International Journal of Innovative Research and Scientific Studies, 8(12) 2025, pages: 108-117

IJIRSS
International Journal of Innovative Research & Scientific Studies

**ISSN:** 2617-6548

URL: www.ijirss.com


# AI-based early warning mechanism for poultry farms: Evaluating acoustic signal algorithms for bird health and sustainable production

Halleluyah Oluwatobi Aworinde

*Information Technology Department, Durban University of Technology, Durban KwaZulu-Natal, South Africa.*

(*Email: halleluyaha@dut.ac.za*)

## Abstract

This study examines the rising consumption of animal products in Africa amid concerns about declining production. It suggests that food production needs to increase by 25% to meet the demands of a growing population. The experimental study involved 100 poultry birds divided into two groups: one inoculated with chronic respiratory disease (CRD), and one uninoculated. Over 65 days, audio signals were collected three times daily in a controlled environment with ethical approval. A nano 32 BLE sensor was used to collect a dataset of 346 audio signals from the farm. These signals were categorized as healthy, disease-related, or noisy. To identify the most effective model for early detection of poultry diseases, three algorithms utilizing audio signals were evaluated: MFCC, MFE, and Spectrogram. Results showed the Spectrogram algorithm outperformed others, with 99.2% accuracy, 99.3% F1-score, and 0.05 loss. The MFCC algorithm had 85.6% accuracy, 85% F1-score, and 0.38 loss, while the MFE algorithm achieved 97.4% accuracy, 97.3% F1-score, and 0.08 loss. Implementing it can support sustainable development goals 1 (No Poverty), 2 (Zero Hunger), 3 (Good Health and Well-being), and 12 (Responsible Consumption and Production) by improving poultry farming and reducing economic losses.

**Keywords:** Algorithms, Artificial intelligence, Audio signal processing, Deep learning techniques, Machine learning, Smart poultry.

**DOI:** 10.53894/ijirss.v8i12.11019
**Funding:** This study received no specific financial support.
**History: Received:** 16 October 2025 / **Revised:** 7 November 2025 / **Accepted:** 10 November 2025 / **Published:** 5 December 2025

**Competing Interests:** The author declares that there are no conflicts of interests regarding the publication of this paper.
**Transparency:** The author confirms that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.
**Acknowledgement:** I am deeply grateful to my Postdoctoral Research Fellowship host, Prof. Brett van Niekerk and to Prof. Richard Millham for their generous mentorship, constructive feedback, and steady encouragement throughout the development of this paper. Their thoughtful and incisive comments substantially improved the clarity and rigour of this manuscript.
**Publisher:** Innovative Research Publishing

## 1. Introduction

Protein is vital for human health and growth, especially in a populous country like Nigeria. However, due to various factors such as high prices, limited availability, and poor quality, the consumption of animal products like meat, milk, and eggs—which are excellent sources of protein—has decreased in Nigeria. In 2017, Nigerians consumed 9.2 kg of meat per person, which is significantly lower than the recommended 50 kg and the global average of 34.1 kg, according to the Food and Agriculture Organization (FAO) [1-3]. Similarly, per capita consumption of milk and eggs was 10.6 kg and 2.8 kg, respectively, compared to global standards of 113.9 kg and 9.1 kg [4]. Because a lack of protein can lead to stunted growth, weakened immunity, and increased vulnerability to infections and diseases, this issue poses a major challenge to Nigeria's food security and nutrition [5-12].

Boosting the production and consumption of chicken products, which are generally more affordable, accessible, and appealing than other animal products in Nigeria, offers a practical solution to this problem [13]. One of Nigeria's most important agricultural subsectors is poultry farming, making up about 25% of total livestock production and providing jobs for millions of people [14]. In addition to offering high-quality protein, essential amino acids, vitamins, minerals, and fatty acids, poultry products are also highly nutrient-dense [15]. Therefore, improving the productivity and profitability of poultry farming can significantly enhance Nigeria's food security, nutrition, revenue, and efforts to reduce poverty [16-18].

Unfortunately, the global poultry industry faces numerous infectious and non-infectious diseases that cause significant economic losses. Likewise, Nigerian poultry farming encounters various challenges that hinder its ability to meet the increasing demand for animal protein. The widespread presence of illnesses and health issues negatively affects poultry health and welfare, reduces performance and output, increases mortality, and results in financial losses. Poultry diseases can be either digestive or respiratory, but respiratory diseases contribute notably to the mortalities experienced by poultry farmers [19]. Respiratory diseases may result from viral, bacterial, fungal, and mycoplasma infections. There are five viral respiratory diseases linked to the respiratory system: Avian influenza (AI), Newcastle disease (ND), Infectious bronchitis (IB), Infectious laryngotracheitis (ILT), and Avian metapneumovirus (AE). It is essential to detect these diseases early and keep them under control or vaccinate when needed. Viral respiratory diseases show common symptoms, including coughing, sneezing, and rales.

The health condition of a poultry flock reflects their overall physical, mental, and social well-being, as well as their ability to produce meat and eggs. Keeping poultry healthy is essential to prevent disease transmission and ensure the safety and quality of poultry products [20]. Assessing poultry health includes observing their behavior, feed and water intake, body condition, and any signs of illness. Good health in poultry is shown by active birds with clean feathers and bright eyes, consistent feed and water consumption, and normal body weight. In contrast, signs of poor health include lethargy, decreased food and water intake, abnormal vocalizations, respiratory problems, and unusual fecal or urinary output [21].

Various researchers have explored automatic Newcastle disease detection through sound technology and deep learning. They introduced the Deep Poultry Vocalization Network (DPVN), a new method for early ND detection based on changes in poultry vocalizations. This technique uses a multi-sub-band identification algorithm combined with multi-window spectral subtraction, high-pass filtering, and noise reduction. Five models are employed, with audio features feeding into a deep learning network, achieving top results of 98.50% accuracy, 96.60% recall, and a 97.33% F1-score. The method demonstrates detection accuracy between 82.15% and 98.50% within the first four days post-infection, offering promising potential for improving animal welfare and automating monitoring in chicken farms.

Similarly, a chicken sound convolutional neural network (CSCNN) has been developed as an innovative method for detecting chickens infected with avian influenza. This technique isolates chicken sounds from complex audio data and generates feature maps based on four attributes: Logfbank, MFCC, MFCC Delta, and MFCC Delta-Delta. On days two, four, and six after H9N2 virus injection, the recognition accuracies of CSCNN-S and CSCNN-F reach 93.01%, 95.05%, and 97.43%, and 89.79%, 93.56%, and 95.84%, respectively. This approach enables rapid and accurate detection of infected hens through sound, which is crucial for preventing and managing the spread of avian influenza in poultry [22].

Mahdavian, et al. [23] explored a vocal activity identification algorithm in bioacoustics, focusing on chicken calls. Their findings demonstrate an effective method for extracting calls from both healthy and unhealthy birds based on sound signals. The algorithm was tested on 120 birds across two genotypes, revealing that older age and illness reduced accuracy. Specifically, detection accuracy was 95% for healthy young birds but dropped to 72% for unhealthy ones. This approach can aid in distinguishing animal vocalizations, an important advance in bioacoustics research [23]. However, the study encountered issues with calls being misclassified as non-vocal segments, which could diminish accuracy and weaken the significance of the results. Further refinement of the algorithm is necessary to improve the classification of vocalization fragments.

Another study on poultry health monitoring analyzed five acoustic parameters of bird calls to identify health problems. The signals were recorded from broilers divided into three groups: control, bronchitis-challenged, and Newcastle disease-challenged [21]. Among the five features examined, wavelet entropy performed the best, detecting bronchitis with 83% accuracy on the third day after inoculation, with a type II error of less than 14%. For Newcastle disease, wavelet entropy was more reliable in identifying healthy birds, while Mel cepstral coefficients were more effective in recognizing challenged birds.

Early detection and intervention are crucial for controlling disease outbreaks, but current methods for monitoring bird health are often invasive, time-consuming, and expensive. Vocal acoustics analysis is a promising non-invasive technique for real-time monitoring of bird health. However, there seems to be a lack of research on the acoustic differences between healthy and diseased birds, and the effectiveness of vocal analysis in farm conditions remains largely unknown. This work, therefore, explores the potential of using artificial intelligence-based vocal acoustics analysis to develop an early warning system for poultry farms to assess the health status of poultry amid other environmental noises.

## 2. Materials and Methods

Figure 1 shows the comprehensive experimental setup for monitoring poultry health through sound classification. Audio data from a poultry farm was collected via an embedded device, the Arduino Nano BLE 33 Sense. The device is built on the nRD52840 processor and runs on **Arm® Mbed™ OS** [24]. It is equipped with an audio sensor along with other sensors such as color, proximity, motion, temperature, and humidity. The audio sensor was used to collect audio signals corresponding to healthy, unhealthy, and environmental noise. Accurate dataset categorization is essential for enabling the model to differentiate key poultry health indicators from irrelevant background noise.

After gathering data, preprocessing improves the audio quality and consistency. First, signals are normalized to achieve uniform amplitude and quality across all samples. The normalized audio is then segmented into smaller parts, which simplifies management and helps the model generalize better. Finally, the dataset is divided into training and testing sets to facilitate learning and evaluate the model's performance.

Feature extraction techniques transform raw audio signals into meaningful features. These include Mel-Frequency Cepstral Coefficients (MFCC), which capture the audio's timbral qualities; Mel-Frequency Energy (MFE), highlighting energy distribution across frequencies; and Spectrograms, providing visual representations of frequency over time. Combining these methods results in a robust feature set that enhances classification accuracy.

Feature clustering is a crucial subsequent step. UMAP (Uniform Manifold Approximation and Projection) was employed to uncover intrinsic patterns in the dataset, providing insights into how sound classes—Healthy, Unhealthy, and Noise—are distributed within the feature space. This clustering is essential for improving classification accuracy by revealing overlaps or distinct separations among the classes.

After completing feature extraction, the data is processed by a neural network hosted on the Edge Impulse platform. This model classifies audio signals into categories: healthy, unhealthy, and noise. The training involves adjusting the model's architecture and hyperparameters to enhance accuracy and robustness. Once trained, the model is tested with data to ensure it can reliably categorize poultry sounds.

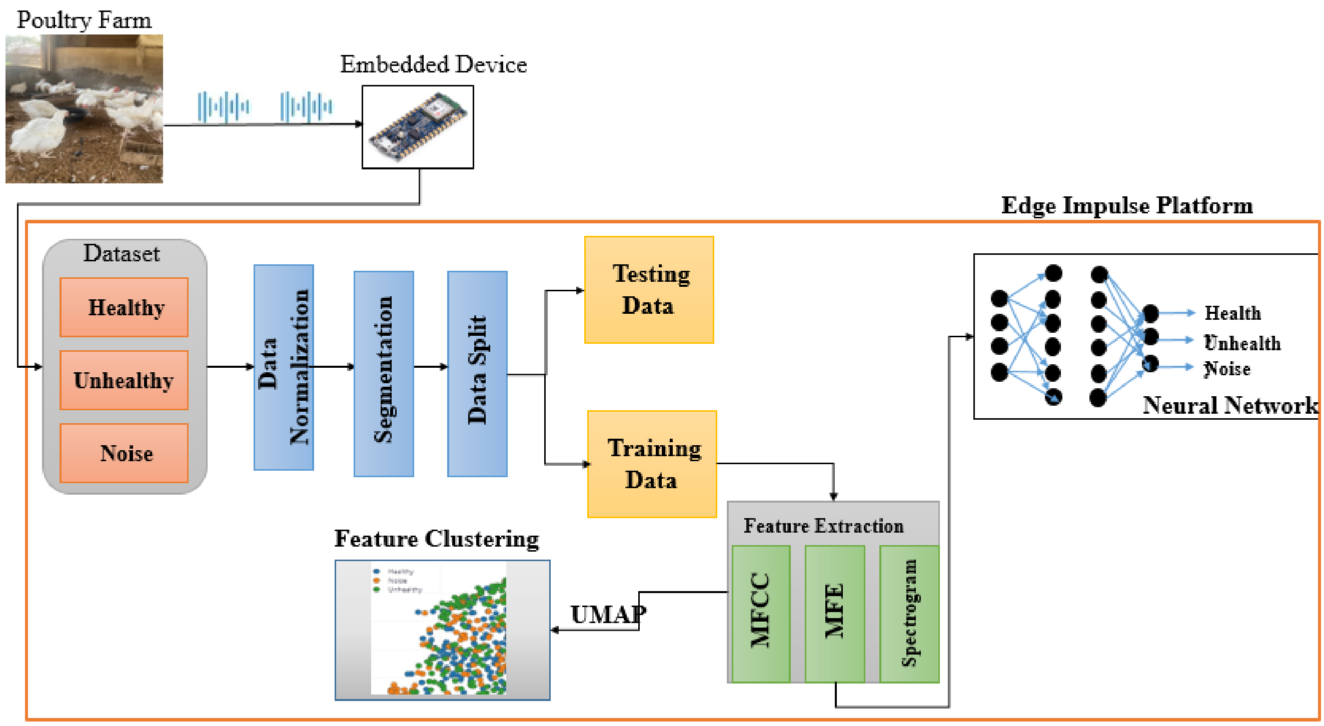


**Figure 1.**
System Functionality Diagram.

### *2.1. Dataset Description*

A total of 346 audio files were successfully gathered from the poultry farm. This dataset comprises 139 healthy, 121 unhealthy, and 86 noise audio recordings. It spans a broad spectrum of audio types, supporting a thorough analysis of various signal categories. A large dataset is crucial for achieving accurate and dependable results in analysis and classification tasks. The 139 healthy audio files serve as a strong baseline for defining normal audio patterns and traits.

The dataset contains 121 audio files showing birds with health issues, allowing us to study and categorize various audio anomalies and disturbances. Examining these signals helps us understand the distinct patterns and features linked to different types of audio irregularities.

Also, the dataset also contains 86 audio files labeled as noise, representing various sources of interference that mimic real-world conditions where environmental factors or technical problems influence audio signals. The distribution indicates that the model must accurately differentiate between diverse sound classes despite uneven data representation. This imbalance, particularly with the underrepresented Noise class, could impact classification accuracy. Hence, data augmentation was employed to mitigate the imbalance and enhance the model's performance generalization.

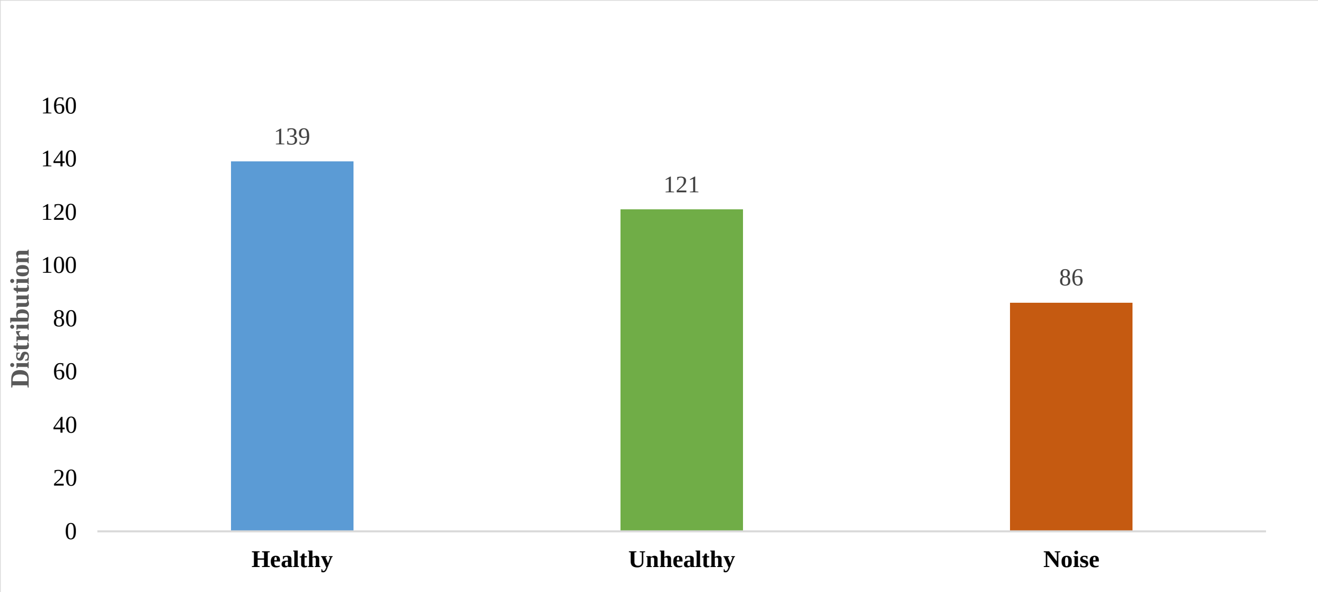


**Figure 2.**
Dataset Distribution.

*2.2. Feature Extraction*

*2.2.1. Mel-Frequency Cepstral Coefficients*

Mel-Frequency Cepstral Coefficients (MFCCs) are crucial features in audio signal processing, particularly for speech and sound classification. They accurately capture the spectral characteristics of audio signals by simulating the human ear's response, emphasizing low-frequency areas where the majority of perceptually important information is found. Extracting MFCCs involves several steps, including framing, windowing, Fourier transform, Mel filter bank processing, logarithmic compression, and discrete cosine transform (DCT).

Given an audio signal x(n), it can be divided into short overlapping frames to ensure the stationarity of the signal within each frame. If the frame length is N and the overlap is M, then the ith frame can be represented as:

$$x_i(n) = x\big(n + i(M)\big),\ \ 0 \leq n < N \qquad (1)$$

Applying a Hamming window to each frame reduces the spectral leakage and the windowed signal is:

$$x_w = x_i(n) * w(n) \qquad (2)$$

Where $w(n) = 0.54 - 0.46\cos\left(\frac{2\pi n}{N-1}\right)$. The Discrete Fourier Transform (DFT) is then applied to obtain the magnitude spectrum of the signal:

$$X_k = \sum_{n=0}^{N-1} x_w(n) e^{-j\frac{2\pi kn}{N}} \qquad (3)$$

Where $X_k$ is the DFT of the frame and $N$ is the number of samples in the frame. The magnitude spectrum is then passed through a set of triangular filter banks, spaced on the Mel scale to approximate human auditory perception. The Mel scale is defined by:

## 3. Results and Discussion

Our dataset includes 346 audio signal files, providing a comprehensive collection of healthy, unhealthy, and noisy audio samples. This extensive collection is a valuable resource for training and testing our classification algorithms, helping us develop effective and precise audio signal classification models. Figure 3 shows the distribution of categories in the dataset.

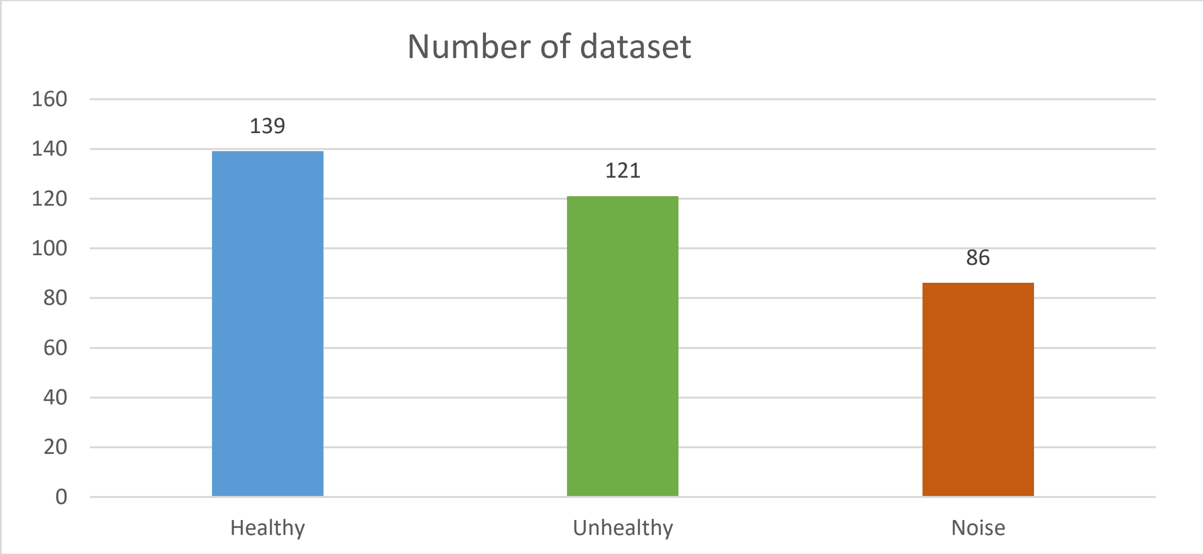


**Figure 3.**
Dataset Distribution.

To extract various features from the raw input data, Digital Signal Processing (DSP) blocks were used during Edge Impulse's data processing phase. Figures 4, 5, and 6 display the DSP of the extracted features using Spectrogram, MFCC, and MFE, respectively.

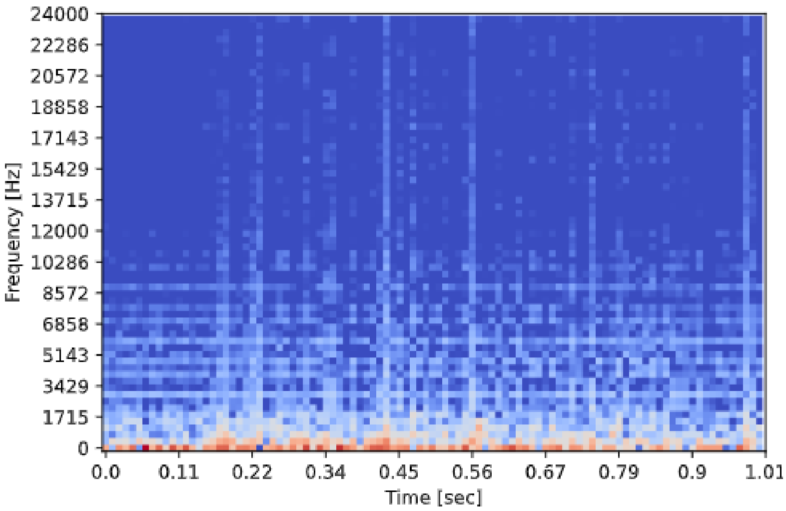


**Figure 4.**
DSP Result for Spectrogram.

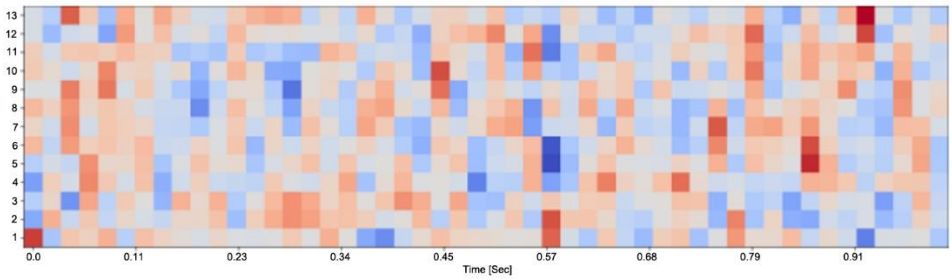


**Figure 5.**
DSP Result for MFCC.

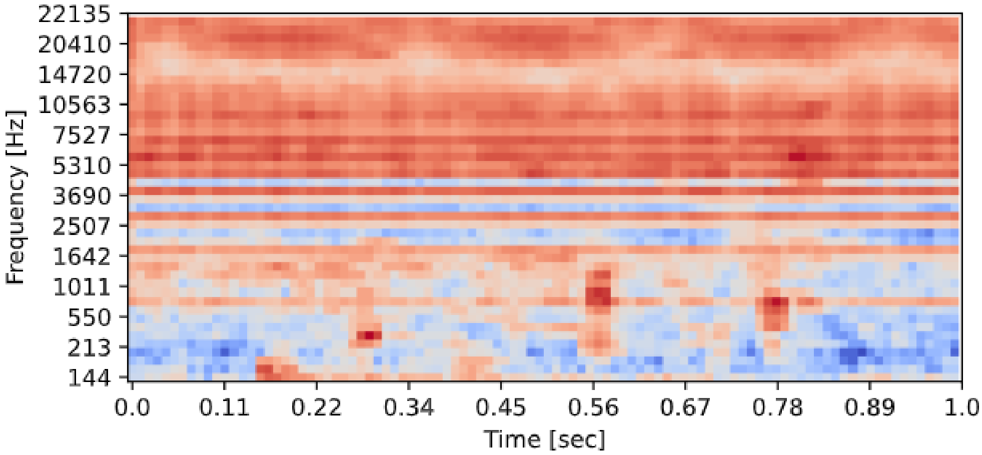


**Figure 6.**
DSP Result for MFE.

*3.1. Feature Selection*

Dimensionality reduction was performed to create a set of primary variables. To project these features into a 2D space, the data explorer first attempts to extract relevant features from the data using signal processing and neural network embeddings. This provides a quick overview of the entire dataset. Figures 7, 8, and 9 show the complete visual representations of the datasets in MFCC, MFE, and Spectrogram.

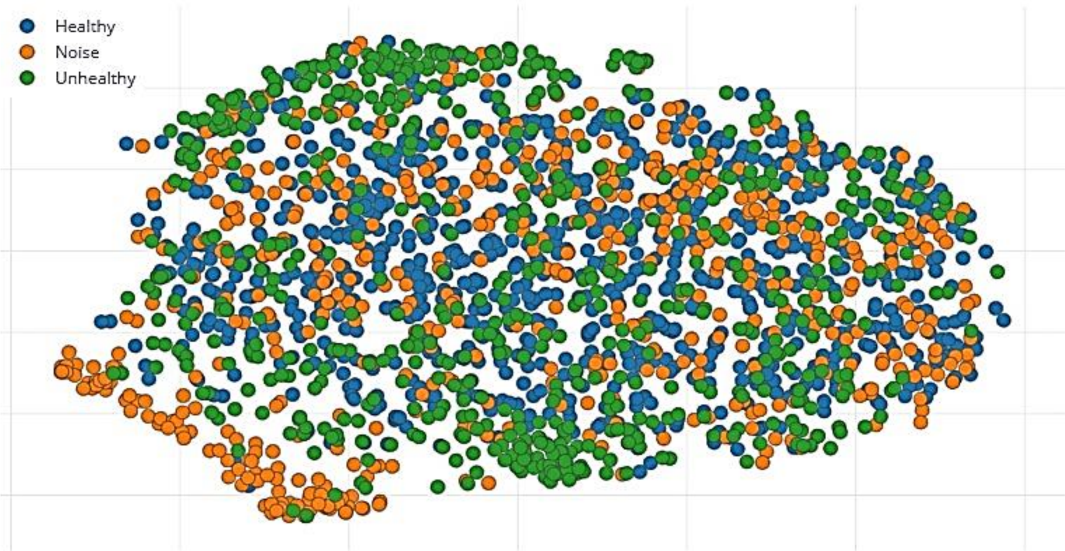


**Figure 7.**
MFCC Feature Selection.

From Figure 7 above, the healthy, unhealthy, and noisy features obviously overlap each other and follows no order. Hence, overfitting is feasible.

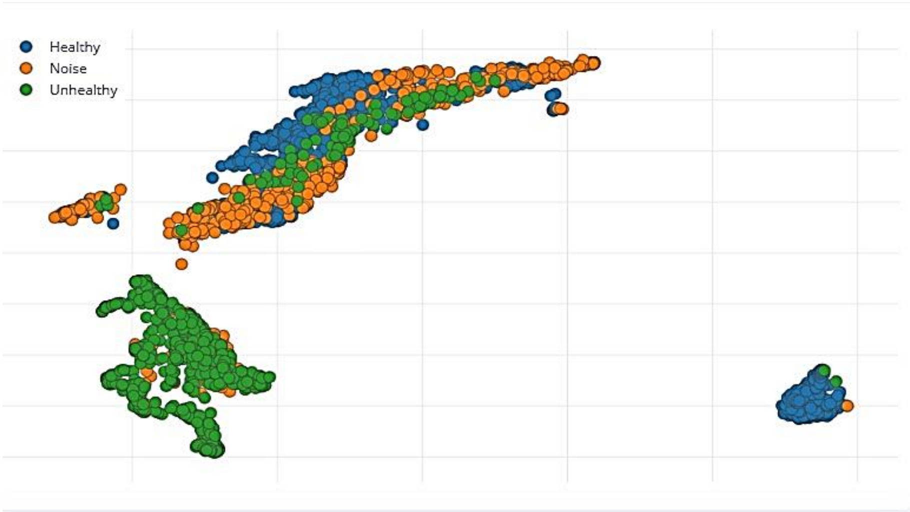


**Figure 8.**
Spectrogram Feature Selection.

Figure 8 above shows that the healthy, unhealthy, and noisy features are clustered separately, though other features seem to be slightly present in each cluster.

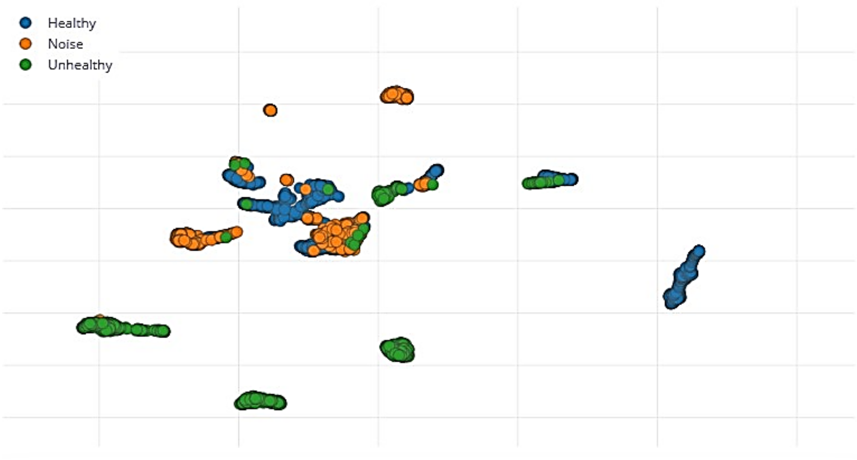


**Figure 9.**
MFE Feature Selection.

Figure 9 above shows that the healthy, unhealthy, and noisy features are both clustered and overlapping.

*3.2. Model Performance Evaluation*

**Table 1.**
Model Performance Evaluation.

| Type of model | Model accuracy | F1-score | Loss |
|---|---|---|---|
| MFCC | 85.6% | 85% | 0.38 |
| Spectrogram | 99.2% | 99.3% | 0.05 |
| MFE | 97.4% | 97.3% | 0.08 |

Table 1 above shows that the MFCC model achieved an accuracy of 85.6%, demonstrating its effectiveness in predicting labels. It also has an F1 score of 85%, reflecting the model's overall performance by balancing precision and recall. Additionally, the model has a loss value of 0.38, indicating how well it fits the training data; this is shown in Figure 12. The spectrogram achieved an accuracy of 99.2%, demonstrating its ability to predict labels. It also has an F1 score of 99.3% and a loss value of 0.05. The MFE model recorded an accuracy of 97.4%, an F1 score of 97.3%, and a loss of 0.08.

*3.3. Model Testing*

For model testing, 74 out of 346 collected data points were used. The spectrogram algorithm correctly classified 58 audio signals while 16 were classified incorrectly; details are shown in Figure 10.

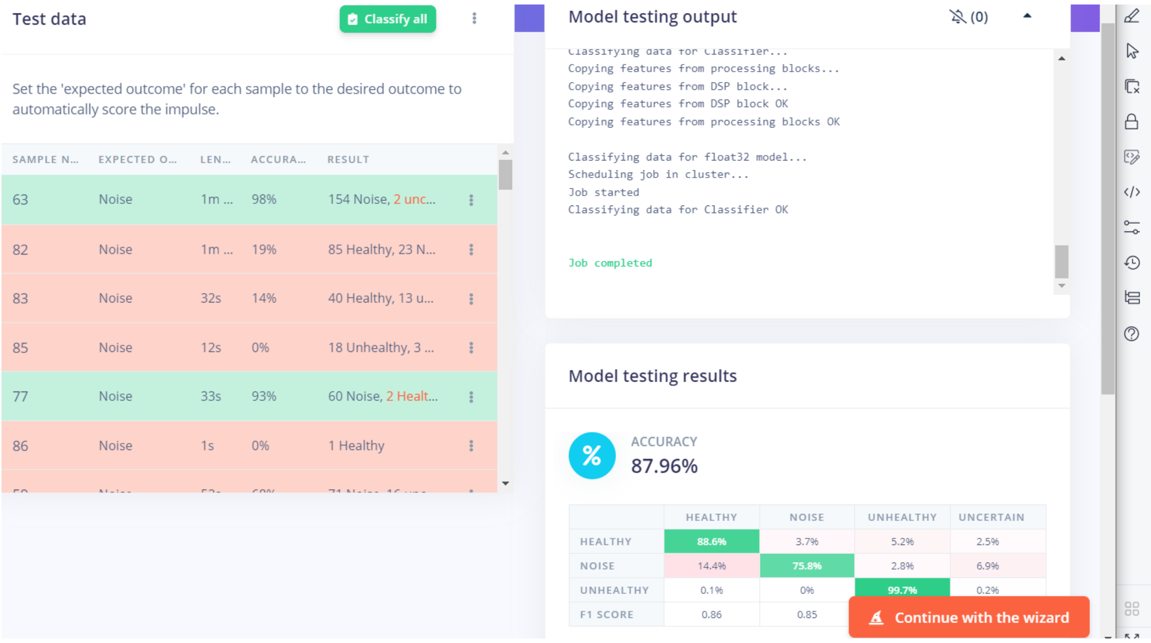


**Figure 10.**
Model Testing Output for Spectrogram.

MFCC correctly classified 24 out of 74 audio signal files, while 50 files were misclassified. This is shown in Figure 11 below.

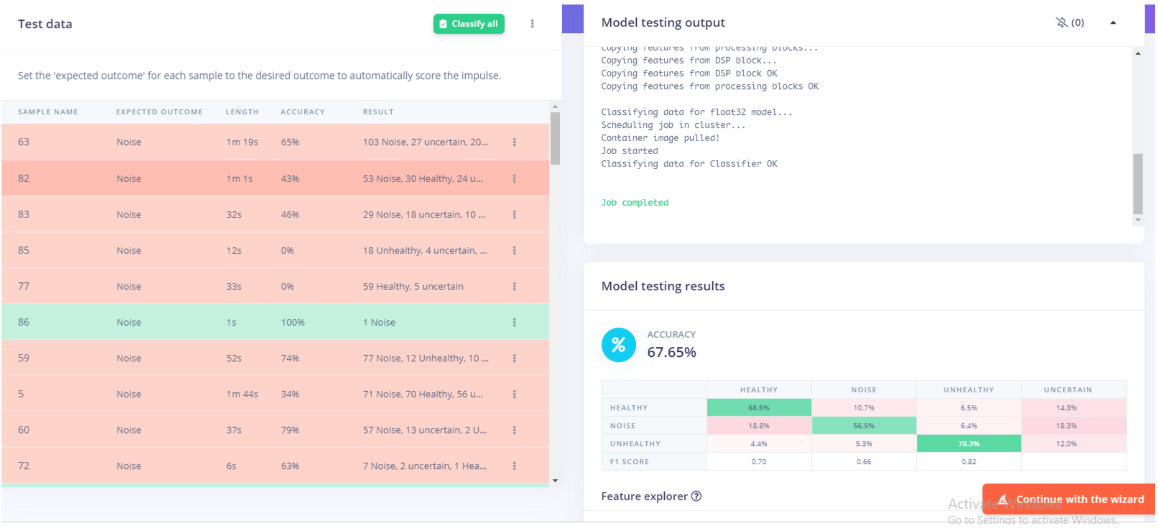


**Figure 11.**
Model Testing Output for MFCC.

For the MFE algorithm, 65 of the 74 audio signal files were correctly classified, while 9 files were misclassified. The model testing output is shown in Figure 12.

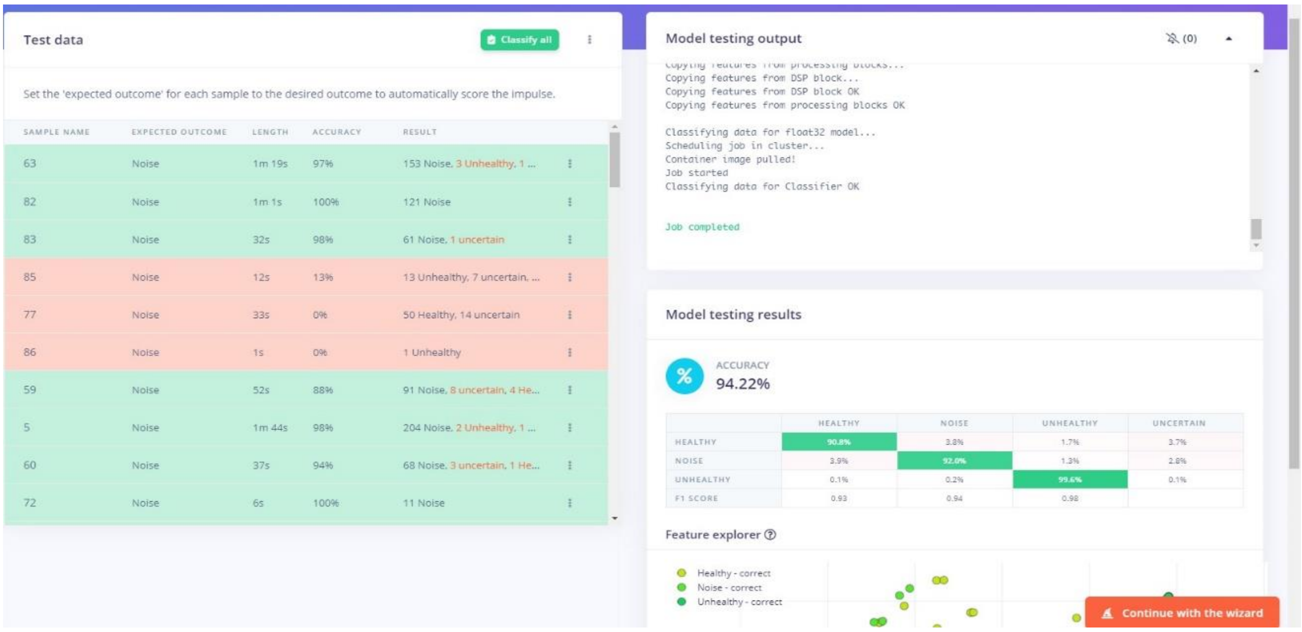


**Figure 12.**
Model Testing Output for MFE.

Based on the testing results, MFE demonstrates the best classification ability for audio signal files compared to the MFE and Spectrogram algorithms.

## 4. Conclusion

This study has established the feasibility and effectiveness of using vocal acoustics analysis on poultry farms to identify changes in bird health, even in the presence of environmental noise. It is anticipated that the full adoption of this approach will significantly impact poultry health monitoring, providing valuable insights to current knowledge. This will establish a solid foundation for future advancements in utilizing audio signals and machine learning techniques for early disease detection in poultry management.

## References

[1] Protein Sources For The Animal Feed Industry, "Protein sources for the animal feed industry," 2023. https://www.fao.org/3/y5019e/y5019e03.htm
[2] J. De Vries-Ten Have, A. Owolabi, J. Steijns, U. Kudla, and A. Melse-Boonstra, "Protein intake adequacy among Nigerian infants, children, adolescents and women and protein quality of commonly consumed foods," *Nutrition Research Reviews*, vol. 33, no. 1, pp. 102-120, 2020. https://doi.org/10.1017/S0954422419000222
[3] T. Beal *et al.*, "Friend or foe? The role of animal-source foods in healthy and environmentally sustainable diets," *The Journal of Nutrition*, vol. 153, no. 2, pp. 409-425, 2023. https://doi.org/10.1016/j.tjnut.2022.10.016
[4] F. Faostat, "Food and agriculture organization of the united nations-statistic division," 2019. https://www.fao.org/faostat/en/#data/QC
[5] L. Akissoé *et al.*, "Impact of traditional processing on proximate composition, folate, mineral, phytate, and alpha-galacto-oligosaccharide contents of two West African cowpea (Vigna unguiculata L. Walp) based doughnuts," *Journal of Food Composition and Analysis*, vol. 96, p. 103753, 2021. https://doi.org/10.1016/j.jfca.2020.103753
[6] J. Wong *et al.*, "Small-scale poultry and food security in resource-poor settings: A review," *Global Food Security*, vol. 15, pp. 43-52, 2017. https://doi.org/10.1016/j.gfs.2017.04.003
[7] R. U. Onyeneke *et al.*, "Impact of poultry farmers' participation in modern food retail markets on household dietary diversity: Lessons from southeast nigeria," *Animals*, vol. 10, no. 4, p. 611, 2020. https://doi.org/10.3390/ani10040611
[8] K. Pawlak and M. Kołodziejczak, "The role of agriculture in ensuring food security in developing countries: Considerations in the context of the problem of sustainable food production," *Sustainability*, vol. 12, no. 13, p. 5488, 2020. https://doi.org/10.3390/su12135488
[9] M. Y. Birhanu, R. Osei-Amponsah, F. Yeboah Obese, and T. Dessie, "Smallholder poultry production in the context of increasing global food prices: roles in poverty reduction and food security," *Animal Frontiers*, vol. 13, no. 1, pp. 17-25, 2023.
[10] S. Adebayo, A. Akinwunmi, H. Aworinde, and E. Ogunti, "Increasing agricultural productivity in Nigeria using wireless sensor network (WSN)," *African Journal of Computing & ICT*, vol. 8, no. 3, pp. 121-128, 2015.
[11] H. O. Aworinde *et al.*, "Poultry fecal imagery dataset for health status prediction: A case of South-West Nigeria," *Data in Brief*, vol. 50, p. 109517, 2023. https://doi.org/10.1016/j.dib.2023.109517
[12] S. Adebayo, H. O. Aworinde, A. O. Akinwunmi, A. Ayandiji, and A. O. Monsir, "Convolutional neural network-based crop disease detection model using transfer learning approach," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 29, no. 2023, pp. 365-374, 2023. http://doi.org/10.11591/ijeecs.v29.i1.pp365-374
[13] A. Afolayan, E. Omisope, A. M. Ajayi, O. S. Adeoti, and O. F. Ogunjinmi, "Analysis of credit access and utilization among poultry farmers in Nigeria," 2021.
[14] A. Cattaneo, *The state of food and agriculture 2018: migration, agriculture and rural development*. Rome: Food and Agriculture Organization of the United Nations (FAO), 2018.

[15] N. Mduma and H. Laizer, "Machine learning imagery dataset for maize crop: a case of Tanzania," *Data in Brief*, vol. 48, p. 109108, 2023. https://doi.org/10.1016/j.dib.2023.109108

[16] A. T. Adesogan, A. H. Havelaar, S. L. McKune, M. Eilittä, and G. E. Dahl, "Animal source foods: Sustainability problem or malnutrition and sustainability solution? Perspective matters," *Global Food Security*, vol. 25, p. 100325, 2020. https://doi.org/10.1016/j.gfs.2019.100325

[17] C. C. Kpomasse, O. E. Oke, F. M. Houndonougbo, and K. Tona, "Broiler production challenges in the tropics: A review," *Veterinary medicine and science*, vol. 7, no. 3, pp. 831-842, 2021. https://doi.org/10.1002/vms3.435

[18] H. M. Hafez and Y. A. Attia, "Challenges to the poultry industry: current perspectives and strategic future after the COVID-19 outbreak," *Frontiers in veterinary science*, vol. 7, p. 516, 2020. https://doi.org/10.3389/fvets.2020.00516

[19] O. C. Nwinyi *et al.*, "Review of drinking water quality in Nigeria: towards attaining the sustainable development goal six," *Ann Sci Technol*, vol. 5, no. 2, pp. 58-77, 2020.

[20] D. Machuve, E. Nwankwo, N. Mduma, and J. Mbelwa, "Poultry diseases diagnostics models using deep learning," *Frontiers in Artificial Intelligence*, vol. 5, p. 733345, 2022. https://doi.org/10.3389/frai.2022.733345

[21] A. Mahdavian, S. Minaei, P. M. Marchetto, F. Almasganj, S. Rahimi, and C. Yang, "Acoustic features of vocalization signal in poultry health monitoring," *Applied Acoustics*, vol. 175, p. 107756, 2021. https://doi.org/10.1016/j.apacoust.2020.107756

[22] K. Cuan, T. Zhang, Z. Li, J. Huang, Y. Ding, and C. Fang, "Automatic Newcastle disease detection using sound technology and deep learning method," *Computers and Electronics in Agriculture*, vol. 194, p. 106740, 2022. https://doi.org/10.1016/j.compag.2022.106740

[23] A. Mahdavian, S. Minaei, C. Yang, F. Almasganj, S. Rahimi, and P. M. Marchetto, "Ability evaluation of a voice activity detection algorithm in bioacoustics: A case study on poultry calls," *Computers and electronics in agriculture*, vol. 168, p. 105100, 2020. https://doi.org/10.1016/j.compag.2019.105100

[24] Arduino Nano, "Arduino nano 33 BLE sense product reference manual, ABX00031," 2022.