Open Access Research Journal of
Science and Technology
Journals home page: https://oarjst.com/
ISSN: 2782-9960 (Online)

OARJ OPEN ACCESS RESEARCH JOURNALS

(RESEARCH ARTICLE)

Check for updates

Design of an AI-based egg fertility detection system for incubators

Davison Musara, Blessed Sarema, Destine Mashava *, Kudakwashe Chinguwo and Takudzwa M. Muhla

Department of Industrial and Manufacturing Engineering, National University of Science and Technology, Bulawayo, Zimbabwe.

Open Access Research Journal of Science and Technology, 2024, 12(01), 001–009

Publication history: Received on 15 July 2024; revised on 26 August 2024; accepted on 29 August 2024

Article DOI: https://doi.org/10.53022/oarjst.2024.12.1.0109

Abstract

The conventional approach to determine the fertility of chicken eggs, called candling, is subjective, time-consuming, and ineffective and thereby results in low hatching rates and financial losses. As a result, a more reliable, accurate, and sustainable system that uses artificial intelligence and automated systems to improve the process of assessing egg fertility for incubation. The system proposes capturing of images of eggs at the early stages of incubation by a camera and sent to a cloud server, where a Convolutional Neural Network (CNN) analyses and classifies the data to determine the fertility status of the eggs. The system aims to increase the quality and hatching rate of chicken eggs, lower labour expenses and human error, and boost the poultry industry's sustainability and profitability. The framework of the system is based on the current poultry egg fertility assessment methods in Zimbabwe, which include candling, infrared thermography, ultrasound, heart rate detection, oxygen flux detection, visible or near-infrared transmittance spectroscopy, and thermal imaging. The system is expected to perform better than existing systems in terms of accuracy, speed, and cost-effectiveness. The experimental results show that, the method's average identification time is 0.210 seconds, and its identification accuracy is 98.40 percent. These results demonstrate the viability of the suggested AI-based method for automatically determining an egg's fertility without human intervention, greatly increasing hatcheries' and related businesses' productivity.

Keywords: Artificial Intelligence; Egg Fertility; Computer Vision; Hatch rate; Convolutional Neural Network (CNN)

1. Introduction

Poultry farming is a significant source of income and food security for many people in Zimbabwe. However, one of the challenges faced by poultry farmers, particularly smallholder farmers is the low hatch rate of eggs following incubation [1]. This can be attributed to a lack of efficient egg quality assessment systems before and incubation. To improve the hatch rate, farmers need to use efficient systems to detect and monitor the fertility status of the eggs before or at least in the early days of incubation. Most poultry farmers use manual inspection of the eggs, which can be inaccurate and time-consuming.

The Zimbabwe Poultry Association (ZPA) estimates that the poultry sector adds 1.3 percent to the country's GDP and roughly 4.5 percent to the GDP of agriculture. Because there is frequently a greater demand than supply for day-old chicks, Zimbabwe's hatchery output rates are now quite low [2]. The average hatch rate in Zimbabwe is 83 percent, according to Zimbabwe Incubators, an indigenous business that specializes in the production of incubators and egg hatcheries.

* Corresponding author: Destine Mashava

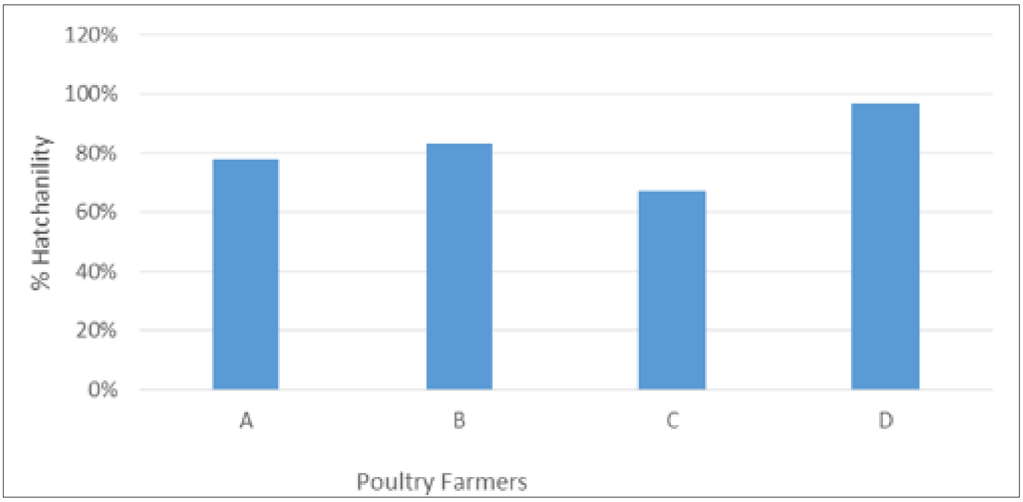

Figure 1 Hatch rates for poultry farmers using conventional method

In addition, poultry farmers deal with issues like power interruptions, expensive upkeep, and restricted market access. The surveyed hatchery service provider by ZPA, as shown in Figure 1, Company A, asserts a 78 percent hatch rate but acknowledges challenges in obtaining high-quality viable eggs and sustaining appropriate humidity and temperature conditions. The hatch rates are much lower for smallholder growers [2]. There is also the risk of contamination in hatching eggs if dead embryos are not removed early and accurately [3].

The fertility of eggs laid by a hen depends on whether the hen was raised together with roosters, otherwise, the eggs would be infertile [4]. When the adult hen's ovum and rooster sperm unite, either spontaneously or artificially by insemination, egg fertilization results. Grocery store eggs come from hens grown without roosters, but most hatchery eggs worldwide are generated from a mother hen kept with roosters [5]. Fertile eggs reach their full potential for embryonic development when they are incubated at 37.8 ∘C and around 55 per cent relative humidity. But not every egg that is thought to be fertile hatches into chicks under incubation conditions; some eggs do eventually prove to be non-fertile at the end of the incubation process. Therefore, there is a need to know and understand the difference between hatchery fertile and non-fertile eggs [5].

According to Bakst and Cecil [6], a fertilized egg contains a blastoderm, while an unfertilized egg contains a germinal disc called, blastodisc. The blastoderm can be viewed as a symmetrical circular ring of about 3-4mm in diameter. Egg fertility detection can be achieved using manual candling but the approach is exceedingly time-consuming, error-prone, and labour-intensive [7]. Fertility assessment methods also include sperm penetration assay and counting sperm in the outer perivitelline layer [7]. Even though these techniques are useful, non-destructive and quick technology is still needed to help identify chicken egg fertility early on.

There are several non-destructive techniques for detecting egg fertility and these include computer vision, thermal imaging, spectroscopy, ultrasound signal measurement, hyper spectral imaging and dielectric characteristics measurement [8-12]. Önler et al.,[9] studied fertility discrimination of brown eggs using ultrasonographic images. Although the model had an accuracy of up to 86%, it was pointed out that the ultrasound signal could not penetrate the eggshell so holes needed to be created on the eggs before acquiring the ultrasound signals. A thermal imaging system was used for filtering and recognition of fertilized eggs and the accuracy reported was 96% for 14 days of incubated eggs [10]. These incubation days (18 and 14 respectively) are, however, too late for early identification desired in the poultry industries.

Lawrence, et al. [11] developed an RGB system equipped with a pressure chamber to identify minute cracks in eggshells. A tiny chamber was constructed to generate force and vacuum to crack an egg, after which digital pictures of the egg were taken. The system's intended purpose was to inspect one egg at a time. They later revealed a modified pressure method to find tiny flaws in 15 eggs simultaneously. Zhao, et al.,[12] also evaluated the possibilities for early embryonic identification in fertile chicken eggs using a spectrophotometer, a device that is recognized for blood detection in table eggs. According to Zhao, et al [12], it is possible to detect embryonic development as early as day 5 or 120 hours of incubation. This late detection may have something to do with the spectroscopic technique's point information acquisition mode, which makes it unfavourable when relevant information is absent from the measured pixel spot

Poultry farmers face significant challenges due to the low hatchability rate of their eggs, which impacts their revenue and food security. The conventional methods that are used to assess egg fertility are unreliable, or require manual inspection of the eggs, which can be time-consuming and inaccurate since they are subjective. There is a need for a low-cost, reliable, and automated inspection system that can provide optimal conditions for egg fertility assessment, and utilizing Artificial Intelligence (AI) such as convolutional neural networks can be used for image processing providing a much better solution in pattern recognition [13]. Such a system would reduce the cost and labour involved in egg inspection and sorting, increase the hatchability rate and productivity rate of poultry farming, and enhance the quality and safety of poultry products.

2. Methodology

The primary aim of the research was to design an artificial intelligence-based detection system for assessing egg fertility and an automated system for facilitating that. To meet the aim, the following objectives were formulated:

- To design a microcontroller-based system to capture images of hatching eggs for incubation.
- To develop a detection and segmentation algorithm to differentiate between fertile and infertile eggs.
- To develop a conveying system to facilitate the movement of the eggs in and out of the classification booth.
- To develop a working prototype.

2.1. Research Methods

The authors utilised the research methodology outlined in Table 1 below to meet the research objectives.

Table 1 Research Methodology

Objective	**Methodology**	**Tools/Techniques**	**Expected Outcome**
To design a microcontroller-based system to capture images of hatching eggs for incubation.	Identification of suitable micro-controller; Hardware Layout Design; Integrate camera module with microcontroller	Microcontroller selection criteria; Circuit design software; Camera module; Programming language	Functional image capture system that is integrated with the microcontroller
To develop a detection and segmentation algorithm to differentiate between fertile and infertile eggs.	Collection of a data set of fertile and infertile eggs; Pre-process images to enhance features; Develop and train detection algorithm using machine learning techniques; Test and validate the algorithm's accuracy	Image processing software; Machine learning libraries	Accurate algorithm for detecting and segmenting fertile and infertile eggs.
To develop a conveying system to facilitate the movement of the eggs in and out of the classification booth.	Design a mechanical system to transport the eggs; Select appropriate components and materials; Integrate the conveyance system with the micro controller; Test and optimise the movement process	CAD software for Design; Mechanical components; Micro-controller integration	Efficient conveying system that seamlessly integrates with the classification booth.
Develop a working prototype	Integrate all subsystems into a single prototype; Conduct system testing and troubleshooting; Iterate design based on test results	Prototyping tools; Testing equipment; Debugging tools	Fully functional prototype that demonstrates the entire process of egg classification.

3. Results

3.1. Proposed design principle of operation

The process begins with the transfer of the crate of eggs using a conveyor belt into the candling booth where image acquisition and classification occurs as shown by the schematic model diagram on Figure 2.

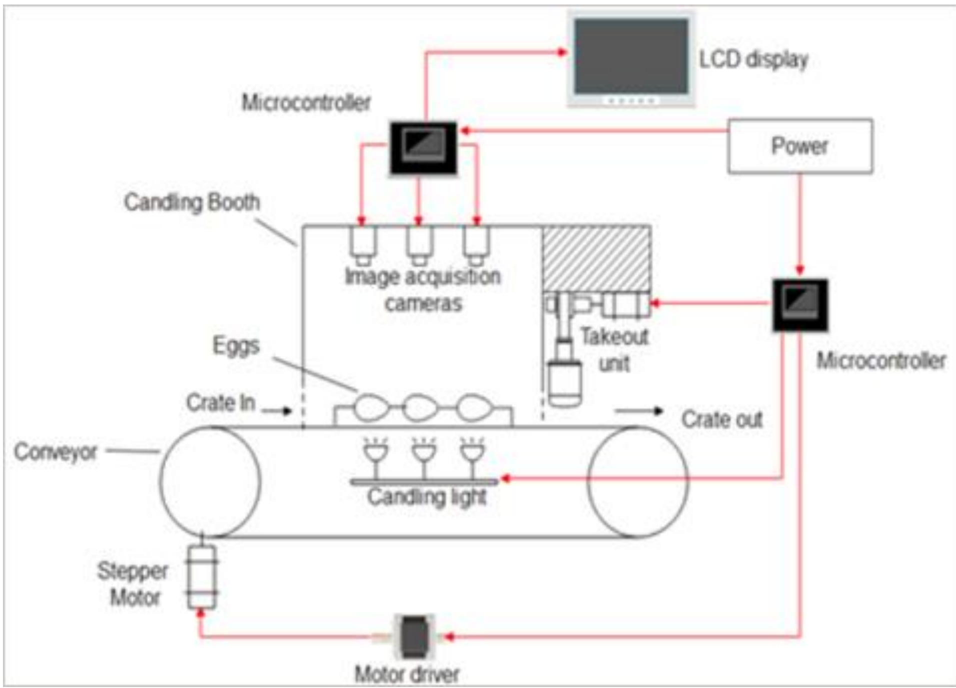

Figure 2 Proposed system schematic

Then followed by capturing images of the hatching eggs using a camera at the top of the candling booth. The images are obtained under consistent lighting conditions to ensure accuracy. The captured images then undergo pre-processing to enhance their quality and prepare them for computer vision algorithms. This includes image resizing, normalization, noise reduction, and contrast enhancement.

Computer vision algorithms in the microcontroller extract relevant features from the pre-processed images. The extracted features include characteristics such as egg shape, size, colour, texture, and surface irregularities. Some of the specific features that may be identified to show fertility include; the presence of blood vessels as well as embryo development. The extracted features are then analysed using machine learning algorithms. These algorithms are trained on a dataset of labelled images, where each image is annotated with its corresponding fertility status (fertile or infertile). With this, the eggs are classified as fertile or infertile and this is displayed on the LCD screen. The eggs are then conveyed out of the candling booth, where they are marked upon exit

3.2. Developed system components

The developed design consists of an Arduino UNO which serves as a microcontroller that controls the movement of the conveyor belt by actuating a Stepper motor. Additionally, it is employed to collect data from the ESP CAM and control a Servo motor for the take out unit that sorts out the infertile eggs. The orthographic projection and 3-dimensional representation of the developed system is given in Figure 3.

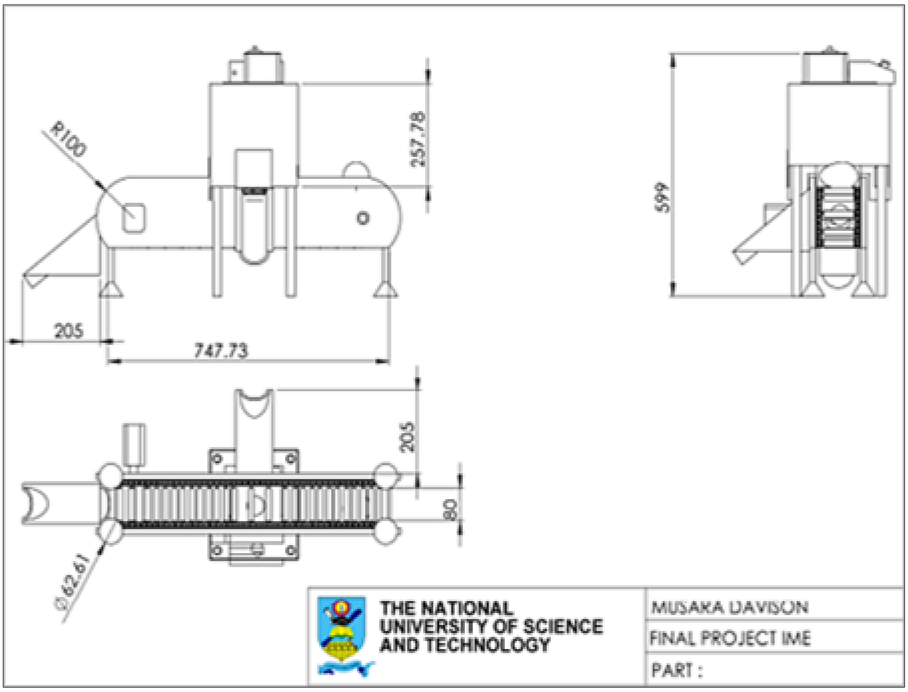

Figure 3 Developed system Orthographic projection schematic

The Convolutional Neural Network was chosen as the image classification algorithm for accurate results in differentiating between fertile and infertile eggs. The final concept will therefore include the egg image acquisition, segmentation and feature extraction mechanism which is enhanced by a Near Infrared filter integrated with the camera. The 3-dimensional representation of the developed system is given in Figure 4. Which shows the orientation of the machine, its structure and layout

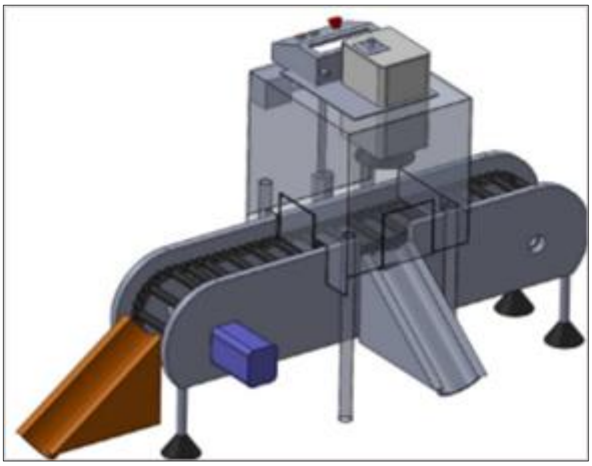

Figure 4 3D model of the developed system

3.3. Image classification system architecture

The approach applied in the development of the image classification system is given in Figure 5 below. The system architecture combines image processing techniques (feature extraction and segmentation) with a machine learning approach (CNN algorithm) in a bid to automate the classification of eggs into infertile and fertile categories.

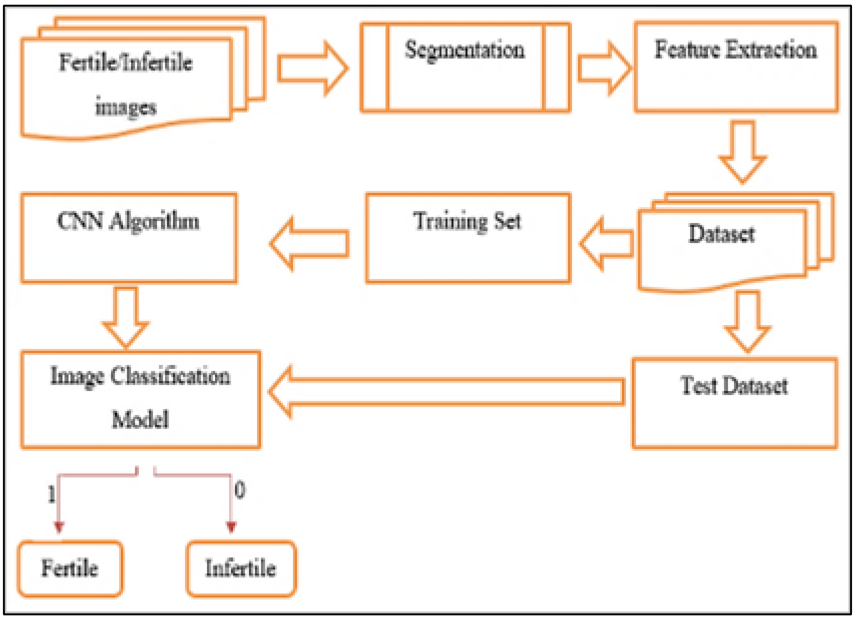

Figure 5 Image classification system architecture

The flow of the System Architecture in essence begins with the acquisition of the image, continuing through training of the model and validation, and concludes with a model that can predict the fertility of an egg with accuracy.

3.3.1. Model Training

Google Teachable machine learning and Edge Impulse was used to train a model on the specific task of classifying egg images for both fertile and infertile.

The output differentiated between fertile and infertile eggs and classified the intensity in percentage ratings. The data input to the model is shown in Figure 6 prior to classification.

Figure 6 Data input

3.3.2. Model Training Results

The developed system's average identification time was 0.210 seconds, and its identification accuracy was 98.40 % and the model output are illustrated on figure 7. In which the model accurately differentiates between fertile and infertile eggs.

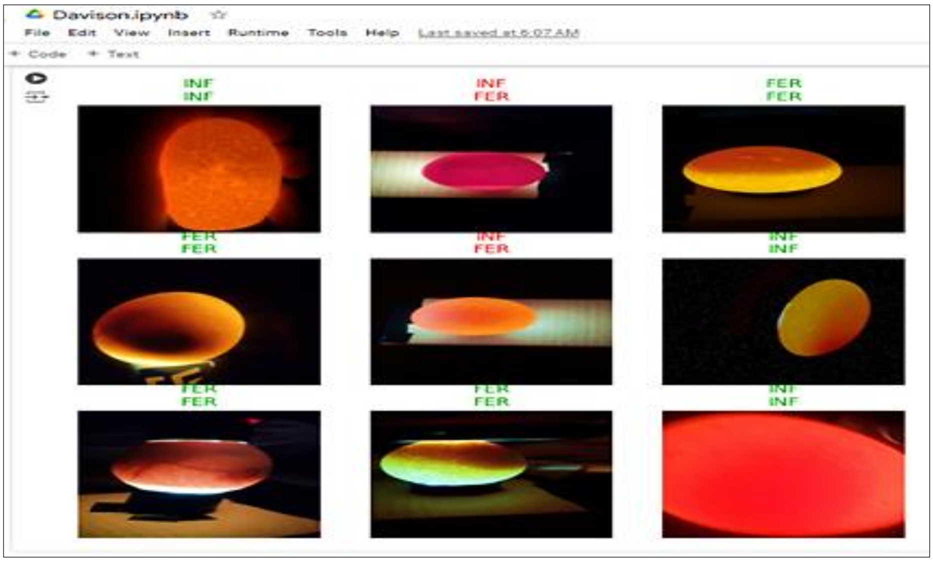

Figure 7 Model prediction results

3.4. Prototype Design

The prototype layout design developed to demonstrate the functionality of the system design is shown in Figure 8 below. The prototype makes use of a conveyer system driven by a stepper motor and controlled by an Arduino UNO micro-controller to automate the egg classification process. The ESP32-CAM captures images of the eggs under LED lighting, which ensures clear images for accurate classification. The eggs are securely held in place as they move along the conveyor, and the stepper motor provides precise control on the movement. The take-out unit which sorts the eggs based on their classification is managed by a servo motor. The entire system is powered by a 12V DC/AC converter.

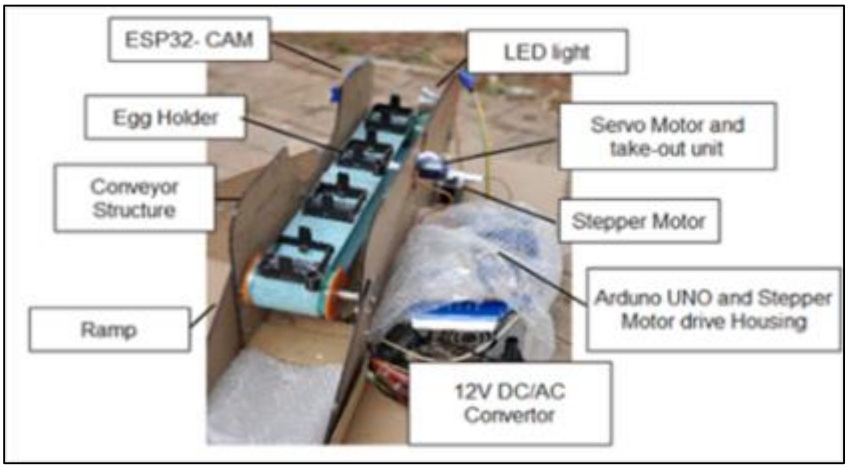

Figure 8 System prototype

The entire prototype setup demonstrates a practical, automated solution for accurately distinguishing between fertile and infertile eggs.

4. Discussion

The research focused on enhancing accuracy and efficiency in the poultry industry, through the design of an Artificial Intelligence based egg fertility detection system. This system involves the integration of an automated conveyor belt mechanism that moves eggs into and out of an analysis chamber. The conveyor belt ensures gentle handling of the eggs, thereby preventing damage and maintaining integrity of the eggs. The automation process also reduces the need for manual labour, thereby paving the way for scalable and ongoing operation.

4.1. Recommendations and future work

In order to improve and expand the use of the AI-based egg fertility detection system in the future, various improvements can be realized thorough refining the CNN algorithm using more and more varied datasets, its accuracy and resilience to varying environmental factors and egg types might be enhanced. Further improvement of efficiency could be realized by incorporating real-time data analytics and feedback mechanisms, which would allow for dynamic changes to the imaging parameters and conveyor belt speed. Also investigating the application of cutting-edge sensors, including hyper spectral imaging, may offer more in-depth understanding of egg fertile traits than visual cues and may improve detection accuracy. Working with various industry partners could make it easier to test and improve the system on a wide scale in the field, guaranteeing its applicability and dependability in business environments.

5. Conclusion

In conclusion, the development and implementation of an AI-based egg fertility detection system equipped with an automated conveyor belt and a Convolutional Neural Network (CNN) algorithm mark a significant leap forward in agricultural automation. This research has successfully demonstrated the potential of combining advanced AI techniques with mechanical automation to address critical challenges in the poultry industry. The system not only enhances the accuracy and efficiency of egg fertility assessment but also reduces dependency on manual labour, thereby paving the way for more scalable and sustainable operations. The gentle handling of eggs through the automated conveyor belt ensures the integrity of the samples, while the CNN algorithm's high precision in distinguishing between fertile and non-fertile eggs underscores the robustness of this technological approach.

The promising results of this project indicate a transformative impact on egg fertility detection processes, with broader implications for precision agriculture. The findings highlight the viability and benefits of integrating AI-based solutions in routine farming operations, ultimately contributing to enhanced productivity and resource management. As the agricultural sector continues to evolve, the insights gained from this research will serve as a valuable foundation for ongoing advancements, ensuring that the industry remains at the forefront of technological progress and sustainability.

Compliance with ethical standards

Acknowledgments

I am grateful to the National University of Science and Technology for offering facilities and resources for this research. Their support facilitated the smooth execution of the research.

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Mapiye, C., Mwale, M., Mupangwa, J. F., Chimonyo, M., Foti, R., & Mutenje, M, A research review of village chicken production constraints and opportunities in Zimbabwe. Asian-Australasian Journal of Animal Sciences, 2008 21(11), 1680-1688.

[2] Zimbabwe Poultry Association [internet] Harare: Zimbabwe Poultry Association 2019 [cited 20 Aug 2024] Available from https://agriculture.co.zw/directory-finder/listing/the-zimbabwe-poultry-association-zpa/

[3] Geng L, Hu Y, Xiao Z, Xi J. Fertility detection of hatching eggs based on a convolutional neural network. Applied Sciences. 2019 Apr 3;9 (7):1408.

[4] Barber, J. and Joseph. C., The chicken: A natural history. Princeton University Press; 2018

[5] Adegbenjo, Adeyemi O., Li Liu, and Michael O. Ngadi. "Non-destructive assessment of chicken egg fertility." Sensors 2020, 20.19: 5546.

[6] Bakst, M. R. & Cecil, H. C. Techniques for Semen Evaluation, Semen Storage, and Fertility Determination. 2nd ed. Buffalo, Minnesota: Midwest Poultry Federation; 2014

[7] Syduzzaman, M. and Khaliduzzaman, A., Grading of Hatching Eggs. In Informatics in Poultry Production. In: A Technical Guidebook for Egg and Poultry Education, Research and Industry. Singapore: Springer Nature Singapore, 2022, pp. pp. 53-75.

[8] Chan, V. and Perlas, A., 2011. Basics of ultrasound imaging. In: Chan, V. and Perl Atlas of ultrasound-guided procedures in interventional pain management. s.l.: s.n., pp.13-19; 2011

[9] Önler, E.; Çelen, I.H.; Gulhan, T.; Boynukara, B. A study regarding the fertility discrimination of eggs by using ultrasound. Indian J. Anim Res. 2017, 51, 322–32

[10] Liu, L.; Ngadi, M. Detecting fertility and early embryo development of chicken eggs using near-infrared hyper spectral imaging. Food Bioprocess. Technol.2013, 6, 2503–2513

[11] Lawrence, K.; Park, B.; Heitschmidt, G.; Windham, W.; Thai, C. Evaluation of LED and tungsten-halogen lighting for fecal contaminant detection. Appl. Eng. Agric. 2007, 23, 811–818

[12] Zhao, Q. et al., 2019. Potential use of spectroscopic techniques for assessing table eggs and hatching eggs. World's Poultry Science Journal, 75(3), pp.445-456.

[13] Mashava, D., Kimotho, J. K., & Muvengei, O. M. 2022. Gearbox Multiple Faults Diagnosis under Stationary and Non-Stationary Operating Conditions Using Convolutional Neural Networks. Engineering Advances, 2(1), 1-17.