



## **PROPOSING A POULTRY SOUND CLASSIFICATION APPROACH BASED ON DCT AND YOLO V8M TO IDENTIFY CHICKEN STRESS TYPE**

**Haitham Al Akabi<sup>1</sup> and Tawfiq Al-assadi<sup>2</sup>**

<sup>1</sup> Master's Degree Student in College of Information Technology, University of Babylon, Republic of Iraq. Email: haithammohammeda.sw@student.uobabylon.edu.iq

<sup>2</sup> Assistant Prof. at College of Information Technology, University of Babylon, Republic of Iraq. Email: Tawfiqasadi@itnet.uobabylon.edu.iq

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### **ABSTRACT**

Most animals make sounds and calls to express their condition or to communicate with other members of the group communicate with other group members. Poultry chickens live in groups and communicate with each other socially through their sounds. The lack of food or stress that chickens are exposed to negatively affects the global production of eggs and meat. Therefore, in this paper, we present a deep learning-based approach to classifying the status of farm chickens by their vocalization, which helps improve production and monitor the animals. First, all the sounds are converted to the time domain, and the Discrete Cosine Transform (DCT) is calculated to produce distinct features. Then, A two-dimensional grayscale image is generated from the coefficient matrix. Secondly, these gray images are utilized as input into the YOLO v8m model to perform classification. The results showed that the proposed model achieved a high classification accuracy of 91.6% without data augmentation and 98.6% with data augmentation, although there is noise interfering with the recordings or the sounds of chickens nearby. This study may play an important role in animal acoustic signal analysis studies.

### **KEYWORDS**

Chicken vocalization, Deep learning, Grayscale image, Data augmentation, Signal analysis.



## 1. INTRODUCTION

One of the most important sources of protein and eggs worldwide is poultry, an important livestock resource that must be preserved. The condition of chickens, such as illness, well-being, or stress, can be monitored by human experts, but it requires additional effort and expensive labor. It may exceed the limits of real-time, so modern technologies have helped to bridge this gap. Some of these technologies have relied on images of chickens; others have relied on their sounds or on analyzing the sounds resulting from chicken behavior (Pecking, Preening, Dustbathing, etc.) (Yajie, Johar and Hajamydeen, 2023). Relying on a microphone to record sounds is inexpensive, and chickens are social animals that communicate with each other through their vocalization (Lee *et al.*, 2015). Most of these sounds are made by chickens during hunger, fear, anger, satisfaction, and unhealthy, so deep learning techniques have been exploited to bridge the communication gap between animals and humans (Cheok, Cai and Yan, 2023). Deep learning techniques have proven to be extremely powerful at extracting features (Al-Shakarchy and Ali, 2019). Some of the specific sounds that chickens may make (alarm, squawk, and gavel), the gavel sounds are indicators of animal welfare (Collias, 1987), while alarm sounds indicate negative events or a distress call (Zimmerman, Koene and Van Hooff, 2000). Therefore, these sounds serve as a basis for assessing the condition of the chickens. Most studies have relied on pre-processing the raw audio signal before entering it into machine learning or deep learning techniques for the following reasons:

- 1- Reduce the effect of noise associated with recordings.
- 2- Extract the features effectively (Wang, Makis and Yang, 2010) .
- 3- Obtain a distinctive shape for the signal.

This paper aims to propose an approach to detect the status of chickens (“distress”, “egg laying”, and “feeding”) based on the analysis of their sounds using deep learning techniques. The effective contribution of this study is highlighted in the following points:

- a- The power of our study compared to traditional methods is that it involves effectively extracting features despite the noise associated with the recordings.
- b- A unique way to create 2D gray images that makes it easier for neural networks to recognize patterns more effectively.
- c- Initialize YOLO v8m to perform classification depending on the gray images created.

The following are the remaining sections of this article: Section 2 discusses related studies, Section 3 explains the proposed method, Section 4 displays the analysis and findings of the experiment, and Section 5 offers a conclusion with recommendations for further research.

## 2. RELATED WORKS

Analyzing chicken calls is of great importance to poultry farms to ensure better care and preservation of this livestock. These calls help us understand the pressures facing poultry chickens or their health status. Early detection of the chickens' condition helps avoid many diseases or changes in the surrounding environment. In 2016, Banakar et al. Proposed a device to diagnose three types of diseases in chickens through their sounds (New Castle, Infectious Bronchitis virus, and Avian Influenza), the sounds converted into the frequency domain and the time-frequency domain respectively, Utilizing the Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT) to features extracted by using Support Vector Machine (SVM). Despite the good results of this method, it is limited to diagnosing specific types of diseases and has not been tested with noise accompanying sounds (Banakar, Sadeghi and Shushtari, 2016). In 2019, Jakovljević et al. Developed an approach to detect chicken stress using audio data by extracting features and classifying them using SVM. More than one feature extraction technique was applied, the best of which was the Mel Frequency Cepstral Coefficient (MFCC). A dataset of 86 audio recordings was used, which is insufficient to obtain a reliable assessment (Jakovljević et al., 2019). In 2020, Liu et al. Presented an approach to detect abnormal sounds in broiler chickens by developing a Hidden Markov Model (HMM) algorithm based on using MFCC for feature extraction and Correlation Distance Fisher (CDF) for feature selection. This study is affected by many factors, including fan noise accompanying the recordings, the weight, and the age of the animal, which leads to their classification as abnormal sounds (Liu et al., 2020). In 2020, Du et al. Proposed a system to monitor the health of chickens through their vocalization based on SVM and the effect of changing their temperature on their vocalization. The Discrete Fourier Transform (DFT) was calculated for each frame, and two filters were applied to it. Each frame was manually labeled, which required additional time and effort (Du et al., 2020). In 2021, Ahmed et al. Developed an IoT-based approach to predict chicken disease from their vocalizations, and the data was expanded using a GAN. A comparative study of the results was conducted using traditional machine learning methods with deep learning, and the deep learning network (Tabnet) showed a significant superiority compared to traditional methods. Relying on generated data may raise questions about the reliability of the results of this study (Ahmed et al., 2021). In 2022, Mao et al. Presented a Light-VGG11 neural network-based model for classifying chicken distress calls (3363 distress calls, 1973 natural barn sounds). All sounds were converted to color images as a Log-mel spectrogram in a pre-processing stage and fed into the network. Despite the high detection speed achieved by the model, its performance deteriorated with more sound recordings longer than one second (Mao

et al., 2022). In 2022, Li et al. Developed a method to separate the sex of chicks by analyzing their vocalizations. The vocalizations were converted into three types of images (Spectrogram, Cepstrogram, and MFCC +log fbank) and fed into ResNet-50. The MFCC+ log fbank converted images achieved the highest test accuracy. The test was conducted on three types of chicks, and the results showed that the vocalizations differ from one type to another, so the method cannot be generalized to all types (Li et al., 2022). In 2024, Banakar et al. Discovered the relationship between sound structure and sexual status in broiler breeder roosters. It showed that certain voice features may be indicators of sperm quality, which enhances production (Banakar, Sharafi and Li, 2024). Eventually, the above refers to there are many challenges facing the analysis of chicken vocalization, including the overlapping of sounds and the presence of accompanying noise, in addition to the differences in species, age, and weight, which makes it difficult to classify these sounds. Therefore, deep learning frameworks must be developed that are capable of generalizing in different environments and conditions.

### 3. THE PROPOSED SYSTEM

The procedure for classifying poultry vocalization utilizing the YOLO v8m by converting the sounds of chicken into images is suggested. The sound first converts into a time domain, then applies DCT to construct a gray image. Lastly, YOLO v8m is used to classify the gray pictures. Fig.1 illustrates the block diagram for the proposed system. The suggested approach is explained in two phases. The first phase displays pre-processing and gray picture creation. The

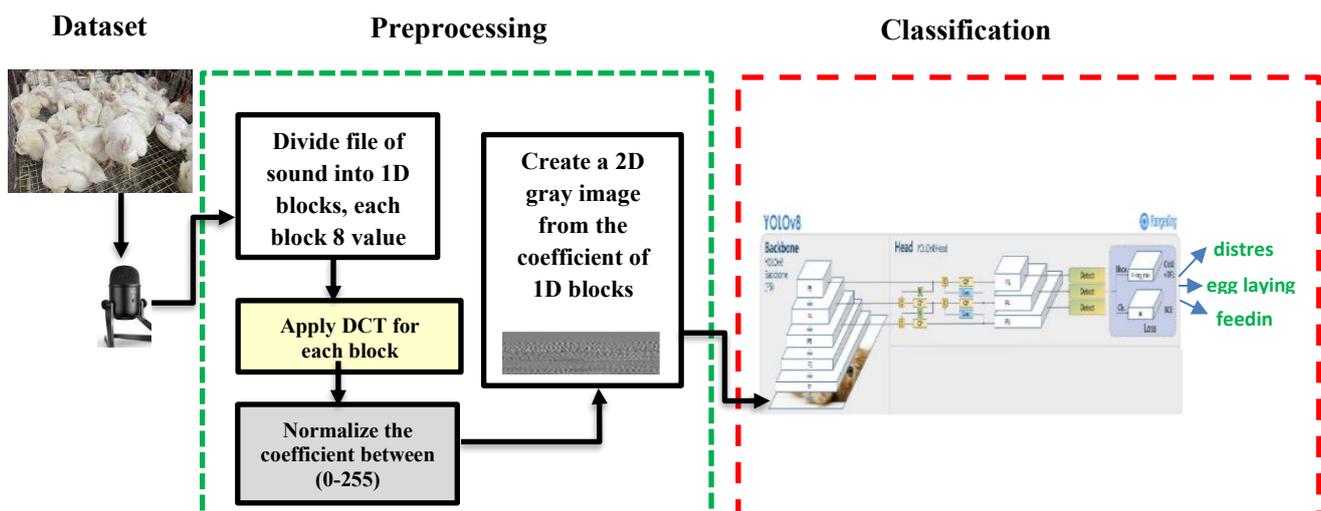


Fig. 1. Block diagram of the proposed system.

#### 3.1. First Phase: Preprocessing (Transforming Signal to RGB Image)

##### 3.1.1. Transform signal to time domain

Sound is a body that moves (energy) that is transmitted to the air molecules. The molecules

move up and down, resulting in a change in air pressure, spreading as waves through the air. One of the most prominent visual representations of sound is the waveform, which shows the change in pressure over time (Constantinescu and Brad, 2023). Fig. 2 illustrates an audio signal converted to a digital representation of wave shape in the time domain of a chicken's call (egg-laying). The Scipy, Libros, and matplotlib libraries in Python perform this representation.

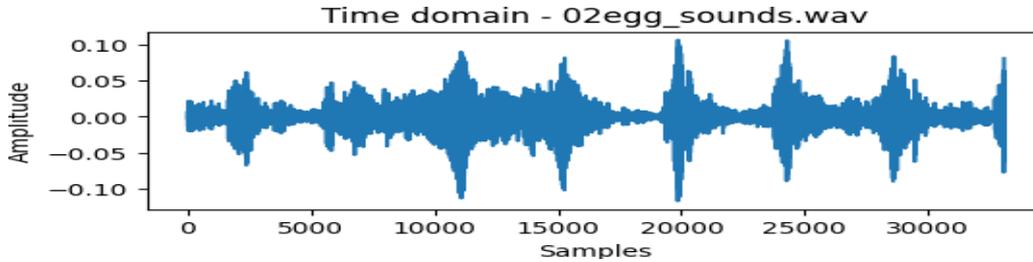


Fig. 2. Time domine signal.

The points below explain the mathematical conversion of an audio signal into a wave in the time domain (Hsu, 2011).

- a- The audio signal is represented as  $x(t)$ , where  $x(t)$ : The audio signal.
- b- According to Eq.1, the signal is divided into samples at regular time intervals to convert it to the time domain.

$$x[n] = x[n.T] \tag{1}$$

where  $n$ : Sample number;  $T$ : Sampling interval (constant).

- c) Each sample is assigned a level ranging from 0 to  $N-1$ , the samples are represented as equation (2):

$$sample = \{x[0], x[1], \dots, x[N]\} \tag{2}$$

- d) Equation (3) shows the final step in constructing the signal.

$$x(t) = \sum_{n=0}^N x[n]. \delta(t - nT) \tag{3}$$

where  $\delta$ : Delta function,  $\delta = 0$  if  $t \neq 0$ , else  $\delta = 1$ .

The time-domain signal values are then stored in a 1D array to be prepared for further processing. Fig. 3 illustrates an audio signal in the time domain converted to a 1D array for digital values, where the symbol (V) indicates the digital value for the signal. The Scipy and Librosa libraries in Python read and store the signal values.



Fig. 3. 1D array for digital values (time domain).

### 3.1.2. Apply Discrete Cosine Transform (DCT) for each block

This study depends on DCT transform rather than time domain, frequency domain (FFT), and time-frequency domain (STFT), due to relying on the time domain only may lose important frequency information, while the frequency domain assumes that the signal is stationary, and

this does not happen in reality for sound of chickens, which leads to the loss of information related to time. The STFT representation of the time-frequency domain provides a better representation of the non-stationary signal, but it has some limitations, including choosing the window size to compare between time and frequency accuracy, a larger window may provide better frequency accuracy with lower time accuracy, and vice versa, which may hinder good identification of a type of class. The DCT of the digital values of the signal in the time domain is calculated (one dimensional array) to extract features according to Eq.4 (Lam and Goodman, 2000).

$$c(u) = \alpha(u) \sum_{k=0}^{N-1} f(x) \cos \left[ \frac{\pi(2x + 1)u}{2N} \right] \quad (4)$$

where  $u = 0, 1, 2, \dots, N - 1$ ;  $N=8$ ; and  $\alpha(u) = \begin{cases} \sqrt{\frac{1}{N}}, & \text{for } u = 0 \\ \sqrt{\frac{2}{N}}, & \text{for } u \neq 0 \end{cases}$

The main goal of the DCT transformation is to create distinctive features for each class and make it easy for YOLO to distinguish them. The resulting matrix of coefficients will be called a signal in the frequency domain. Fig. 4 illustrates applying DCT on a 1D array for the time domain and producing 1D coefficient values in the frequency domain, where the symbol (C) indicates the coefficient value produced from applying DCT, and the symbol (B) indicates the block of eight values.

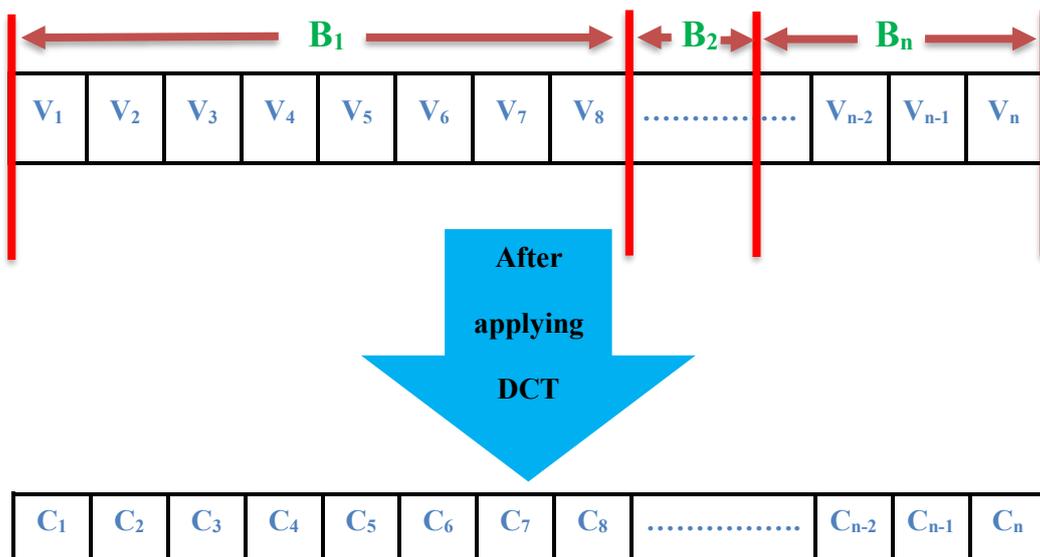


Fig. 4. 1D array for coefficient values (frequency domain).

### 3.1.3. Normalize the Coefficient Between (0-255)

Machine learning models handle single-channel grayscale images highly efficiently in terms of training speed and storage compared to multi-channel color images (Hashim and Mazinani,

2025). Therefore, Min-Max normalization was performed on the values of the resulting coefficients after applying DCT and making them limited to 0-255 (gray values). Since most of the resulting coefficients are real numbers, we use the (Round) function to round them to the nearest integer according to Eq.5 (Di, Magistrale and Gaizo, 2023).

$$X_{new} = \text{round} \left\{ \frac{x - \min(x)}{\max(x) - \min(x)} \times 255 \right\} \quad (5)$$

where  $X_{new}$ : the new value;  $x$ : (DCT) coefficient;  $\max(X)$ : is the maximum value in the (DCT) coefficient; and  $\min(X)$ : is the minimum value in the (DCT) coefficient. Fig. 5 illustrates applying a normalization operation to the previous 1D coefficients array and converting it into a 1D normalization array, where the symbol (X) indicates the normalize value produced from applying normalization for the DCT coefficient array.

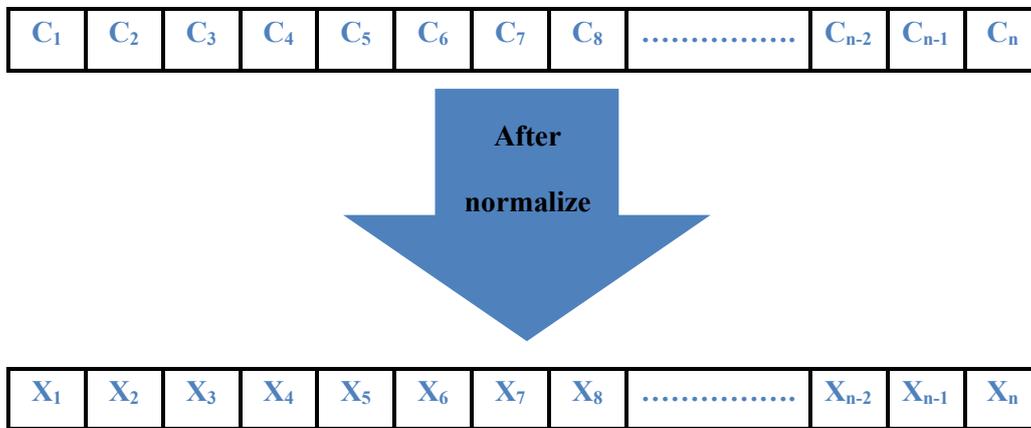


Fig. 5. 1D normalization array.

### 3.1.4. Construct a 2D Gray Image

In this process, the 1D normalize array is divided into M equal blocks. where the size of each block (M) is  $\sqrt{n}$ , n indicates the 1D normalize array length, the number of blocks is n/M. As shown in Fig. 6 (Uddin et al., 2014).

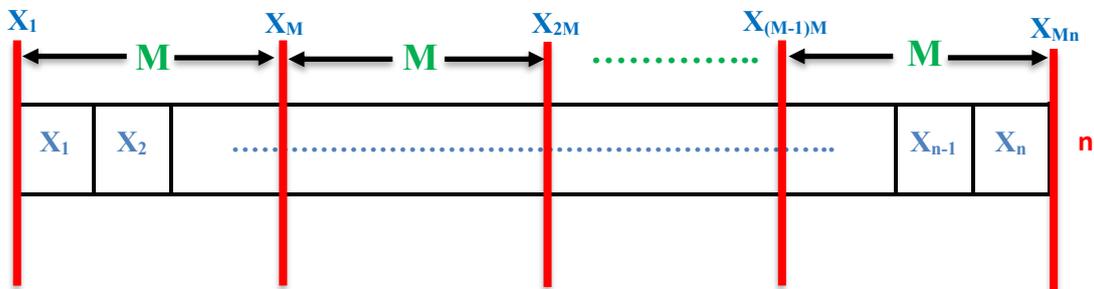


Fig. 6. Segmentation of the 1D normalization array.

After segmenting the 1D normalize array, we got a definite number of blocks, which along with the block size, helped to define the rows and columns of the 2D gray matrix. The number of rows in a gray matrix is equal to the size of each block, and the number of columns in the gray

matrix is equal to the number of blocks. For instance, if the length 1D normalize array =9, so the block size M is ( $\sqrt{9}=3$ ), the number of blocks should be 3, because the number of blocks is  $n/M$  ( $9/3=3$ ), so the size of the gray matrix is  $M \times M$  ( $3 \times 3$ ). Finally, each block is put in a row, followed by a row in the gray matrix, as shown in Fig. 7 (Islam, Uddin and Kim, 2018).

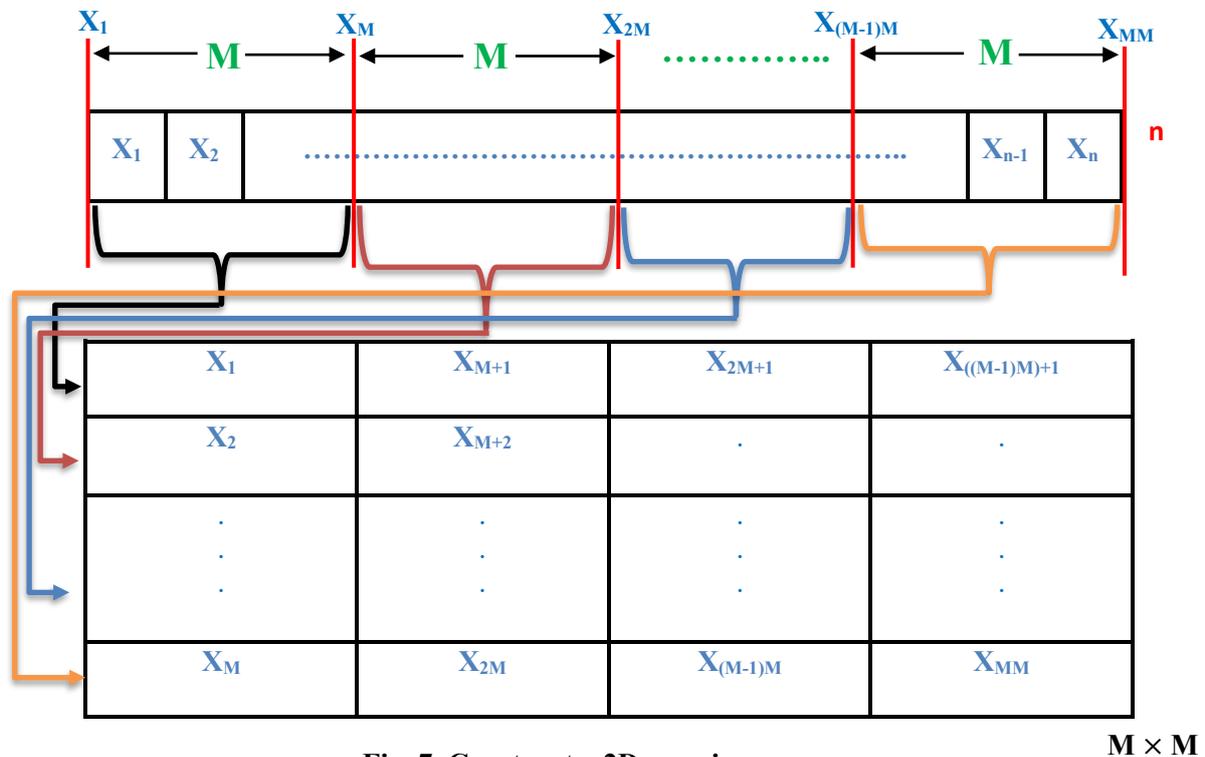


Fig. 7. Construct a 2D gray image.

Therefore, the gray images resulting from these treatments are shown in Fig. 8.

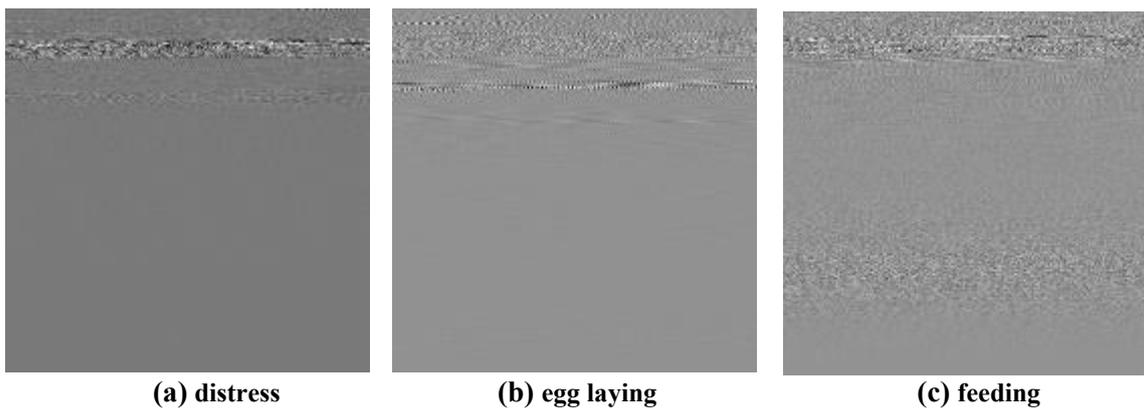


Fig. 8. Converted image from the chicken sounds.

### 3.2. Second Phase: Image Classification (YOLO v8m)

In 2016, the emergence of YOLO revolutionized computer vision object detection (Hussain, 2023). whereas traditional approaches relied on two phases (feature extraction and classification), YOLO relied on bounding boxes and probability, with real-time response speed (Koubaa et al., 2022).



Consequently, in this study, the images resulting from the previous stage were fed into YOLO for training and testing for classification purposes. Simultaneously, all the images resulting from the preprocessing of sounds were not resized because they were all the same size due to the uniform length of the recordings (1.5 seconds).

#### 4. EXPERIMENTS AND RESULTS

For the high capabilities and speed in terms of GPU, CPU, and RAM, the Kaggle environment was selected for testing and training. The GPU P100 was employed. The following aspects will be covered: dataset, evaluation and metrics, YOLO v8m performance, and data augmentation.

##### 4.1. Dataset

The dataset used in this study includes recordings of chicken vocalizations of three classes (distress, egg laying, feeding) collected from a Kaggle (<https://www.kaggle.com/pcaackdataset/datasets>). All sounds are records for chicken calls, each audio file is 1.5 seconds long and in (.wav) format. The number of recordings in each file is (662, 351, 271) respectively. Some recordings show overlapping sounds for chicken or accompanying noises, such as chicken movement, human talking, or other sounds from the barn environment. The location and number of microphones used are not mentioned.

##### 4.2. Evaluation and Metrics

The classification results are evaluated using the following criteria (Precision, Recall, F1 Score, and Accuracy), as shown in the equations below (6,7,8, and 9) respectively (Sivalingan, 2024):

$$\text{Precision} = \frac{TP(\text{True Positive})}{TP(\text{True Positive})+FP(\text{False Positive})} \quad (6)$$

$$\text{Recall} = \frac{TP(\text{True Positive})}{TP(\text{True Positive})+FN(\text{False Negative})} \quad (7)$$

$$\text{F1-Score} = \frac{2*\text{Precision}*\text{Recall}}{\text{Precision}+\text{Recall}} \quad (8)$$

$$\text{Accuracy} = \frac{TP(\text{True Positive})+TN(\text{True Negative})}{TP(\text{True Positive})+TN(\text{True Negative})+FP(\text{False Positive})+FN(\text{False Negative})} \quad (9)$$

##### 4.3. YOLO v8m Performance and Result Analysis

After completing the conversion of all sounds into gray images in the pre-processing stage, the data was divided into 70% (923 images) for training, 20% (230 images) for validation, and 10% (131 images) for testing. Table 2 shows the hyperparameters that were adjusted in the training stage.

**Table 2. Hyperparameter tuning**

key	value
epochs	100
batch size	16
optimizer	Adam
Learning rate	0.0002
momentum	0.5
dropout	0.1

Training continued until epochs = 100. The model accuracy during the training phase was 89.1%. Fig. 10 illustrates the training flow chart, while the model accuracy during the test was 91.6%. Fig. 11 illustrates the confusion matrix. However, all recordings were of uniform length (1.5 sec), which greatly increased the resolution because the time domain matrix became consistent in size, in addition to the DCT applied, which greatly helped to extract features.

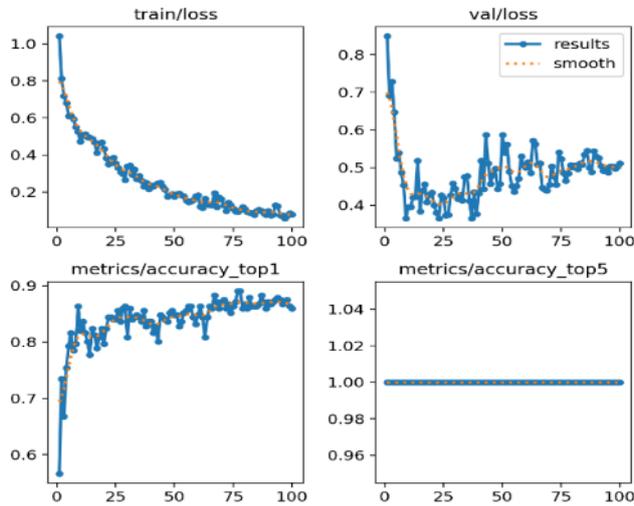


Fig. 10. Training operation.

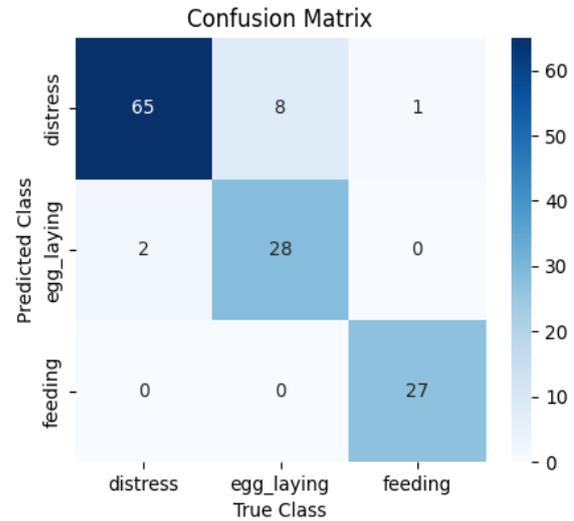


Fig. 11. Confusion matrix.

Table 3 summarizes the results of classifying each class using the metrics Precision, Recall, and F1 Score.

Table 3. The performance evaluation classification by different metrics.

class	Precision	Recall	F1 Score	support
distress	0.970	0.878	0.921	67
egg laying	0.777	0.933	0.847	36
feeding	0.964	1.0	0.981	28
<b>Total Accuracy</b>		0.916		131

#### 4.4. Data Augmentation

It is a widely used technique to address data scarcity and make the model capable of learning and generalization (Nanni, Maguolo and Paci, 2020). Deep learning models need a lot of training data to be able to distinguish features and learn efficiently (Abduljaleel and Ali, 2024). Furthermore, the model's performance improves with more training data (Al-Shakarchy and Hadi Ali, 2019). Data augmentation was done for grayscale images (flip vertical, translate, contrast) to simulate the real complexity of noise or interference present in recordings and their reflection on images. The data after data augmentation was divided into 70% (2693 images) for training, 20% (772 images) for validation, and 10% (348 images) for testing. The training lasted for 30 min for 100 epochs and achieved an accuracy of 98.4% during the training phase and 98.6% during the testing phase. Fig. 12 illustrates the training operation after data

augmentation. Fig. 13 illustrates the confusion matrix for the testing phase after data augmentation is applied.

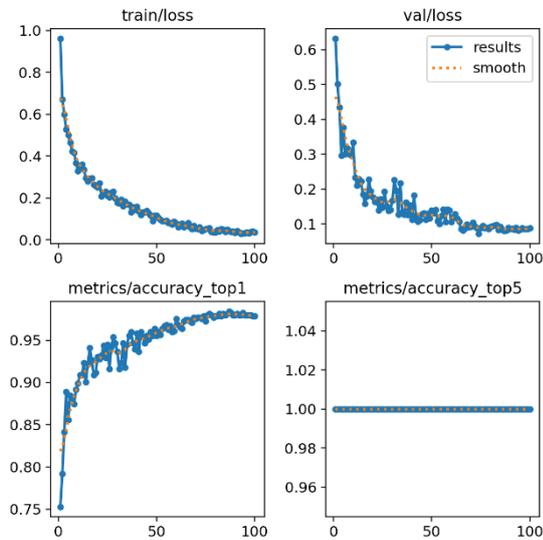


Fig. 12. Training operation.

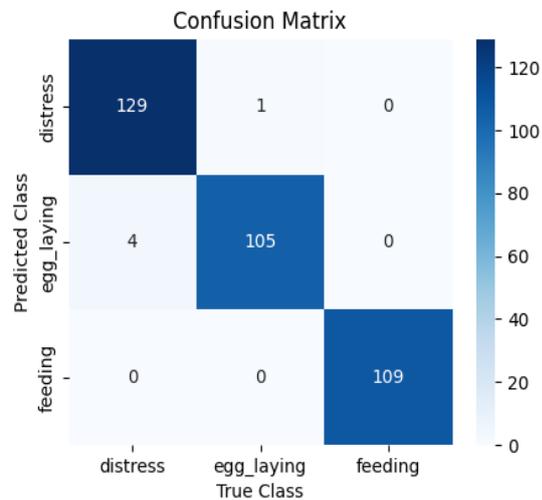


Fig. 13. Confusion matrix.

Therefore, Table 4 compares the current study with previous studies of monitoring chicken sounds using different methods.

Table 4. Comparison of this study with previous studies.

Reference	Year	Analysis	Objective	Network	Augmentation	Accuracy
(Banakar, Sadeghi and Shushtari, 2016)	2016	Sound	Diseases diagnosis	SVM	No	91%
(Jakovljević et al., 2019)	2019	Sound	Stress detection	SVM	No	83%
(Mao et al., 2022)	2022	Sound	Stress detection	Light-VGG11	Yes	95.07%
(Hassan et al., 2024)	2024	Sound	Diseases diagnosis	CNN	Yes	98.55%
This study	2024	Sound	Stress detection	YOLO v8m	Yes No	98.6% 91.6 %

## 5. CONCLUSION

In general, this study aims to analyze and classify chicken calls in different conditions and take better care of them to increase production. The study provides an excellent approach to processing and interpreting calls by integrating DCT with deep learning techniques. All sounds were converted to gray images, and YOLO was used to classify the call images. The pre-processing stage contributed significantly to extracting features and eliminating noise overlapping with the calls. The YOLO v8m model showed a superior and great ability to recognize the generated gray images despite the slight differences between the pictures and the small dataset. Data augmentation was performed with specific types to simulate noise and

process the lack of data, which helped increase the accuracy of classification. The model achieved an accuracy of 91.6% without data augmentation and an accuracy of 98.6% with data augmentation. The future study aims to deal with the sounds of chickens overlapping in the barn and work to resolve their interference and detect the disease or stress emitted by the animal to generalize an intelligent early warning system to take appropriate measures in real time.

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#### **6. REFERENCES**

Abduljaleel, I.Q. and Ali, I.H. (2024) ‘Deep Learning and Fusion Mechanism-based Multimodal Fake News Detection Methodologies: A Review’, *Engineering, Technology and Applied Science Research*, 14(4), pp. 15665–15675. Available at: <https://doi.org/10.48084/etasr.7907>.

Ahmed, G., Malick, R., Akhunzada, A., Zahid, s., Sagrim, M. and Gain, A. (2021) ‘An approach towards iot-based predictive service for early detection of diseases in poultry chickens’, *Sustainability (Switzerland)*, 13(23), pp. 1–16. Available at: <https://doi.org/10.3390/su132313396>.

Al-Shakarchy, N.D. and Ali, I.H. (2019) ‘Abnormal head movement classification using deep neural network DNN’, in *AIP Conference Proceedings*. American Institute of Physics Inc., pp. 1–13. Available at: <https://doi.org/10.1063/1.5123123>.

Al-Shakarchy, N.D. and Hadi Ali, I. (2019) ‘OPEN AND CLOSED EYES CLASSIFICATION IN DIFFERENT LIGHTING CONDITIONS USING NEW CONVOLUTION NEURAL NETWORKS ARCHITECTURE’, *Journal of Theoretical and Applied Information Technology*, 97(7), pp. 1970–1979. Available at: [www.jatit.org](http://www.jatit.org).

Banakar, A., Sadeghi, M. and Shushtari, A. (2016) ‘An intelligent device for diagnosing avian diseases: Newcastle, infectious bronchitis, avian influenza’, *Computers and Electronics in Agriculture*, 127, pp. 744–753. Available at: <https://doi.org/10.1016/j.compag.2016.08.006>.

Banakar, A., Sharafi, M. and Li, G. (2024) ‘Relationship between reproductive indicators and sound structure in broiler breeder roosters’, *Applied Animal Behaviour Science*, 270, pp. 1–8. Available at: <https://doi.org/10.1016/j.applanim.2023.106135>.

Cheok, A., Cai, J. and Yan, Y. (2023) 'Deciphering Avian Emotions: A Novel AI and Machine Learning Approach to Understanding Chicken Vocalizations', Research Square, pp. 1–24. Available at: <https://doi.org/10.21203/rs.3.rs-3034567/v1>.

Collias, N.E. (1987) 'THE VOCAL REPERTOIRE OF THE RED JUNGLEFOWL: A SPECTROGRAPHIC CLASSIFICATION AND THE CODE OF COMMUNICATION', The Cooper Ornithological Society, pp. 510–524. Available at: <https://academic.oup.com/condor/article/89/3/510/5188941>.

Constantinescu, C. and Brad, R. (2023) 'An Overview on Sound Features in Time and Frequency Domain', International Journal of Advanced Statistics and IT&C for Economics and Life Sciences, 13(1), pp. 45–58. Available at: <https://doi.org/10.2478/ijasitels-2023-0006>.

Di, T., Magistrale, L. and Gaizo, D. Del (2023) 'Enhancing Drone Spectra Classification: A Study on Data-Adaptive Pre-processing and Efficient Hard-ware Deployment', IEEE (Institute of Electrical and Electronics Engineers). Politecnico.

Du, X., Carpentier, L., Teng, G., Liu, M., Wang, C. and Norton, T. (2020) 'Assessment of laying hens' thermal comfort using sound technology', Sensors (Switzerland), 20(2), pp. 1–14. Available at: <https://doi.org/10.3390/s20020473>.

Hashim, A. and Mazinani, M. (2025) 'DETECTION OF KERATOCONUS DISEASE DEPENDING ON CORNEAL TOPOGRAPHY USING DEEP LEARNING', Kufa Journal of Engineering, 16(1), pp. 463–478. Available at: <https://doi.org/10.30572/2018/KJE/160125>.

Hassan, E., Elbedwehy, S., Shans, M., Abd El-Hafeez, T. and El-Rashidy, T. (2024) 'Optimizing poultry audio signal classification with deep learning and burn layer fusion', Journal of Big Data, 11(1), pp. 1–29. Available at: <https://doi.org/10.1186/s40537-024-00985-8>.

Hsu, H.P. (2011) 'Signals and Systems'. Second Edition. Audubon, Pennsylvania: McGraw Hill Professional.

Hussain, M. (2023) 'YOLO-v1 to YOLO-v8, the Rise of YOLO and Its Complementary Nature toward Digital Manufacturing and Industrial Defect Detection', Machines, 677(11), pp. 1–25. Available at: <https://doi.org/10.3390/machines11070677>.

Hussain, M. (2024) 'YOLOv1 to v8: Unveiling Each Variant-A Comprehensive Review of YOLO', IEEE Access, 12, pp. 42816–42833. Available at: <https://doi.org/10.1109/ACCESS.2024.3378568>.

Islam, R., Uddin, J. and Kim, J.-M. (2018) 'Texture analysis based feature extraction using Gabor filter and SVD for reliable fault diagnosis of an induction motor Texture analysis based feature extraction using Gabor filter and SVD 21', *Int. J. Information Technology and Management*, 17(2), pp. 20–32.

Ismael, H., Jasim, M., Sharif, M. and Jasim, F. (2025) 'ARTIFICIAL INTELLIGENCE IN ROBOTIC MANIPULATORS: EXPLORING OBJECT DETECTION AND GRASPING INNOVATIONS', *Kufa Journal of Engineering*, 16(1), pp. 136–159. Available at: <https://doi.org/10.30572/2018/KJE/160109>.

Jakovljević, N., Maljkovic, N., Knezevic, P. and Delic, V. (2019) 'A Broiler Stress Detection System Based on Audio Signal Processing', in *27th Telecommunications forum TELFOR 2019*. Serbia, Belgrade: 27th Telecommunications forum TELFOR 2019, p. 1.

Koubaa, A., Ammar, A., Kanhouc, A. and Alhabashi, Y. (2022) 'Cloud versus Edge Deployment Strategies of Real-Time Face Recognition Inference', *IEEE Transactions on Network Science and Engineering*, 9(1), pp. 143–160. Available at: <https://doi.org/10.1109/TNSE.2021.3055835>.

Lam, E.Y. and Goodman, J.W. (2000) 'A mathematical analysis of the DCT coefficient distributions for images', *IEEE Transactions on Image Processing*, 9(10), pp. 1661–1666. Available at: <https://doi.org/10.1109/83.869177>.

Lee, J., Noh, B., Jang, S., Park, D., Chung, Y., and Chang, H. (2015) 'Stress detection and classification of laying hens by sound analysis', *Asian-Australasian Journal of Animal Sciences*, 28(4), pp. 592–598. Available at: <https://doi.org/10.5713/ajas.14.0654>.

Li, Z., Zhang, T., Cuan, K., Fang, C., Zhao, H., Guan, C., Yang, Q. and Qu, H. (2022) 'Sex Detection of Chicks Based on Audio Technology and Deep Learning Methods', *Animals*, 12(22), pp. 3–25. Available at: <https://doi.org/10.3390/ani12223106>.

Liu, L., Li, B., Zhao, R., Yao, W., Shen, M. and Yang, J. (2020) 'A novel method for broiler abnormal sound detection using WMFCC and HMM', *Journal of Sensors*, 2020, pp. 1–7. Available at: <https://doi.org/10.1155/2020/2985478>.

Mao, A., Giraudet, C., Liu, K., DeAlmeida, I., Xie, Z., Xie, Z., Gao, Y., Theobald, J., Bhatta, D., Stewart, R. and McElligott, A. (2022) 'Automated identification of chicken distress vocalizations using deep learning models', *Journal of the Royal Society Interface*, 19(191), pp. 1–11. Available at: <https://doi.org/10.1098/rsif.2021.0921>.

Nanni, L., Maguolo, G. and Paci, M. (2020) 'Data Augmentation Approaches for Improving Animal Audio Classification', *Ecological Informatics*, 57, pp. 1–8. Available at: <https://doi.org/10.1016/j.ecoinf.2020.101084>.

Sivalingan, H. (2024) 'CLOUD-SMART SURVEILLANCE: ENHANCING ANOMALY DETECTION IN VIDEO STREAMS WITH DF-CONVLSTM-BASED VAE-GAN', *Kufa Journal of Engineering*, 15(4), pp. 125–140. Available at: <https://doi.org/10.30572/2018/KJE/150409>.

Uddin, J., Kang, M., Nguyen, D. and Kim, J. (2014) 'Reliable fault classification of induction motors using texture feature extraction and a multiclass support vector machine', *Mathematical Problems in Engineering*, 2014, pp. 1–10. Available at: <https://doi.org/10.1155/2014/814593>.

Wang, X.Y., Makis, V. and Yang, M. (2010) 'A wavelet approach to fault diagnosis of a gearbox under varying load conditions', *Journal of Sound and Vibration*, 329(9), pp. 1570–1585. Available at: <https://doi.org/10.1016/j.jsv.2009.11.010>.

Yajie, L., Johar, M.G.M. and Hajamydeen, A.I. (2023) 'Poultry disease early detection methods using deep learning technology', *Indonesian Journal of Electrical Engineering and Computer Science*, 32(3), pp. 1712–1723. Available at: <https://doi.org/10.11591/IJEECS.V32.I3.PP1712-1723>.

Zimmerman, P.H., Koene, P. and Van Hooff, J.A.R.A.M. (2000) 'Thwarting of Behaviour in Different Contexts and the Gakel-Call in the Laying Hen', *Applied Animal Behaviour Science*, 69, pp. 255–264. Available at: [www.elsevier.com/locate/applanim](http://www.elsevier.com/locate/applanim).