Power System Protection and Control
ISSN:1674-3415

ACOUSTIC PEST DETECTION AND NOISE REDUCTION TECHNIQUES FOR PRECISION AGRICULTURE

Dr. Avinash G M[1], Dr. Dilna U[2], Dr. Keerthi Kumar N[3], Sunil D M [4]

[1]Associate Professor, Department of CS&E, SJMIT, Chitradurga, Karnataka, India., avinshgm09@gmail.com
[2]Assistant Professor School of ECE, REVA University, Bengaluru, Karnataka, India., dilna.u@reva.edu.in
[3]Associate Professor, Department of Mechanical Engineering, BMS Institute of Technology & Management , Bengaluru, Karnataka, India., keerthikumarn@bmsit.in
[4]Assistant Professor, School of ECE, REVA University, Bengaluru, Karnataka, India., sunildm15@gmail.com

Received: 03/05/2026 **Revised:** 10/06/2026 **Accepted:** 08/07/2026

***ABSTRACT*:**

In this paper, we have provided a noninvasive acoustic sensing system that can be employed for detecting agricultural pests through the analysis of their bio-acoustic signals. The proposed system focuses on Tribolium confusum, also known as the confused flour beetle. For collecting the bio-acoustic signals generated by the insects, sensitive microphones were used while maintaining controlled experimental conditions. The collected signals were then filtered in MATLAB using FIR and IIR band pass filters in order to reduce environmental noise from wind and agricultural machinery. The next step was extracting spectral information from the signals and classifying them into respective categories employing deep learning models such as Convolutional Neural Network (CNN) and Support Vector Machine (SVM). Experiments confirmed that the background noise can be efficiently reduced using the described algorithm with almost 10 dB improvement in signal intensity.

Keywords: *Acoustic Pest Detection, FIR Filter, IIR Filter, SNR, MATLAB, Noise Reduction, Precision Agriculture*

INTRODUCTION

Pest infestations continue to pose a significant challenge in modern agriculture, leading to substantial crop losses and economic impact. Traditional detection approaches, including visual inspection and chemical trapping, are often labor-intensive and time-consuming, and they may not reliably detect early-stage infestations.

In this context, acoustic-based pest detection has emerged as a non-invasive and real-time monitoring alternative, leveraging characteristic sounds produced by insects during feeding, movement, and mating activities. Growing emphasis on sustainable and environmentally friendly farming practices has further driven research toward reducing reliance on chemical pesticides through advanced monitoring solutions. Despite its potential, acoustic detection in field conditions remains challenging due to the presence of strong background noise from wind, agricultural machinery, and other environmental disturbances. These interferences can mask weak insect-generated signals and reduce detection accuracy. Consequently, effective noise suppression and signal enhancement techniques are essential to improve the robustness, reliability, and practical applicability of acoustic-based pest monitoring systems in precision agriculture. This study employs digital signal processing techniques in MATLAB, with particular emphasis on Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) filtering methods, to isolate insect-generated acoustic signals and improve their detectability. The implemented filtering framework effectively suppresses environmental noise while enhancing the clarity of biologically relevant sound patterns. Improved signal quality enables more accurate real-time monitoring of pest activity and supports reliable acoustic analysis under field conditions. The proposed approach contributes to the development of sustainable and precision-oriented pest management systems by facilitating early pest detection and reducing dependency on conventional chemical control methods.

DOI: 10.46121/pspc.54.3.27

Power System Protection and Control
ISSN:1674-3415

Fig.-1.1: Tribolium confusum

The present study considers *Tribolium confusum*, commonly referred to as the confused flour beetle, as a representative case study to evaluate the feasibility of acoustic-based pest detection in stored grain environments. *Tribolium confusum* is a small reddish-brown beetle, typically 3–4 mm in length, and is recognized as a major pest of stored grains and processed food products, including flour, cereals, and pasta. It thrives under warm and humid storage conditions, where rapid reproduction contributes to persistent and long-term infestations.

During feeding and movement, the insect produces distinct acoustic emissions that are generally observed within the 1–7 kHz frequency range, with stronger spectral components often appearing around 0.3 kHz. These acoustic patterns vary depending on the developmental stage and behavioral activity of the insect, making frequency-domain analysis important for accurate detection and characterization. Taxonomically, *T. confusum* belongs to the order Coleoptera and the family Tenebrionidae, underscoring its relevance in stored-product pest monitoring and management systems.

DESIGN & IMPLEMENTATION

2.1 FIR Filter Design and Implementation in MATLAB.

Finite Impulse Response (FIR) filters are widely used in digital signal processing due to their inherent stability, linear phase response, and straightforward implementation. Unlike Infinite Impulse Response (IIR) filters, FIR structures do not incorporate feedback, which results in stable and predictable performance. These properties make FIR filters well suited for processing delicate acoustic signals in pest detection and agricultural monitoring, where maintaining signal integrity is critical.

The FIR filter design process typically involves defining key parameters such as filter type, cutoff frequency, sampling frequency, and filter order. Based on application requirements, the filter can be configured as low-pass, high-pass, band-pass, or band-stop. MATLAB supports FIR filter design through functions such as fir1 and fir2, along with additional tools available in the Signal Processing Toolbox. Among these, fir1 is commonly preferred for window-based design due to its simplicity and computational efficiency.

In acoustic-based pest monitoring systems, FIR filters are used to isolate frequency components associated with insect-generated emissions while attenuating unwanted background noise. Careful selection of filter parameters enables effective suppression of interference without distorting biologically relevant signal features. As a result, FIR-based preprocessing in MATLAB provides a reliable and efficient framework for signal enhancement, supporting accurate acoustic analysis in precision agriculture applications.

2.2 IIR Digital Filter design and Implementation in MATLAB.

Infinite Impulse Response (IIR) filters are an important class of digital filters widely used in signal processing due to their computational efficiency and ability to achieve sharp frequency selectivity with relatively low filter orders. In contrast to Finite Impulse Response (FIR) filters, IIR structures employ feedback, resulting in an impulse response that theoretically persists indefinitely. This property enables efficient real-time processing, making IIR filters particularly suitable for acoustic pest detection systems where fast and effective noise suppression is required.

The design of IIR filters typically involves selecting parameters such as filter structure, cutoff frequency, sampling frequency, pass-band ripple, and stop-band attenuation. MATLAB supports several standard design approaches through functions such as butter, cheby1, cheby2, and ellip, which correspond to Butterworth, Chebyshev Type I, Chebyshev Type II, and Elliptic filter designs, respectively. Among these, the Butterworth filter is often preferred because of its smooth and maximally flat pass-band response.

In acoustic pest monitoring applications, IIR filters are effective in extracting insect-related frequency components while suppressing environmental noise. Their lower computational complexity also makes them suitable for embedded and wireless sensor-based agricultural systems that require real-time operation. Overall, IIR-based filtering provides a practical and efficient solution for improving signal quality in precision agriculture applications.

2.3 Evaluating Filter Performance: SNR and Noise Reduction

In digital signal processing applications—such as audio engineering, communication systems, and biomedical signal analysis—evaluating filter performance is crucial. Two key performance indicators used for this purpose are the **Signal-to-Noise Ratio (SNR)** and **noise suppression** capability. These metrics help determine how effectively a filter isolates the useful signal from unwanted disturbances.

Signal-to-Noise Ratio (SNR): The Signal-to-Noise Ratio (SNR) quantifies the relationship between the strength of the desired signal and the background noise level. It is a critical metric for assessing the clarity and quality of a signal after filtering.

Measurement: SNR is typically expressed in **decibels (dB)** and can be calculated using the formula:

$$\textbf{SNR (dB)} = 10 \cdot_{\log 10(} P_{noise} / P_{signal}) \text{ -----------------} \rightarrow (1)$$

Where:

P_{signal} is the power of the signal of interest.

P_{noise} is the power of the noise.

a) A higher Signal-to-Noise Ratio (SNR) indicates a cleaner signal with reduced noise interference, reflecting the effectiveness of the filtering approach in preserving the integrity of the original acoustic signal. In this study, the FIR filter achieved an SNR of 25.67 dB, whereas the IIR filter produced a higher value of 28.74 dB, indicating comparatively better noise suppression performance.

b) Noise suppression refers to the capability of a filtering technique to reduce or eliminate unwanted components such as electrical interference, background environmental sounds, and system-generated noise, while retaining the essential characteristics of the desired signal. Effective noise suppression is critical for maintaining signal quality and ensuring reliable analysis in acoustic signal processing applications.

ACOUSTIC PEST DETECTION METHODOLOGY

This section outlines the methodology adopted for acoustic-based pest detection in agricultural settings. The proposed approach involves capturing bioacoustics signals generated by pest activity using sensitive microphones and vibration sensors placed in proximity to crops or stored grain samples. The recorded audio signals are then processed to extract relevant acoustic features associated with insect movement and feeding behavior.

These extracted features are analyzed to identify and classify the presence of pest species. By enabling continuous and non-invasive monitoring, the proposed method supports early detection of infestations and facilitates timely intervention. Overall, this approach contributes to reducing crop losses and improving decision-making in precision agriculture systems through reliable acoustic-based monitoring.

3.1 Experimental Methodology

In the present investigation, wheat samples with a moisture content of 13% were selected to provide suitable environmental conditions for insect activity and acoustic analysis. Adult and larval stages of *Tribolium confusum* were cultured in wheat-filled containers to maintain adequate pest populations throughout the experiments. All recordings were conducted between 8:00 AM and 6:00 PM under controlled laboratory conditions. Prior to data acquisition, adult beetles were acclimatized for 24 hours in a test tube containing a thin layer of wheat grains.

For each experimental trial, the test tube was filled with pest-free wheat up to a height of 10 cm, and a fine mesh barrier was inserted to restrict insect movement. Acoustic signals were recorded using sensors positioned approximately 10 cm above the grain surface through a DSP interface. The captured 30-minute recordings were automatically segmented into 30-second audio files for detailed analysis. During larval-stage experiments,

DOI: 10.46121/pspc.54.3.27

Power System Protection and Control
ISSN:1674-3415

infested grains were placed over clean wheat without a separator veil, since larvae remain embedded within kernels. All experiments were performed at an ambient temperature of approximately 20 °C to ensure consistent recording conditions.

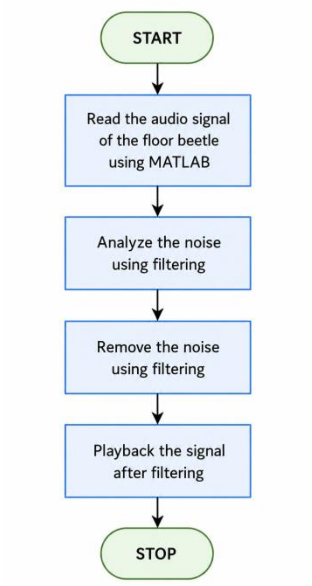

Fig.-3.1: Architectural flow diagram of acoustic signal detection and signal analysis

Figure 3.1 illustrates the overall workflow adopted for acoustic signal acquisition and analysis. The audio signals captured by the sensing unit were initially stored in MATLAB-compatible .wav format and subsequently imported for further processing using the wavread function. Preliminary spectral analysis indicated the presence of considerable background interference and signal distortion caused by environmental noise.

To improve signal quality and isolate pest-related acoustic components, both Infinite Impulse Response (IIR) and Finite Impulse Response (FIR) digital filtering techniques were applied during the preprocessing stage.

The frequency responses of the implemented filters were analyzed to evaluate their pass-band characteristics and filtering performance. Following the application of FIR and IIR filtering techniques, the resulting audio spectra exhibited smoother signal distributions, indicating effective suppression of background noise. The processed acoustic signals demonstrated improved clarity during playback, enabling better interpretation of pest-generated sound patterns.

For larval-stage analysis, MATLAB was employed to investigate the complex acoustic emissions produced by multiple active larvae within the grain medium. The recorded signals contained several prominent sound-pressure peaks corresponding to larval movement and feeding activity. A representative frequency-domain representation of the larval acoustic signal is illustrated in Figure 3.1, highlighting the spectral characteristics associated with insect activity.

RESULTS AND DISCUSSION

During the larval-stage investigation, MATLAB was utilized to analyze the recorded acoustic emissions generated by active larval movement within the grain samples. The acquired signals exhibited multiple sound-pressure peaks corresponding to larval feeding and locomotion activities. Frequency-domain analysis revealed that the dominant acoustic components were distributed within the 1–7 kHz range, with a significant spectral peak observed near 0.3 kHz, which lies within the audible frequency range.

The raw acoustic recordings were affected by considerable environmental interference, resulting in irregular amplitude fluctuations and reduced signal clarity. To address this issue, digital filtering techniques were applied during preprocessing. The filtered outputs demonstrated smoother waveform characteristics and enhanced signal definition, confirming the effectiveness of the proposed noise reduction approach for improving acoustic pest detection performance.

Power System Protection and Control
ISSN:1674-3415

4.1 Noise Reduction in Beetle Sound Recordings Using Band-Pass FIR and IIR Filtering

Finite Impulse Response (FIR) filters represent a fundamental component of digital signal processing systems due to their linear phase response and capability to achieve precise amplitude-frequency characteristics. One of the primary advantages of FIR filters is their finite-duration impulse response, which inherently ensures system stability during signal processing operations. Owing to their robustness, predictable behavior, and design flexibility, FIR filters are extensively employed in diverse applications including telecommunications, biomedical engineering, audio analysis, and image processing. Their ability to preserve signal integrity while effectively suppressing unwanted noise makes them particularly suitable for acoustic signal enhancement and precision monitoring applications.

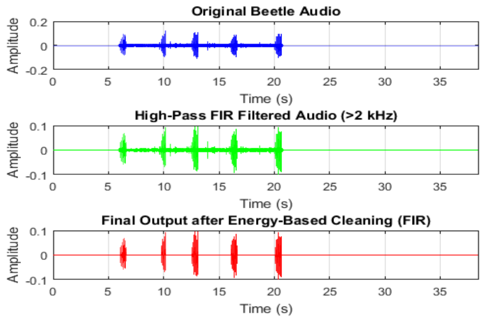

Fig.-4.1: FIR band pass filter applied to remove noise

Figure 4.1 illustrates the sequential noise reduction procedure applied to beetle acoustic recordings using a high-pass FIR filtering approach combined with energy-based signal enhancement. The original waveform presented in the upper subplot contains substantial background interference, which obscures the characteristic beetle-generated clicks. Following the application of a 2 kHz high-pass FIR filter, as shown in the middle subplot, low-frequency environmental noise components are significantly attenuated, resulting in improved visibility of the target acoustic signals. Residual noise components were further minimized through an energy-based cleaning process applied in the final stage. The resulting waveform exhibits clearer and more isolated beetle click patterns, thereby enhancing the overall detectability and reliability of acoustic pest activity analysis.

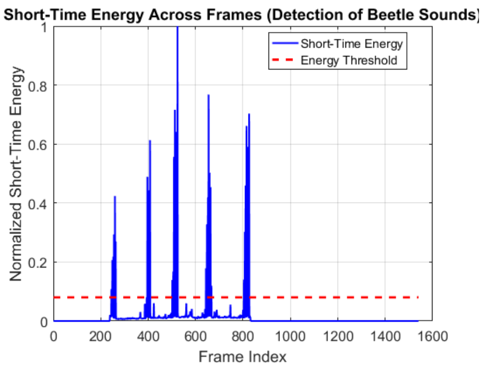

Fig.-4.2: Short-Time Energy Analysis for Beetle Sound Detection (FIR).

Figure 4.2 presents the variation of short-time energy (STE) across successive audio frames for the detection of beetle-generated acoustic signals. In the plot, the blue curve represents the normalized short-time energy of the recorded signal, whereas the red dashed line denotes the predefined energy threshold used for activity detection. Signal peaks exceeding this threshold are identified as potential beetle acoustic events, enabling the system to distinguish biologically relevant sound patterns from background noise. This energy-based analysis facilitates efficient segmentation and extraction of pest-related acoustic components for subsequent signal processing and classification tasks.

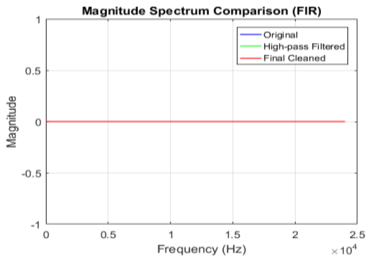

Fig.-4.3: Magnitude spectrum Comparison (FIR)

Figure 4.3 presents the magnitude spectrum of beetle acoustic signals at different stages of the signal processing pipeline. The comparison includes the original recorded signal, the high-pass FIR-filtered output, and the final cleaned signal obtained after noise suppression. The original spectrum contains considerable background interference distributed across multiple frequency components. Following high-pass filtering, low-frequency noise components are substantially attenuated, improving the visibility of insect-generated acoustic features. The final processed spectrum exhibits a significantly smoother response with reduced unwanted frequency components, indicating effective signal cleaning and enhanced spectral clarity. These improvements contribute to more reliable acoustic analysis and increased accuracy in pest detection applications.

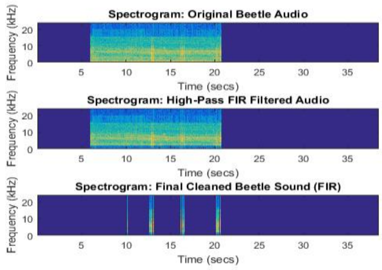

Fig.-4.4: Frequency spectrum Comparison Beetle Sound (FIR).

Figure 4.4 illustrates the spectrogram representations of the beetle acoustic recordings at three distinct processing stages: the original signal, the high-pass filtered output, and the final cleaned signal. The original spectrogram exhibits a wide frequency distribution accompanied by significant background interference across the spectrum. Following the application of high-pass filtering, low-frequency noise components are noticeably attenuated, resulting in improved visibility of the target acoustic patterns. In the final processed spectrogram, the beetle-generated sound signatures appear more distinct and well-isolated in both time and frequency domains. The enhanced spectral separation achieved through the filtering process significantly improves the clarity of the acoustic signals and supports more accurate pest detection and analysis.

4.2 Noise Reduction in Beetle Sound Recordings Using Band-Pass IIR Filtering.

In contrast, Infinite Impulse Response (IIR) filters employ a recursive structure that incorporates feedback mechanisms within the filtering process. This feedback-based operation enables IIR filters to achieve sharp and highly efficient amplitude-frequency responses with comparatively lower filter orders. Although IIR filters generally do not preserve linear phase characteristics, they offer superior computational efficiency and precise frequency selectivity in many signal processing applications. Consequently, IIR filters are widely utilized in systems requiring effective real-time filtering, where minor phase distortions are acceptable in exchange for improved processing performance and reduced computational complexity.

DOI: 10.46121/pspc.54.3.27

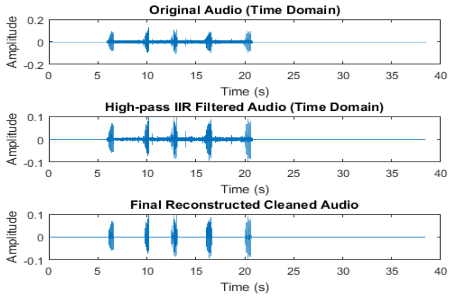

Fig.-4.5: IIR band pass filter applied to remove noise.

Figure 4.5 illustrates the sequential processing stages applied to beetle acoustic recordings using an Infinite Impulse Response (IIR) band-pass filtering approach for noise suppression and signal enhancement. The upper subplot presents the original time-domain waveform, where beetle-generated acoustic events are partially obscured by environmental and ambient noise components, making direct interpretation difficult.

The middle subplot represents the signal obtained after applying the IIR high-pass filtering process. This stage effectively attenuates low-frequency background interference while preserving the dominant frequency components associated with beetle activity. Consequently, the filtered waveform exhibits improved signal definition, although limited residual noise remains.
In the final stage, an energy-based post-processing technique was employed to reconstruct a cleaner acoustic signal by retaining only high-energy segments corresponding to beetle-generated sounds. The resulting waveform demonstrates clearly isolated beetle click patterns with substantially reduced noise interference, thereby improving the accuracy and reliability of acoustic pest detection and classification.

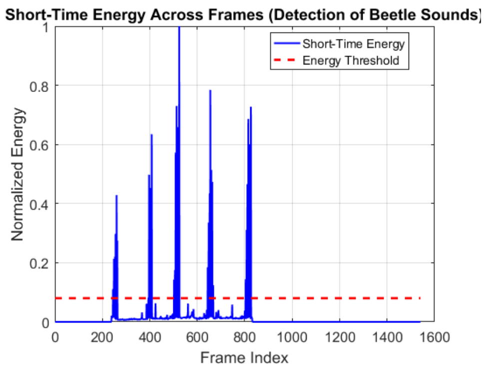

Fig.-4.6: Short-Time Energy Analysis for Beetle Sound Detection (IIR).
The figure-4.6 shows the Short-Time Energy (STE) plot where beetle-generated sound spikes surpass the energy threshold, enabling effective detection of pest activity.

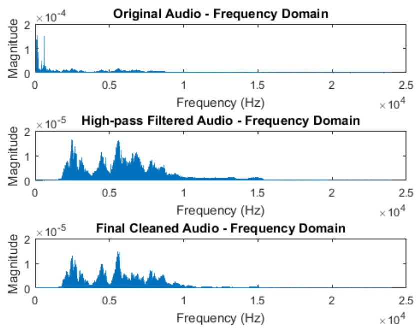

Fig.-4.7: Magnitude spectrum Comparison (IIR)

DOI: 10.46121/pspc.54.3.27

Power System Protection and Control
ISSN:1674-3415

Figure 4.7 presents the frequency-domain analysis of the beetle acoustic signal before and after IIR-based filtering. The spectral representation demonstrates a substantial attenuation of low-frequency background noise following the filtering process, while the dominant frequency components associated with beetle activity are effectively preserved. The final processed spectrum exhibits improved signal clarity and enhanced separation of relevant acoustic features, thereby supporting more reliable pest detection and frequency-based analysis.

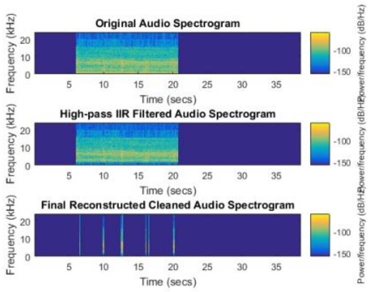

Fig.-4.8: Frequency spectrum Comparison Beetle Sound (IIR).

Figure 4.8 presents a comparative spectrogram analysis illustrating the progressive enhancement of beetle-generated acoustic signals throughout the filtering stages. The spectrograms demonstrate a gradual reduction of background noise components and improved visibility of biologically relevant sound patterns after signal processing. In the final cleaned audio representation, the beetle acoustic signatures appear more distinct and well-isolated in both time and frequency domains, confirming the effectiveness of the filtering approach in enhancing signal clarity and improving acoustic pest detection performance.

Table-4.1 shows the acoustic frequency characteristics of Triboium confusum larvae recorded from infected mass of wheat grain.

Distance sensor (cm)	**Sound level in dB**	**Frequency in kHz**
10	-29 (Before noise filtering)	1.9-7
10	-29 (after noise filtering)	1.9-7

Table 5.1 presents the relationship between sensor distance, sound intensity measured in decibels (dB), and the corresponding frequency range before and after the application of noise filtering techniques. At a sensor distance of 10 cm, the recorded acoustic signal exhibited a sound level of approximately −29 dB within a frequency range of 1.9–7 kHz. Following the implementation of noise filtering, both the sound level and the dominant frequency range remained substantially unchanged. This observation indicates that the filtering process effectively suppressed environmental interference while preserving the original spectral characteristics of the beetle-generated acoustic signal.

The near-constant dB values observed in Table 5.1 can be attributed to the adopted measurement methodology, where the sound level was determined based on the peak amplitude of the target pest frequency rather than the total signal energy across the spectrum. The implemented FIR and IIR filtering techniques were designed as narrow band-pass filters to retain the dominant frequency components associated with *Tribolium confusum* larvae while attenuating unrelated background noise frequencies.

CONCLUSION

This study presents an acoustic signal enhancement approach for improving the detection of *Tribolium confusum* activity in stored wheat grains. Acoustic emissions produced by adult beetles were recorded using sensors positioned approximately 10 cm above the grain surface under controlled experimental conditions. To improve signal quality and increase the detectability of insect-generated acoustic events, Finite Impulse Response (FIR) and Infinite Impulse Response (IIR) band-pass filtering techniques were applied during the preprocessing stage. The filtering process effectively suppressed background noise and produced an improvement of nearly 10 dB in

DOI: 10.46121/pspc.54.3.27

signal magnitude, resulting in clearer and more distinguishable acoustic recordings. Enhanced signal quality enabled more accurate observation and analysis of beetle activity and behavioral patterns within the grain environment. The proposed approach demonstrates the effectiveness of digital signal processing techniques in developing reliable and non-invasive acoustic-based pest monitoring systems for stored grain protection and precision agriculture applications.

REFERENCE

1. S. M. Nourbakhsh, Y. Bai, G. D. N. Maia, Y. Ouyang, And L. Rodriguez, "Grain Supply Chain Network Design And Logistics Planning For Reducing Post-Harvest Loss," Biosyst. Eng., Vol. 151, 2016, Doi: 10.1016/J.Biosystemseng.2016.08.011.
2. Amoussouhoui, Rico & Akpa, Kuassi Auxence Aristide & Nkhata, Smith & Banout, Jan. (2023). Analyzing The Impact Of Reducing Food Losses Of Rice On Food Security In Benin. Ekonomika poljoprivrede. 70. 99-116. 10.59267/ekoPolj230199A.
3. Erekalo, Kassa & Kelem, Fasika. (2022). Assessment of Mango Post-Harvest Losses along Value Chain in the Gamo Zone, Southern Ethiopia. International Journal of Fruit Science. 22. 170-182. 10.1080/15538362.2021.2025194.
4. B. Minten, S. Tamru, And T. Reardon, "Post-Harvest Losses In Rural-Urban Value Chains: Evidence From Ethiopia," Food Policy, Vol. 98, 2021, Doi: 10.1016/J.Foodpol.2020.101860.
5. M. W. Hassan, J. Iqbal, And M. Jamil, "Comparative Study Of Tribolium Castaneum H. (Coleoptera: Tenebrionidae) Occurred On Different Wheat Varieties In Pakistan," Pakistan J. Sci. Ind. Res. Ser. B Biol. Sci., Vol. 61, No. 1, 2018, Doi: 10.52763/Pjsir.Biol.Sci.61.1.2018.47.51.
6. Aidoo, R., Danfoku, R. A., & Mensah, J. O. (2014). Journal of Development and Agricultural Economics Determinants of postharvest losses in tomato production in the Offinso North district of Ghana. 6(8), 338–344. https://doi.org/10.5897/JDAE2013.0545
7. Appiah, F., Guisse, R., & Dartey, P. K. A. (2011). Post-harvest losses of rice from harvesting to milling in Ghana. Journal of Stored Products and Postharvest Research, 2(4),6471. https://academicjournals.org/journal/JSPPR/article-full-text pdf/ 4FA055 C8791
8. Babatunde, R., Omoniwa, A., & Aliyu, J. (2019). Post-Harvest Losses along the Rice Value Chain in Kwara State, Nigeria: An Assessment of Magnitude and Determinants. Cercetari Agronomice in Moldova, 52(2), 141–150.
9. Balana, B. B., Aghadi, C. N., & Ogunniyi, A. I. (2022). Improving livelihoods through postharvest loss management: evidence from Nigeria. Food Security, 14(1), 249–265. https://doi.org/10.1007/S12571-021-01196-2/TABLES/7
10. Hashim, N., Onwude, D. I., & Maringgal, B. (2022). Technological advances in postharvest management of food grains. Research and Technological Advances in Food Science, 371–406. https://doi.org/10.1016/B978-0-12-824369-5.00016-6
11. Aliano Filho, A., de Oliveira Florentino, H., Pato, M. V., Poltroniere, S. C., & da Silva Costa, J. F. (2019). Exact and heuristic methods to solve a bi-objective problem of sustainable cultivation. Annals of Operations Research. https://doi.org/10.1007/s10479-019-03468-9.DOI: 10.1007/s10479-019-03468-9
12. An, K., & Ouyang, Y. (2016). Robust grain supply chain design considering post-harvest loss and harvest timing equilibrium. Transportation Research Part E: Logistics and Transportation Review, 88, 110–128. DOI: 10.1016/j.tre.2016.01.009

13. Asgari, N., Farahani, R. Z., Rashidi-Bajgan, H., & Sajadieh, M. S. (2013). Developing model-based software to optimise wheat storage and transportation: A real-world application. Applied Soft Computing Journal, 13(2),1074–1084.DOI: 10.1016/j.asoc.2012.10.002
14. Chauhan, A., Kaur, H., Yadav, S., & Jakhar, S. K. (2019). A hybrid model for investigating and selecting a sustainable supply chain for agri-produce in India. Annals of Operations Research. https://doi.org/10.1007/s10479-019-03190-6.DOI: 10.1007/s10479-019-03190-6
15. Ali, A., Sarwar, M., Khanzada, S., Abro, G.H. 2011. Evaluating resistance of wheat germplasms to attack by red flour beetle, Tribolium castaneum. H (Coleoptera). Pakistan Journal of Zoology, 43: 793-797.
16. Appiah, F., Guisse, R., & Dartey, P. K. A. (2011). Post-harvest losses of rice from harvesting to milling in Ghana. Journal of Stored Products and Postharvest Research, 2(4),64–71. https://academicjournals.org/journal/JSPPR/article-full-text pdf/ 4FA055 C8791
17. Allaoui, H., Guo, Y., Choudhary, A., & Bloemhof, J. (2018). Sustainable agro-food supply chain design using two-stage hybrid multi-objective decision-making approach. Computers & Operations Research, 89, 369–384. DOI: 10.1016/j.cor.2016.10.012
18. Diabat, A., Govindan, K., & Panicker, V. V. (2012). Supply chain risk management and its mitigation in a food industry. International Journal of Production Research, 50(11),3039–3050. DOI: 10.1080/00207543.2011.588619
19. Florentino, H. D. O., Cantane, D. R., Jones, D. F., Ouelhadj, D., Khosravi, B., & Irawan, C. A. (2020). An optimization model for combined selecting, planting and harvesting sugarcane varieties. Annals of Operations Research. https://doi.org/10.1007/s10479-020-03610-y. DOI: 10.1007/s10479-020-03610-y
20. Y. Yang, "Design and Application of Intelligent Agriculture Service System With LoRa-based on Wireless Sensor Network," 2020 International Conference on Computer Engineering and Application (ICCEA), Guangzhou, China, 2020, pp. 712-716, doi: 10.1109/ICCEA50009.2020.00155
21. LoRa Based Green House Monitoring and Control System using IoT", International Journal of Emerging Technologies and Innovative Research ISSN:2349-5162, Vol.12, Issue 3, page no. ppd347-d354, March-2025, Available at : http://www.jetir.org/papers/JETIR2503339.pdf