spectrum at frequency domain

2.6. Quantitative parameter calculation

Figure 6 displays the Matlab interface used for quantitative parameter extraction, including recording duration, Nyquist frequency, dominant frequency range, lower-side and upper-side band frequencies, filter order, and SNR values. This Figure 6 highlights the systematic and repeatable nature of the analysis process, ensuring transparency and reproducibility of the proposed signal processing framework.

Steps taken to calculate quantitative parameters:

– Calculating the (SNR in general).
– Band-based SNR (in-band vs. out-of-band).

- Calculating and plotting the PSD using the Welch approach to assess power distribution per frequency.
- Comparing Filter Orders. Filters were tested at orders 4–8 to determine their effect on SNR and PSD.
- Comparing the SNR analysis results to recording durations of 10, 15, 20, and 25 seconds.

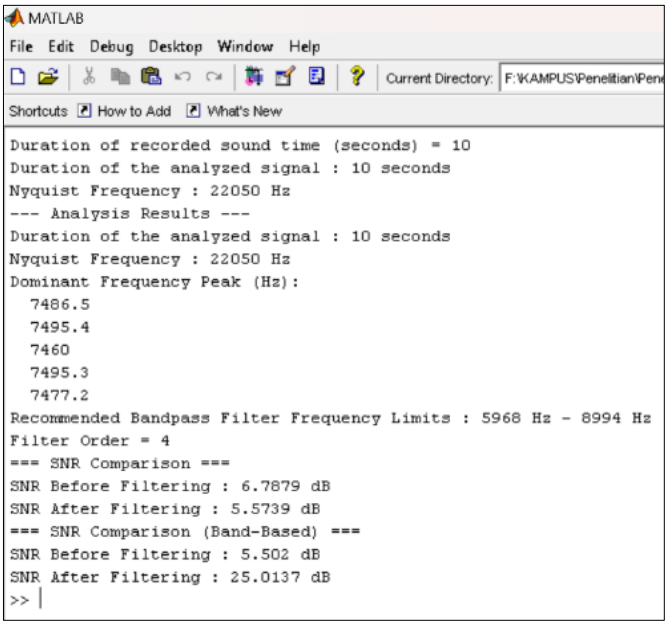

Figure 6. Display of input and output parameters in the MATLAB window. It shows the values: Duration of the grasshopper acoustic signal, Nyquist frequency, dominant frequency range at the 5 highest amplitudes, LSB and USB frequencies, filter order, SNR before and after filtering (SNR before and after being applied to the PSD method with the Welch approach)

2.7. Validation dan evaluation

The results of SNR calculations using different parameters were compared with reference recordings of grasshoppers that had been visually verified in the field. Figure 7 presents a comparison of the PSD before and after filtering. The filtered PSD shows a strong concentration of energy within the grasshopper's dominant frequency band, while energy outside this range is significantly attenuated. This result confirms that PSD-based analysis provides a more representative assessment of spectral clarity than direct time-domain SNR.

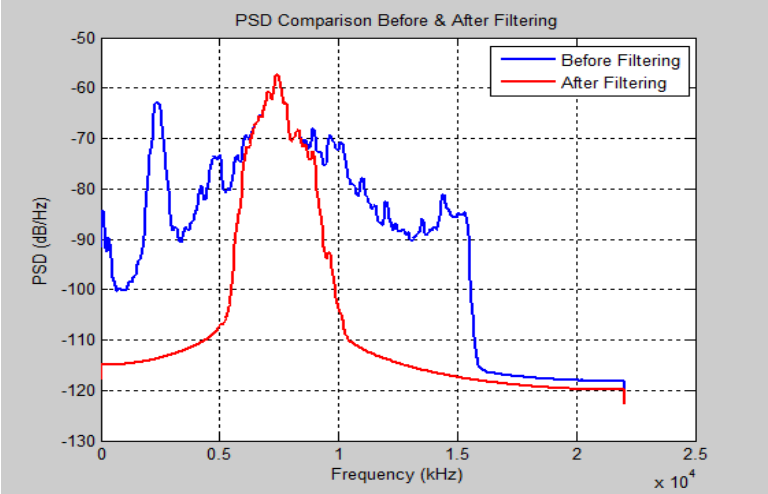

Figure 7. PSD comparison before and after filtering

3. RESULTS AND DISCUSSION

The results of the calculation analysis with variations in recording duration are presented in Tables 1-4. Although recordings were obtained from a single agricultural location, robustness was partially evaluated through repeated analysis using multiple recording durations (10–25 s) and filter orders (4–8). The consistent trend observed in PSD-based SNR improvement across these variations indicates methodological stability under different signal conditions. Figure 8 illustrates the comparison of SNR values before and after filtering for a 10-second recording duration. Although the direct SNR slightly decreases after filtering, the figure demonstrates that time-domain SNR alone does not fully capture spectral improvement, reinforcing the need for PSD-based evaluation.

Table 1. SNR calculation results of grasshopper sounds recorded for 10 seconds

Parameter	Grasshopper sound recording for 10 seconds dominant frequency range 5968 Hz – 8994 Hz				
Filter order	4	5	6	7	8
SNR before filtering (dB)	6,7879	6,7382	6,7077	6,6876	6,6735
SNR after filtering (dB)	5,5739	5,5476	5,5327	5,5239	5,5185
SNR PSD before filtering (dB)	5,502	5,502	5,502	5,502	5,502
SNR PSD after filtering (dB)	25,0137	25,9852	26,7547	27,3925	27,9363

Table 2. SNR calculation results of grasshopper sounds recorded for 15 seconds

Parameter	Grasshopper sound recording for 15 seconds dominant frequency range 5849 Hz - 8977 Hz				
Filter order	4	5	6	7	8
SNR before filtering (dB)	7,0232	6,9621	6,9231	6,8969	6,8784
SNR after filtering (dB)	5,898	5,8595	5,8349	5,8184	5,8069
SNR PSD before filtering (dB)	5,7341	5,7341	5,7341	5,7341	5,7341
SNR PSD after filtering (dB)	25,222	26,234	27,0098	27,636	28,1623

Table 3. SNR calculation results of grasshopper sounds recorded for 20 seconds

Parameter	Grasshopper sound recording for 20 seconds dominant frequency range 5814 Hz - 9016 Hz				
Filter order	4	5	6	7	8
SNR before filtering (dB)	6,8507	6,7524	6,6935	6,6565	6,6323
SNR after filtering (dB)	5,6616	5,5865	5,542	5,5147	5,4971
SNR PSD before filtering (dB)	5,425	5,425	5,425	5,425	5,425
SNR PSD after filtering (dB)	25,1161	26,3867	27,3116	28,0227	28,5985

Table 4. SNR calculation results of grasshopper sounds recorded for 25 seconds

Parameter	Grasshopper sound recording for 25 seconds dominant frequency range 5836 Hz - 9016 Hz				
Filter order	4	5	6	7	8
SNR before filtering (dB)	6,9071	6,7986	6,7346	6,6951	6,6695
SNR after filtering (dB)	5,7165	5,6328	5,5848	5,5561	5,5384
SNR PSD before filtering (dB)	5,4693	5,4693	5,4693	5,4693	5,4693
SNR PSD after filtering (dB)	24,9693	26,2681	27,2027	27,9158	28,4916

Figure 9 shows the PSD-based SNR values after filtering for various recording durations. A consistent improvement trend is observed across all durations, indicating that the proposed filtering and spectral analysis method remains stable and reliable even with different signal lengths. Figure 10 compares PSD-based SNR values before and after filtering for a 20-second recording. The substantial increase in SNR after filtering confirms the effectiveness of the Butterworth bandpass filter in enhancing grasshopper acoustic signatures and suppressing environmental noise under realistic agricultural conditions.

Based on the table and graph above, several things that can be discussed are as follows. Figures 2 and 3 provide an initial depiction of the grasshopper acoustic signal characteristics under real field conditions prior to filtering. The pronounced amplitude fluctuations and strong noise contamination observed in the time-domain waveforms are consistent with the relatively low initial SNR values reported in Table 1. These results indicate that the raw recordings are dominated by environmental noise, thereby justifying the need for subsequent signal preprocessing and filtering stages.

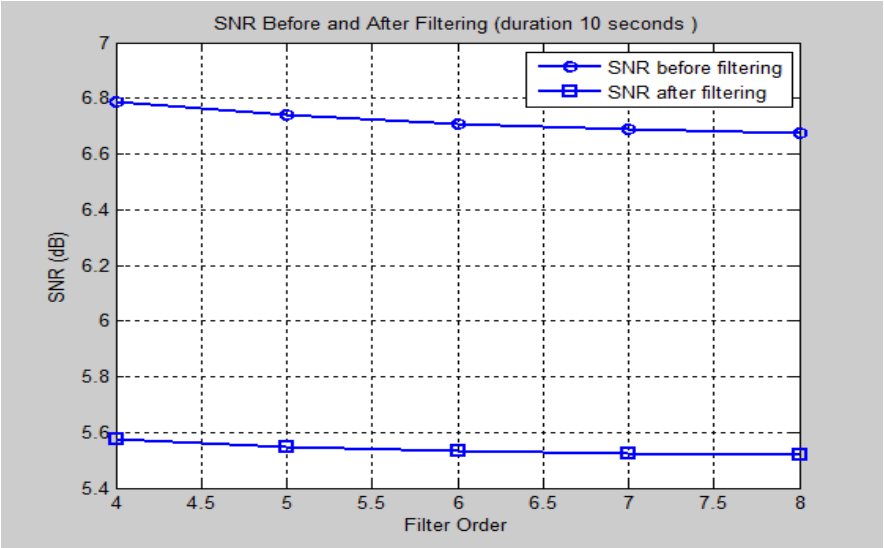

Figure 8. SNR Before and After Filtering (recording duration for 10 seconds)

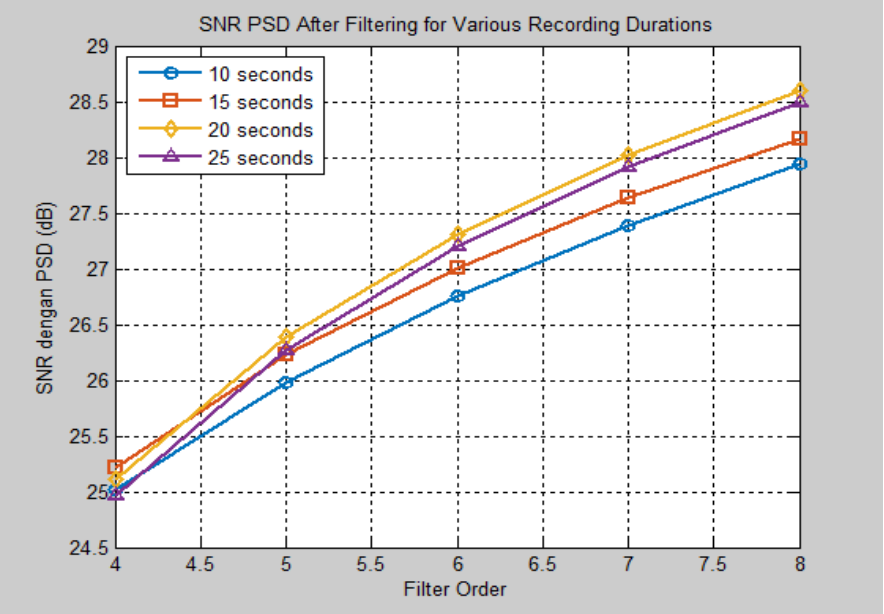

Figure 9. SNR with PSD after filtering for various recording duration

The frequency spectrum and spectrogram presented in Figure 4 illustrate that signal energy is distributed across a wide frequency band before filtering. This observation is quantitatively supported by the FFT results summarized in Table 2, which identify dominant frequency peaks within the range of approximately 5.8–9 kHz. The agreement between the spectral visualization and the numerical FFT outcomes reinforces the validity of selecting this frequency band as the target range for grasshopper acoustic analysis.

Figure 5 demonstrates the effects of Butterworth bandpass filtering and parameter selection on the grasshopper acoustic signal. The visual comparison between the pre-filtered and post-filtered signals, together with the extracted parameter settings, is directly reflected in the SNR variations reported in Table 3. As shown in the table, increasing the filter order leads to improved noise attenuation, albeit at the cost of higher computational complexity. This consistency between visual evidence and numerical results highlights the systematic behavior of the proposed filtering approach.

Figures 7 and 8 emphasize the contrasting behavior of time-domain SNR and PSD-based SNR after filtering. While Figure 8 shows a slight decrease in direct SNR, Table 4 reveals a substantial improvement in PSD-based SNR values. This discrepancy confirms that time-domain SNR alone is insufficient to represent

spectral clarity, whereas PSD-based metrics more accurately capture energy concentration within the biologically relevant frequency band.

Figures 9 and 10 illustrate the consistency of PSD-based SNR improvement across different recording durations. This trend is consistent with the quantitative results presented in Table 4, which show only minor variations in PSD-based SNR for recording durations ranging from 10 to 25 seconds. These findings suggest that the proposed method is robust to variations in signal length and remains reliable for real-time acoustic monitoring applications.

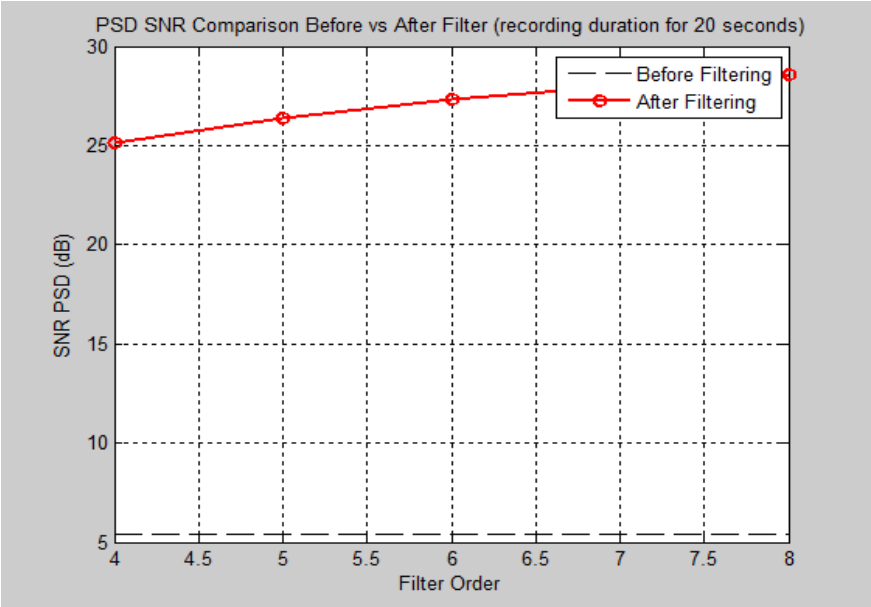

Figure 10. SNR with PSD comparison before and after filtering (recording duration for 20 seconds)

3.1. Filter effectiveness

To evaluate the effectiveness of the filtering process, the SNR was analyzed before and after applying the bandpass filter. In addition to the conventional time-domain SNR calculation, a PSD-based SNR analysis using the Welch method was also performed to provide a more comprehensive assessment of the filter's performance in isolating the dominant frequency components of the grasshopper sound:

- The SNR before the filter is only around 6–7 dB, indicating that the initial recording quality is still low with a lot of environmental noise.
- The general SNR after the filter is actually slightly lower (5.5–5.9 dB). This is because the bandpass filter also removes some of the original signal energy outside the target range, resulting in a noticeable decrease in the direct ratio.
- However, the PSD-based SNR (using the Welch approximation) shows different results:
  - Before the filter: around 5.4–5.7 dB.
  - After the filter: a drastic increase to 25–28 dB.
  - This increase of more than 20 dB indicates that the filter is very effective at reducing energy outside the grasshopper's dominant frequency band (~5.8–9 kHz).

3.2. Effect of filter order

To evaluate the effect of filter design on noise reduction performance, the effect of bandpass filter order on the SNR was analyzed. Filter order determines the sharpness of the frequency response and the ability to suppress unwanted frequency components. The PSD-based SNR values obtained from different filter orders were compared to assess improvements in the quality of the recorded grasshopper sound.

- Consistent trend across all recording durations:
  As the filter order increases (from 4 to 8), the PSD-based SNR after filtering improves
  Example: 20-second duration:
  4^{th}-order: 25.11 dB and 8^{th}-order: 28.59 dB

- The SNR-based PSD increases by approximately 0.7–1 dB with each increment in filter order
- In other words, higher-order filters yield steeper out-of-band attenuation, resulting in more effective noise suppression

3.3. Effect of recording duration

To assess the effect of recording duration on filtering performance, the PSD-based SNR was analyzed using recordings of different lengths. Longer recordings generally provide more stable spectral estimates, leading to more reliable SNR measurements and filter performance evaluation:

- The SNR-based PSD after filtering tends to increase slightly with longer recording durations: 10-second duration: ~27.9 dB (8th order) and 25-second duration: ~28.5 dB (8th order)
- The difference is relatively small (~0.5–0.6 dB), but consistent.
- This occurs because longer recordings provide more stable PSD estimates (more even average noise).

The analysis results show that applying a Butterworth bandpass filter significantly improves the quality of the grasshopper call signal. The PSD-based SNR value increased sharply from around 5 dB in the original signal to 25–28 dB after filtering. This increase of more than 20 dB indicates that the filter is capable of reducing noise energy outside the dominant frequency band of the grasshopper (±5.8–9 kHz), thus clarifying the characteristics of the target signal. In contrast, the SNR calculated using a simpler method (direct comparison between the original signal and the filtered result) showed a slight decrease. This occurs because the filter not only reduces noise but also removes some signal energy outside the specified band, making the PSD method a more representative way to assess filtering success.

Furthermore, there is a positive correlation between filter order and PSD SNR value. Increasing the order from 4 to 8 results in an SNR improvement of approximately 0.7–1 dB per order step. This indicates that higher-order filters have a sharper frequency response in attenuating out-of-band signals, thus more effectively suppressing noise. However, selecting the filter order requires considering the trade-off between performance and complexity, with an order of 6–8 considered optimal.

Recording duration also affects the stability of the analysis results. The SNR of the PSD after filtering tends to increase slightly with longer recordings, with a difference of approximately 0.5–0.6 dB between 10-second and 25-second recordings. This can be explained by the PSD estimation process becoming more stable with a larger sample size, resulting in more even noise fluctuations. However, this increase is relatively small, so even a 10-second recording is sufficient for analysis purposes, while longer recordings are useful for increasing the reliability of the results.

Overall, the combination of FFT, Butterworth bandpass filter, and PSD analysis proved effective in enhancing the frequency signature of grasshopper calls while suppressing environmental noise. These findings confirm that the proposed method can be used as a first step in a signal analysis-based plant pest acoustic detection system. The decrease in direct SNR after filtering occurs because the bandpass filter removes not only noise components but also portions of signal energy outside the defined frequency band. As a result, direct SNR alone is less representative of spectral clarity. In contrast, PSD-based SNR more accurately reflects energy concentration within the biologically relevant frequency range, which explains the significant improvement observed after filtering.

Higher-order filters provide steeper out-of-band attenuation but also increase computational complexity and phase delay. For real-time embedded implementations, filter orders between 6 and 8 offer a practical trade-off between noise suppression performance and processing efficiency. Although the experiments were conducted under controlled field conditions, the identified frequency range (≈5.8–9 kHz) aligns with grasshopper acoustic characteristics reported in previous studies, suggesting reasonable generalizability to similar agricultural environments. While the dataset size is limited, repeated measurements across multiple recording durations and filter orders provide indirect validation of the proposed method. Future work will focus on the use of multi-location and multi-species datasets to further assess robustness under diverse environmental conditions.

4. CONCLUSION

This study aimed to investigate the effectiveness of classical signal processing techniques for enhancing grasshopper acoustic signals under noisy agricultural field conditions. The results demonstrate that this objective has been successfully achieved through the combined application of Butterworth bandpass filtering, FFT, and PSD analysis. The application of the Butterworth bandpass filter significantly improved signal quality, as indicated by an increase in PSD-based SNR from approximately 5 dB to 25–28 dB. Higher filter orders resulted in stronger noise suppression, with filter orders between 6 and 8 providing an optimal balance between spectral enhancement and computational efficiency. Longer recording durations yielded more stable SNR estimates, although their overall impact remained relatively limited.

These findings confirm that environmental noise constitutes a major challenge in bioacoustic pest detection, while also demonstrating that appropriate filtering strategies can effectively mitigate this limitation. The proposed framework reliably enhances the characteristic frequency components of grasshopper calls, which were consistently identified within the 5.8–9 kHz range, thereby improving spectral clarity under real field conditions. Despite these promising results, this study has several limitations. The dataset was collected from a single agricultural location and focused on a limited number of recording conditions. In addition, the analysis was restricted to grasshopper sounds without incorporating automated species classification or multi-source environmental variability. These factors may limit the generalizability of the findings.

Beyond fulfilling the initial research objectives, this study addresses the limited availability of grasshopper acoustic modeling research in Indonesia and provides a scientifically grounded foundation for the development of low-cost, real-time, and environmentally friendly acoustic-based pest monitoring systems aligned with smart farming principles. Future work will focus on integrating the proposed signal processing framework with IoT-based acoustic sensors and automated classification algorithms. Further validation across multiple crop types, environmental conditions, and grasshopper species will be conducted to enhance robustness and generalizability.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Khairunnisa	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			
Sarifudin						✓	✓				✓	✓		✓
Annisa Maulidia				✓			✓			✓	✓	✓	✓	
Damayanti														

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study does not involve human participants or animals; therefore, ethical approval was not required.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, K., upon reasonable request.

REFERENCES

[1] D. Kadyrov, A. Sutin, N. Sedunov, A. Sedunov, and H. Salloum, "Vibro-acoustic signatures of various insects in stored products," *Sensors*, vol. 24, no. 20, p. 6736, Oct. 2024, doi: 10.3390/s24206736.

[2] W. Yu, H. Zhang, R. Xu, Y. Sun, and K. Wu, "Characterization of wingbeat frequency of different taxa of migratory insects in northeast Asia," *Insects*, vol. 13, no. 6, p. 520, Jun. 2022, doi: 10.3390/insects13060520.

[3] M. S. Fernandes, W. Cordeiro, and M. Recamonde-Mendoza, "Detecting Aedes aegypti mosquitoes through audio classification with convolutional neural networks," *Computers in Biology and Medicine*, vol. 129, p. 104152, Feb. 2021, doi: 10.1016/j.compbiomed.2020.104152.

[4] C. Balingbing, S. Kirchner, H. Siebald, N. Van Hung, and O. Hensel, "Determining the sound signatures of insect pests in stored rice grain using an inexpensive acoustic system," *Food Security*, vol. 16, no. 6, pp. 1529–1538, Dec. 2024, doi: 10.1007/s12571-024-01493-6.

[5] J. Branding, D. von Hörsten, J. K. Wegener, E. Böckmann, and E. Hartung, "Towards noise robust acoustic insect detection: from the lab to the greenhouse," *KI - Kunstliche Intelligenz*, vol. 37, no. 2–4, pp. 157–173, Dec. 2023, doi: 10.1007/s13218-023-00812-x.

[6] J. Xie, J. G. Colonna, and J. Zhang, "Bioacoustic signal denoising: a review," *Artificial Intelligence Review*, vol. 54, no. 5, pp. 3575–3597, Jun. 2021, doi: 10.1007/s10462-020-09932-4.

[7] K. L. Hassall, A. Dye, I. Potamitis, and J. R. Bell, "Resolving the identification of weak-flying insects during flight: a coupling between rigorous data processing and biology," *Agricultural and Forest Entomology*, vol. 23, no. 4, pp. 489–505, Nov. 2021, doi: 10.1111/afe.12453.

[8] K. Riede, "Acoustic profiling of Orthoptera: present state and future needs," *Journal of Orthoptera Research*, vol. 27, no. 2, pp. 203–215, Dec. 2018, doi: 10.3897/jor.27.23700.

[9] A. Widmann, E. Schröger, and B. Maess, "Digital filter design for electrophysiological data - a practical approach," *Journal of Neuroscience Methods*, vol. 250, pp. 34–46, Jul. 2015, doi: 10.1016/j.jneumeth.2014.08.002.

[10] J. W. Cooley and J. W. Tukey, "An algorithm for the machine calculation of complex Fourier series," *Mathematics of Computation*, vol. 19, no. 90, pp. 297–301, 1965, doi: 10.1090/s0025-5718-1965-0178586-1.

[11] S. Butterworth, "On the theory of filter amplifiers," *Experimental Wireless and the Wireless Engineer*, vol. 7, no. 6, pp. 536–541, Oct, 1930.

[12] T. Saha, A. P. Genoud, J. H. Park, and B. P. Thomas, "Temperature dependency of insect's wingbeat frequencies: an empirical approach to temperature correction," *Insects*, vol. 15, no. 5, p. 342, May 2024, doi: 10.3390/insects15050342.

[13] B. Wang, "Signal processing based on butterworth filter: Properties, design, and applications," *Highlights in Science, Engineering and Technology*, vol. 97, pp. 72–77, May 2024, doi: 10.54097/3cq7qb95.

[14] K. Riede and R. Balakrishnan, "Acoustic monitoring for tropical insect conservation," *Philosophical Transactions of the Royal Society B: Biological Sciences*, vol. 380, no. 1928, Jun. 2025, doi: 10.1098/rstb.2024.0046.

[15] W. T. Tey, T. Connie, K. Y. Choo, and M. K. O. Goh, "Cicada species recognition based on acoustic signals," *Algorithms*, vol. 15, no. 10, p. 358, Sep. 2022, doi: 10.3390/a15100358.

[16] C. Zhang, P. Wang, H. Guo, G. Fan, K. Chen, and J. K. Kämäräinen, "Turning wingbeat sounds into spectrum images for acoustic insect classification," *Electronics Letters*, vol. 53, no. 25, pp. 1674–1676, Dec. 2017, doi: 10.1049/el.2017.3334.

[17] J. J. Noda, C. M. Travieso-González, D. Sánchez-Rodríguez, and J. B. Alonso-Hernández, "Acoustic classification of singing insects based on MFCC/LFCC fusion," *Applied Sciences (Switzerland)*, vol. 9, no. 19, p. 4097, Oct. 2019, doi: 10.3390/app9194097.

[18] D. Hunter, "World's best practice locust and grasshopper management: accurate forecasting and early intervention treatments using reduced chemical pesticide," *Agronomy*, vol. 14, no. 10, p. 2369, Oct. 2024, doi: 10.3390/agronomy14102369.

[19] B. Fengler, C. Seyidbayli, A. Reinhardt, M. Anders, and C. Westphal, "A review of acoustic systems for insect monitoring: From recording technologies to species recognition performance," *Ecological Informatics*, vol. 95, p. 103733, May 2026, doi: 10.1016/j.ecoinf.2026.103733.

[20] I. Irwandi, M. Marwan, A. H. Mahmud, and A. Abdullah, "Prospects for developing a method for identifying bird species based on sound spectra using spectrogram analysis [in Indonesian : Prospek pengembangan metode identifikasi spesies burung berdasarkan spektrum suara menggunakan analisis spektogram]," *Biota : Jurnal Ilmiah Ilmu-Ilmu Hayati*, pp. 71–78, Nov. 2019, doi: 10.24002/biota.v10i2.2841.

[21] H. Kurniati, "Vocalization of asian striped tree frogs, Polypedates leucomystax (Gravenhorst, 1829) and P. iskandari Riyanto, Mumpuni & McGuire, 2011," *Treubia*, vol. 38, pp. 1–13, Apr. 2011, doi: 10.14203/treubia.v38i0.543.

[22] D. Defrianto, T. Titrawani, L. Umar, and V. Asyana, "Animal identification based on acoustic patterns using wavelet extraction and multi-label classification with artificial neural networks [in Indonesian : Identifikasi Hewan Berdasarkan Pola Akustik Dengan Prinsip Ekstraksi Wavelet Dan Klasifikasi Multi-La," *Komunikasi Fisika Indonesia*, vol. 19, no. 1, p. 51, Mar. 2022, doi: 10.31258/jkfi.19.1.51-56.

[23] P. D. Welch, "The use of fast fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms," *IEEE Transactions on Audio and Electroacoustics*, vol. 15, no. 2, pp. 70–73, Jun. 1967, doi: 10.1109/TAU.1967.1161901.

[24] X. Zhang and S. Jiang, "Application of fourier transform and butterworth filter in signal denoising," in *2021 IEEE 6th International Conference on Intelligent Computing and Signal Processing, ICSP 2021*, IEEE, Apr. 2021, pp. 1277–1281. doi: 10.1109/ICSP51882.2021.9408933.

[25] F. L. Garcia, M. S. Lopez, and T. W. Harris, "Comparative study of digital filters (Butterworth, Chebyshev) for preprocessing acoustic neural data," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 6, pp. 1108–1117, 2019.

[26] J. Branding, D. von Hörsten, E. Böckmann, J. K. Wegener, and E. Hartung, "InsectSound1000 an insect sound dataset for deep learning based acoustic insect recognition," *Scientific Data*, vol. 11, no. 1, p. 475, May 2024, doi: 10.1038/s41597-024-03301-4.

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