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Design of a Non-Invasive Egg Sexing Device Utilizing Artificial Intelligence for Duck Species

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***Abstract*—This study introduces a non-invasive egg sexing device that combines artificial intelligence (AI), spectroscopy, and computer vision technology to accurately determine the sex of duck embryos inside eggs. The device utilizes the plumage color as a reliable indicator of sex, employing a hybrid Convolutional Neural Network (CNN) and Gated Recurrent Unit (GRU) model alongside spectroscopic analysis. Extensive simulations and experiments validate the proposed algorithm, achieving an impressive 98.68% accuracy rate in sex determination, with an average processing time of 37.46 milliseconds, significantly enhancing farming efficiency. Additionally, the research assesses the impact of spectroscopy on egg hatchability, demonstrating a higher hatchability rate of 74.80% within a population of 500 eggs. This finding indicates that spectroscopy does not adversely affect egg viability. Overall, this study presents a sustainable solution for effectively managing male ducklings in the industry, optimizing resource utilization, and mitigating wastage.**

Keywords—Artificial Intelligence, CNN-GRU, Computer Vision, Spectroscopy

I. Introduction

The duck industry in the Philippines plays a significant role in the country's agricultural landscape and economy. Ducks are commonly reared for various purposes, including meat production, egg production, and as pets. The industry has seen notable growth and development over the years, with a rising demand for duck products both domestically and internationally. Currently, the duck industry relies on manual sexing of ducklings shortly after hatching. This process involves trained individuals visually inspecting the ducks to determine their gender [1]. Unfortunately, this process is time-consuming, costly, and not always accurate. Additionally, male ducks are typically less valuable than females in the industry, which has led to the practice of culling male ducklings shortly after birth.

In-egg sexing, also known as in-ovo sexing, is a technique used to determine the gender of a bird embryo before it hatches from its egg [2]. This technique has the potential to revolutionize the duck industry by allowing for more efficient breeding programs and reducing the number of male ducks that are culled.

One of the major benefits of in-egg sexing is that it allows for more efficient breeding programs [3]. With the ability to determine the sex of the embryo before it hatches, breeders can select only the eggs that will produce female ducks. This can lead to higher yields of female ducks, which are typically more valuable than males in the industry. Additionally, breeders can select for specific traits in their breeding programs, such as meat quality or egg production, with greater accuracy and efficiency. Duck hatcheries commonly incubate and hatch duck eggs, but they encounter a significant problem with surplus male ducklings. These excess males are unprofitable due to their higher feed consumption, negative impact on the fertility and growth of female ducks, and limited demand solely for breeding purposes. Moreover, the requirement of one male for every ten females further diminishes the demand and market value of these male ducklings. As a result, they are either sold at low prices or culled and disposed of as waste. In the duck hatchery business, disposing of these surplus male ducks at a loss has been the prevailing norm, offering minimal chances of recovering capital investments [4].

Avian species demonstrate sexual dimorphisms that can manifest during maturity or early developmental stages. For example, Müsse et al. [6] verified the presence of sexual dimorphisms in Ross 308 chickens based on bodyweight, with the weight difference between males and females increasing as they age. This dimorphism is also observed in ducks, including Muscovy, Pekin, and Sudani ducks, as confirmed by Makram et al. [7]. Another sexual dimorphism in avian species relates to egg shape. Yilmaz-Dikmen and Dikmen [8] initially established a correlation between pointed eggs and male chickens, whereas more rounded eggs had a higher probability of hatching female chickens. In ducks, Idahor [9] found that more conical duck eggs were associated with males, while more oval-shaped eggs resulted in more females. However, it is worth noting that this method is not considered a reliable metric for sexing. Ducks exhibit a sexual dimorphism in the asymmetry of the syringeal bulla, where ducks with syringeal bullas are male, while those without are considered females. This was confirmed by Wilson et al. [10] through the examination of common eider embryos. Johnsgard [11] also confirmed this dimorphism in whistling ducks, observing that males have a more oval syringeal bulla structure, while females possess a simpler structure. Additionally, sexual dimorphisms can be

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manifested chromatically in avian species' down feathers. For instance, in Igic et al.'s [12] study of New Zealand whiteheads, males were observed to have brighter head and chest colors compared to females. Similarly, MacArthur and MacIlraith [13] found that female brown leghorn chicks exhibited darker down feathers compared to their male counterparts. However, it is important to note that this sexual dimorphism is not absolute, with a maximum sexing accuracy of 98% [14].

The AI system utilizes various features and indicators to distinguish between male and female duck embryos. These features can include visual characteristics such as plumage color, body size, shape, or internal structures like the syringeal bulla. Machine learning algorithms are trained on large datasets of labeled duck embryo images to learn and classify the sex of the embryos accurately. Only few papers are written for this kind of field. Research studies, such as Dioses et al. [15], have explored the use of advanced machine learning techniques, such as support vector machines (SVM), to analyze morphological features of duck eggs and improve sex determination accuracy. However, despite their efforts, the achieved accuracy of 87% highlights the need for further advancements in AI-based approaches. M. Kayadan and Y. Uzun [16] proposed RUSBoost Classifier to perform sex determination upon chicken eggs.

This paper presents a hybrid deep-learning model for sex determination of duck eggs using a non-invasive system. The main contributions of this paper are as follows:

1) The paper proposes a non-invasive method of sex determination for duck eggs using geometric features and spectral properties using camera and spectrometer.

2) The paper also uses machine learning to classify the duck eggs. The method combines CNN and GRU, with CNN extracting features and GRU capturing their temporal dependencies. Regularization techniques are employed to prevent overfitting, and GRU interprets the extracted features.

The paper is structured as follows. Section II reviews the theoretical foundations of CNN and GRU. Section III presents the proposed method that explains the process of duck sex determination. Section IV reports the results of the experiments. Finally, Section V summarizes the main contributions and implications of the study.

II. Theoretical Background

A. Convolutional Neural Network

The CNN is a type of feedforward neural network that utilizes a convolutional architecture to automatically extract features from data. Unlike traditional feature extraction methods, CNN does not rely on manual feature engineering. Inspired by human visual perception, the architecture of CNN incorporates activation functions that simulate the transmission of neural electric signals exceeding a specific threshold to the subsequent neuron. CNN kernels represent multiple receptors capable of detecting various features, with each artificial neuron corresponding to a biological neuron [16].

To facilitate learning, loss functions and optimizers are employed to train the entire CNN system and align its outputs with the desired expectations. CNN offers several advantages. Firstly, it employs local connections, where each neuron is selectively connected to a subset of neurons in the preceding layer. This localized connectivity effectively reduces the number of parameters and accelerates the convergence of the network. Secondly, weight sharing is employed, allowing a group of connections to share the same weights, further reducing the overall number of parameters. Thirdly, down sampling via pooling layers exploits the inherent local correlation present in images to reduce the data size while preserving essential information. Additionally, pooling can help discard irrelevant or trivial features, contributing to parameter reduction.

B. Gated Recurrent Unit

The vanishing-exploding gradient is likewise dealt with by the GRU, but it reduces the gates and outputs [17]. The GRU's model equations are:

$$z_t = \sigma(b_{rz} + b_{iz} + U_z h_{t-1} + W_z x_t) \quad (1)$$

$$r_t = \sigma(b_{rr} + b_{ri} + U_r h_{t-1} + W_r x_t) \quad (2)$$

$$\tilde{h}_t = \tanh(b_{rh} + b_{ih} + U_h(r_t \circ h_{t-1}) + W_h x_t) \quad (3)$$

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ \tilde{h}_t \quad (4)$$

where z_t, r_t, and h_t represent the update, reset, and candidate activation gates, respectively. Additionally, b_i and b_r: stand for the input and recurring biases. Compared to the LSTM, the GRU contains one extra bias term but just one recurrent output. According to an empirical investigation, the GRU performs better than the LSTM on all tasks besides natural language processing. However, for deep multi-layer networks, gradient decay affects both GRU and LSTM, lengthening the training period.

III. Methodology

The proposed method in this study utilizes a combination of CNN and GRU networks to effectively capture both spatial and temporal features of duck eggs for gender determination. By leveraging CNN's ability to extract spatial features from the images of the eggs and the GRU's capability to capture temporal dependencies in the data, the proposed method aims to achieve improved accuracy in gender classification.

A. Data Gathering

In this study, two sexual dimorphisms, namely the color of the duck's plumage and the shape of the egg, have been selected based on existing literature. To collect the plumage color data, a spectrometer will be employed, as it has been shown to be effective for this purpose according to Corion's study [18]. Additionally, for capturing the egg shape, a conventional USB camera will be utilized, following the techniques outlined by Dioses et al. [15]. These chosen methodologies are supported by previous research and will serve as the data collection methods for the respective sexual dimorphisms in this study.

B. CNN-GRU

To address the challenges in reliability, a Machine Learning Model will be employed. For this specific application, the chosen model needs to be recent, adjustable, and capable of handling the features to be measured. Considering these requirements, the CNN-GRU model has been identified as the most suitable choice for analyzing data from both the spectrometer and USB camera. The CNN-GRU model possesses the necessary capabilities to effectively process and interpret the collected data, making it an optimal solution for this study.

The proposed CNN-GRU model comprises three key blocks as shown in Fig. 1. The first two blocks consist of two Convolutional Layers each, followed by a MaxPooling Layer and a Batch Normalization layer. These blocks are then connected to the final block, which includes a single GRU layer, followed by two fully connected layers with a dropout layer in between.

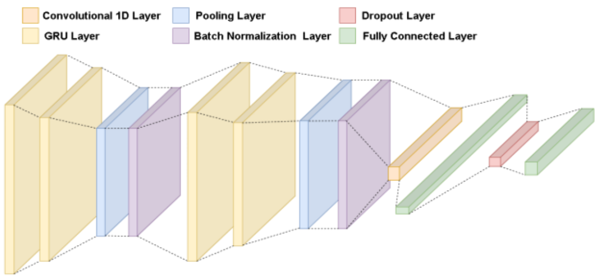

Fig. 1. Architecture of the Proposed CNN-GRU Model

The purpose of the CNN layers is to extract relevant features from the input data. By applying convolutional operations, these layers can effectively capture and represent the distinctive characteristics present in the acquired data. The subsequent MaxPooling Layer reduces the spatial dimensions of the features, while the Batch Normalization layer normalizes the outputs to facilitate stable training.

The GRU layer plays a crucial role in learning the features and their dependencies within the data. It utilizes gated recurrent units to capture the temporal relationships and dependencies present in the sequence of features. This allows the model to effectively interpret the data and generate appropriate activations.

Finally, the fully connected layers with a dropout layer between them help in mapping the learned features to the correct output classes. The dropout layer aids in preventing overfitting by randomly disabling a fraction of the neurons during training, promoting generalization and improving the model's performance.

Overall, the combined CNN-GRU architecture leverages the strengths of both convolutional and recurrent layers. The CNN layers excel in feature extraction, while the GRU layer effectively learns the dependencies and patterns within the features, ultimately leading to accurate predictions in the fully connected layers.

C. *Process Flow of the Proposed Method*

The process flow of the proposed method is shown in Figure 2. The proposed methodology for determining the sex of duck eggs involves a series of technical processes:

1) *Acquisition of duck eggs:* The eggs are obtained for analysis and data collection.

2) *Sampling using sensors for image and spectral data acquisition:* Sensors are employed to capture both image data and spectral data from the sampled eggs. This enables the extraction of visual and spectral features relevant to gender determination.

3) *Cracking of eggs and labeling:* Each egg is cracked to reveal its internal characteristics, and based on the observed color, the true label is assigned. Specifically, eggs with a black color are labeled as male, while those with a brown color are labeled as female.

4) *Training of the CNN-GRU machine learning model:* The acquired image and spectral data, along with the corresponding labels, are utilized to train a CNN-GRU model. The model learns to recognize patterns and relationships between the input data and the gender labels.

5) *Hyperparameter tuning:* The hyperparameters of the CNN-GRU model are fine-tuned to optimize its performance. This involves selecting the appropriate values for parameters such as learning rate, batch size, and regularization techniques to enhance the model's accuracy and generalization.

6) *Testing with labeled and unlabeled data:* The trained CNN-GRU model is evaluated using both labeled and unlabeled image and spectral data. The model predicts the gender of the duck eggs based on the learned features and associations. The accuracy of the model in identifying the sex of the eggs is assessed through this testing process.

By following these technical steps, the study aims to develop a reliable and accurate method for determining the sex of duck eggs using the combined power of CNN-GRU machine learning model and image and spectral data analysis. The block diagram of the whole prototype is shown in Figure 3.

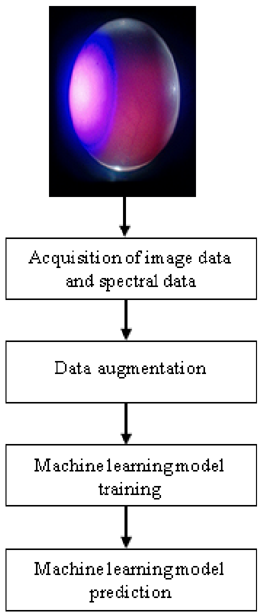

Fig. 2. Process flow of duck sexing using spectral data and image processing.

IV. Results and Discussion

The proposed method has a prototype produced with spectrometer and camera to collect data from the egg. The collected data is analyzed by the CNN-GRU algorithm and interpret as male or female ducks.

A. *Data Collection and Processing*

In this study, a technical approach was employed to investigate fertilized duck eggs. The eggs were sourced from a duck farm located in Zaragosa, Nueva Ecija, Philippines. A

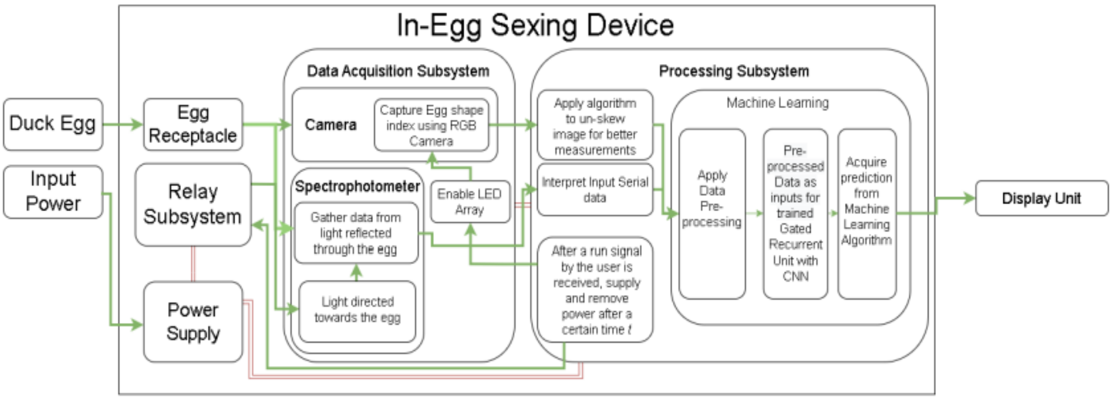

Fig. 3. Block Diagram of Proposed in-Egg Sexing Device

total of 500 duck eggs were selected randomly, disregarding their shape and size. These eggs were obtained from a diverse pool of fertilized duck eggs, ranging in age from 16 to 20 days.

Compared to a previous study referenced as [17], which only considered 170 egg samples, the number of eggs analyzed in this paper is significantly higher. The increase in sample size was implemented to enhance the accuracy of the proposed method.

To collect data from the eggs, two sensors were utilized. These sensors enabled the acquisition of both image data and spectral data from the eggs. Once the data was obtained, the eggs were cracked open, allowing for the acquired information to be labeled based on the gender of the duckling inside. Specifically, a black duckling was labeled as male, while a brown duckling was labeled as female.

Following the labeling of each data point, a Convolutional Neural Network-Gated Recurrent Unit (CNN-GRU) model was employed to train the machine learning algorithm. The image data and spectral data obtained were processed using the Python programming language and executed within a Jupyter Notebook environment.

One of the challenges encountered during data processing was the data imbalance issue, as there were a higher number of labeled female ducklings compared to labeled male ducklings. To address this, a technique called SMOTE (Synthetic Minority Oversampling Technique) was employed to augment and balance the data. SMOTE generates synthetic samples for the minority class (i.e., labeled male ducklings) to achieve a more equitable representation of both classes.

For the automation of egg sexing, the trained CNN-GRU model was integrated into a Raspberry Pi 3B microcontroller. The Raspberry Pi 3B served as the hardware platform for implementing the model and performing sex detection of the eggs.

B. Hatchability

To evaluate the safety of the sexing device, an experiment was conducted using non-invasive visual capture technologies. The device was designed to recognize and process the properties of the eggs without adversely affecting the hatchability rate of the population.

The experiment involved a population of 500 eggs, and the objective was to ensure that the device's operation did not result in a hatchability rate lower than 60%. This hatchability rate is considered acceptable in the context of the study.

To assess the safety of the device, the eggs were subjected to the sexing process using the implemented technology. Throughout the experiment, it was crucial to ensure that the device's operation did not introduce any harmful effects that could compromise the development and viability of the embryos inside the eggs.

Figure 3 shows the comparison of the hatchability between manual and prototype. By utilizing suitable non-invasive visual capture technologies, the device aimed to minimize any potential risks and ensure the safety of the eggs. The properties of the eggs were accurately recognized and processed without negatively impacting their overall hatchability rate, which remained above the targeted threshold of 60%.

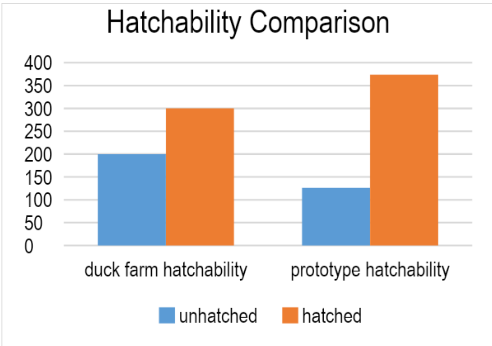

Fig. 3. Hatchability comparison between manual and prototype

C. Comparison of Results

In the design of the machine learning algorithm for sex identification of duck eggs, the primary considerations include achieving an accuracy greater than 86% in accurately identifying the sex of duck eggs between 16-20 days old. Relevant features for distinguishing between male and female duck eggs are determined based on prior literature, and a dataset of 500 duck eggs is obtained from which the data is divided into train, test, and validation sets. The model's performance is assessed using a confusion matrix, with the validation set serving as a measure of the algorithm's accuracy and effectiveness in sex identification, as shown in Table 1.

Table 1 showcases the performance of the optimized CNN-GRU model on a dataset of 152 duck eggs. The model incorporates proprietary hyperparameter tuning by the researchers. Impressively, the model achieves a remarkable accuracy of 98.68% in accurately identifying the sex of the duck eggs. The experimental design for the optimized model involves conducting 100 tests to ensure the precision and reliability of the predictions made by the model.

TABLE I. CONFUSION MATRIX OF THE PROPOSED METHOD

Confusion Matrix			
True Positive	False Positive	True Negative	False Negative
74	1	1	76

The proposed method is also compared to two methods. This section compares the simulation results produced by the proposed approach to those produced by two existing methods [20][21] for image classification. The two existing methods are Convolution Neural Network with XGBoost (ConvXGB) and Differentiable Architecture Search (DARTS).The algorithms' evaluation is based on a sample coming from a 500 duck eggs dataset divided into three sections – train set, test set, and validation set. The assessment yielded the following result.

TABLE II. COMPARISON OF RESULTS

Algorithm	Accuracy	Processing Time (ms)
ConvXGB[20]	81.81%	10.22
DARTS [21]	72.73%	43.99
Proposed Method	98.68%	37.46

The proposed method demonstrates superior performance compared to existing methods, exhibiting a higher level of accuracy in sex determination. When compared to the approach presented by Dioses et al. [15], the proposed method achieves a significantly higher accuracy rate. Additionally, in terms of processing time, the proposed method successfully meets the predetermined target of processing a single egg for sex determination in less than 1 second. This showcases the efficiency and effectiveness of the proposed method in handling the computational tasks associated with sex determination in a timely manner.

V. CONCLUSION AND FURTHER STUDIES

In conclusion, this research project successfully developed a non-invasive device that accurately predicts the sex of duck eggs by leveraging plumage color and egg geometric features. By employing a spectroscope and camera for data collection, the study achieved an impressive accuracy rate of 98.68% in determining the sex of the eggs. Moreover, the processing time for the prediction was efficient, with an average of 37.46 milliseconds, indicating the practicality and real-time applicability of the developed device.

Importantly, the study also demonstrated the safety of the spectroscopy and device, as they did not have any detrimental effects on the eggs. This was evident from the hatchability rate of 74.80%, ensuring the profitability and quality of the duck eggs in the industry. To further enhance productivity, the researchers suggest exploring the possibility of processing a larger number of eggs in a single run, which would be beneficial for duck farmers.

Overall, this research project provides a valuable contribution to the field of sex determination in duck eggs, offering a reliable and efficient non-invasive solution. It holds significant potential for practical implementation in the industry, empowering duck farmers with improved accuracy and productivity in managing the sex distribution of their flocks.

Furthermore, the research focuses on early-stage embryonic development, falling within the range of 16-18 days. Based on the available scientific literature and studies on ducks, it has been well-documented that ducks typically have an embryonic development period of 28 days [23]. According to the University of Illinois Urbana-Champaign Policy on Embryonated Avian Eggs in Research and Teaching [24], exemptions can be made on research involving avian embryos that will be euthanized prior to completing 75% of the total expected incubation period does not require IACUC review. Since the intended target falls significantly earlier than the full 28-day embryonic development, it is reasonable to conclude that the research can be exempted from the IACUC process [25]. The early-stage developmental focus ensures that the research does not involve significant interventions during the later stages of embryonic development, thus reducing potential ethical concerns related to animal welfare.

REFERENCES

[1] R. Molenaar, M. Hammers, and H. van den Brand, "In ovo sexing of chicken and duck embryos using Raman spectroscopy: A review," *Journal of Applied Poultry Research*, vol. 28, no. 2, pp. 223-232, 2019, doi: 10.3382/japr/pfy058.

[2] A. T. Leighton and B. S. Kraus, "In-ovo sexing of chickens and ducks - a review," *Poultry Science*, vol. 98, no. 2, pp. 657-666, 2019, doi: 10.3382/ps/pey353.

[3] R. P. Singh and N. K. Pandey, "In-ovo sexing of poultry: A review," *Indian Journal of Poultry Science*, vol. 53, no. 1, pp. 1-11, 2018, doi: 10.5958/0974-8180.2018.00001.5.

[4] R. A. M. Aya, "Genetic improvement of itik pinas to be continued in new r&d facility," *DOST-PCAARRD*, [Online]. Available: https://www.pcaarrd.dost.gov.ph/index.php/quick-information-dispatch-qid-articles/genetic-improvement-of-itik-pinas-to-be-continued-in-new-r-d-facility.

[5] Duck Situation Report, 2022 [Online]. Available: https://doi.org/ISSN-2546-0625.

[6] J. Müsse, H. Louton, B. Spindler and J. Stracke, "Sexual dimorphism in bone quality and performance of conventional broilers at different growth phases," *Agriculture*, vol. 12, no. 8, p. 1109, 2022.

[7] A. Makram, A. A. Galal, and A. El-attar, "A comparison of three duck strains (Pekin, Muscovy & Sudani) in Egypt for sexual dimorphism with regard to body weight, body measurements and carcass traits," *J. Genet. Environ. Resour. Conserv.,* vol. 9, no. 1, pp. 50–57, Oct. 2020.

[8] B. Yilmaz-Dikmen and S. Dikmen, "A morphometric method of sexing White Layer Eggs," *Revista Brasileira de Ciência Avícola*, vol. 15, no. 3, pp. 203–210, 2013.

[9] K. O. Idahor, L. A. F. Akinola, and S. S. Chia, "Sex Predetermination in Fowl Using some Egg Parameters in North Central Nigeria," *J. Anim. Sci. Adv.*, vol. 5, pp. 1171–1176, Jan. 2015.

[10] R. E. Wilson, S. A. Sonsthagen, and J. C. Franson, "Sex determination of duck embryos: Observations on syrinx development," *Avian Biology Research*, vol. 6, no. 3, pp. 243–246, 2013.

[11] P. A. Johnsgard, "Observations on sound production in the Anatidae," *Paul Johnsgard Collection*, pp. 46–59, 1971.

[12] B. Igic, N. Leuschner, K. A. Parker, S. M. Ismar, B. J. Gill, T. G. Lovegrove, C. D. Millar and M. E. Hauber, "Size dimorphism and avian-perceived sexual dichromatism in a New Zealand endemic bird, the Whitehead mohoua albicilla," *Journal of Morphology*, 2010.

[13] J. W. MacArthur and J. J. MacIlraith, "Color sexing of day-old Brown Leghorns," *Poultry Science*, vol. 25, no. 2, pp. 180–183, 1946.

[14] R. Santiago, K. Villareal, M. San Agustin, R. Balotro, C. Rey, J. P. Esguerra, A. Lambio, and V. Magpantay, "Growth, egg production, and phenotypic characteristics of the commercial hybrid egg-type Philippine Mallard Duck (IP Kayumanggi) under Intensive Management System," *Philippine Journal of Science*, vol. 151, no. 3, 2022.

[15] J. L. Dioses, R. P. Medina, A. C. Fajardo, A. A. Hernandez and I. A. M. Dioses, "Performance of Egg Sexing Classification Models in Philippine Native Duck," *IEEE 12th Control Syst. Grad. Res. Colloq. (ICSGRC),* 2021, pp. 248-253, doi: 10.1109/ICSGRC53186.2021.9515279.

[16] M. Kayadan and Y. Uzun, "High accuracy gender determination using the egg shape index," Scientific Reports, vol. 13, no. 1, 2023. doi:10.1038/s41598-023-27772-4

[17] Z. Li, F. Liu, W. Yang, S. Peng, and J. Zhou, "A survey of Convolutional Neural Networks: Analysis, applications, and prospects," *IEEE Trans. Neural Netw. Learn. Syst.,* vol. 33, no. 12, pp. 6999–7019, 2022. doi:10.1109/tnnls.2021.3084827

[18] J. Bartels *et al.*, "TinyCowNet: Memory- and power-minimized RNNS implementable on tiny edge devices for lifelong cow behavior distribution estimation," *IEEE Access*, vol. 10, pp. 32706–32727, 2022. doi:10.1109/access.2022.3156278

[19] M. Corion, J. Keresztes, B. De Ketelaere, and W. Saeys, "In ovo sexing of eggs from Brown breeds with a gender-specific color using visible-near-infrared spectroscopy: Effect of incubation day and measurement configuration," *Poultry Science*, vol. 101, no. 5, p. 101782, 2022.

[20] G. Mappatao, "Duck egg sexing by eccentricity determination using image processing," *Journal of Telecommunication, Electronic and Computer Engineering*, vol. 10, pp. 71-75 [Online]. Available: https://animorepository.dlsu.edu.ph/faculty_research/992.

[21] S. Thongsuwan, S. Jaiyen, A. Padcharoen, and P. Agarwal, "ConvXGB: A new deep learning model for classification problems based on CNN and XGBoost," *Nuclear Engineering and Technology*, vol. 53, no. 2, pp. 522–531, 2021.

[22] H. Liu, K. Simonyan, and Y. Yang, "DARTS: Differentiable Architecture Search," arXiv:1806.09055v2 [cs.LG], April 2019.

[23] "Hatching duck eggs," *Cornell University College of Veterinary Medicine*, https://www.vet.cornell.edu/animal-health-diagnostic-center/programs/duck-research-lab/hatching-duck-eggs (accessed Jul. 31, 2023).

[24] "Embryonated avian eggs in research and teaching," *Embryonated Avian Eggs in Research and Teaching | Research Animal Care and Safety*, https://animalcare.illinois.edu/policies/embryonated-avian-eggs-research-and-teaching#:~:text=If%20avian%20embryos%20hatch%2C%20intentionally,are%20considered%20the%20model%20species (accessed Jul. 31, 2023).

[25] W. S. University, "Use of avian embryos policy," *Institutional Animal Care and Use Committee*, https://research.wayne.edu/iacuc/avianembryospolicy?fbclid=IwAR2W1pQ5bQ-shwWVqBkzpPjMpDVAkiOuJK9tmvETvT_kUtpUMzO-euahHUQ_aem_AdfmXvnstzf7mRw72FXm5G2VUrRwg9s4L4WpTXdce1cYFh631Jrc-T3uEu5APhPtUhE (accessed Jul. 31, 2023).