Egg Defects Detection Using Bidirectional Long Short-Term Memory Network

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Abstract

Eggs are a vital nutritional resource globally, making their inspection crucial for maintaining quality and ensuring food safety. Motivated by this need, a machine vision system incorporating deep learning techniques was developed to detect egg defects. The machine vision system has a rotating mechanism that allows for comprehensive visualization of the egg surface from various angles, leading to a more accurate assessment. The proposed system leverages deep feature extraction using a pre-trained convolutional neural network and analyses these features with a Bidirectional Long Short-Term Memory (BiLSTM) network. The types of egg defects that this study aimed to detect were bloodstained, cracked and dirty eggs. A total of 400 eggs sample were used with 6 images per egg resulting with a dataset of 2400 images for the proposed deep learning method. The performance evaluation of the model revealed an accuracy of 97.71% in detecting egg defects, with a recall score of 0.9788, a specificity score of 0.9926, a precision score of 0.9770, and a F1 score of 0.9770. Comparisons with other state-of-the-art deep learning and machine learning methods like (SVM, VGG16, YOLOv5) indicate that the proposed model has certain advantages and does not differ much in terms of accuracy for defect detection. The result from this study demonstrates the potential of sequential feature modelling for robust egg defect detection.

1. Introduction

Eggs are a fundamental component of human nutrition, offering a rich source of essential lipids, proteins, vitamins, and minerals at a low economic cost [1]. Beyond their nutritional value, the egg industry holds significant economic importance, contributing substantially to the global economy and impacting the livelihoods of farmers. For instance, in Malaysia, the average production cost of chicken eggs was RM0.48 each in September 2022, with poultry feed accounting for 76.2% of direct costs according to the Department of Statistics Malaysia.

However, the journey from egg production to consumption is fraught with challenges, primarily the occurrence of egg defects. Defects such as bloodstains, cracks, and dirt can pose considerable risks to consumers and lead to significant economic losses for production and distribution cycle, which can reach up to 8% to 11% of total egg production [2]. Bloodstains, though generally harmless, can cause consumer discomfort, while shell cracks compromise structural integrity and allow pathogen entry. Defective eggs, if consumed raw or undercooked, can lead to microbial contamination and health risks, including Salmonella.

Traditional methods for inspecting defective eggs are often slow, labour-intensive, and prone to mistakes. These challenges open the door to using machine vision and machine learning as more efficient and reliable alternatives. By automating the inspection process, these technologies can greatly improve accuracy while cutting down on time and manual labour. While earlier machine learning techniques like Support Vector Machines and Random Forests have been used for this purpose, they typically require a step-by-step process involving image capture, pre-processing, and manual feature extraction. These approaches often depend heavily on expert knowledge and can struggle with inconsistencies in image quality.

In contrast, recent advances in deep learning, especially Convolutional Neural Networks (CNNs), have shown strong potential for identifying defects. However, many existing approaches rely on a single image per egg, which may not provide a complete view for accurate detection. Hence, this study aims to overcome that limitation by using multiple images from different angles, allowing for more comprehensive and reliable assessment. In this regard, the Bidirectional Long Short-Term Memory (BiLSTM) emerges as a strategic choice because it excels in handling sequential data, enabling the capture of dependencies and patterns across a sequence of images. This proves particularly advantageous when dealing with eggs in motion or undergoing dynamic visual transformations. The bidirectional nature of BiLSTM allows it to assimilate contextual information from both past and future frames, thereby enhancing its ability to comprehend the evolving nature of eggs during processing. Therefore, this study aims to design an automated multi-view defect detection framework integrating DenseNet201 for deep feature extraction and BiLSTM for temporal sequence classification.

2. Literature Review

2.1 Introduction to Defective Egg Detection

Egg quality control in the food industry is a rigorous process ensuring safe and nutritionally sound eggs [3]. This comprehensive approach spans from laying to packaging, integrating environmental management, genetic selection, disease prevention, and meticulous handling [4]. Critical aspects include visual defect inspection, continuous monitoring of eggshell quality, and grading based on size, weight, and quality.

Egg defects vary, including surface cracks from mechanical stress or temperature changes [5], blood spots from ruptured blood vessels, and irregular shapes due to formation disturbances. Double yolks in young hen and shell deformities may stem from calcium or nutrient deficiencies during formation, stress, or diseases affecting the laying hen [6]. Causes are multifaceted, including genetic factors, inadequate nutrients, stress, and diseases. Understanding these causes are helpful for developing an effective defect detection system.

Traditional methods like candling involve exposing eggs to a light source for internal examination, are effective for blood spots and internal irregularities [7]. Other manual methods include visual inspection for external anomalies, floatation tests for freshness, manual crack detection, olfactory assessments, sound tests, and light table examinations [8-10]. However, these methods are subjective, labour-intensive, and prone to human error, with some surface defects being imperceptible to the naked eye. Manual inspection can account for over 50% of manufacturing time [11], driving a pressing industry demand for automated and economical systems.

The egg industry is increasingly adopting automated technologies, particularly machine vision and imaging systems, to enhance precision, efficiency, and objectivity in quality control. Machine vision systems, acting as the "eyes," collect visual information using cameras and sensors, while machine learning models provide intelligence for decision-making. These models are trained on labelled datasets of intact and defective eggs to recognize patterns and characteristics of abnormalities.

2.2 Deep Learning Techniques for Defective Object Detection

Deep learning has revolutionized defect detection, especially where traditional methods struggle with intricate and disorderly datasets [12]. Deep learning models autonomously extract complex and hierarchical features directly from raw data, eliminating the need for extensive manual feature engineering [13]. This enables end-to-end learning, enhancing adaptability and eliminating extensive pre-processing. Deep learning models are scalable and benefit from technological advancements and large datasets.

In the food industry, deep learning models have shown considerable promise for defect detection. Pinto et al. [14] used Convolutional Neural Networks (CNN) for classifying green coffee beans by defect types, achieving 72.4% -98.7% accuracy despite limited sample size. Huang et al. [15] developed a real-time classification system distinguishing good/bad green coffee beans with 93% success rate. Fan et al. [16] used CNN with computer vision for defective apple detection, outperforming traditional methods with 96.5% accuracy, 100% recall, and 92.9% specificity.

## 2.3 Applications of Machine Learning and Deep Learning in Egg Quality Control

Extensive research has explored machine learning and deep learning for egg quality control. Deng et al. [17] used Support Vector Machine for eggshell fracture detection with 98.9% accuracy. Nasiri et al. [18] proposed an automatic sorting system for unwashed eggs using a modified VGG16, achieving 94.84% accuracy in classifying intact, bloodstained, and broken eggs, though with a limited sample of 105 eggs.

Turkoglu [19] introduced a novel technique incorporating BiLSTM networks to address the single-image limitation by considering multiple views of each egg, achieving 99.17% accuracy. Botta et al. [20] proposed a CNN method for automatic eggshell fracture identification, achieving 95.38% accuracy, but focused primarily on eggshell cracks with a limited sample size. Liu et al. [21] proposed a 6-position egg image acquisition method for crack detection using EfficientNet network model, achieving 98.6% recognition rate.

3. Methodology

3.1 Project Framework

This study introduces a machine vision system designed for defective egg detection, integrating deep learning models and continuous rotation mechanisms. The project framework, illustrated in Fig. 1, involved the design and creation of a rotating apparatus, followed by image acquisition and pre-processing. Feature extraction was performed using DenseNet201, while the BiLSTM was utilized for deep learning analysis. The results from then underwent rigorous evaluation and comparison.
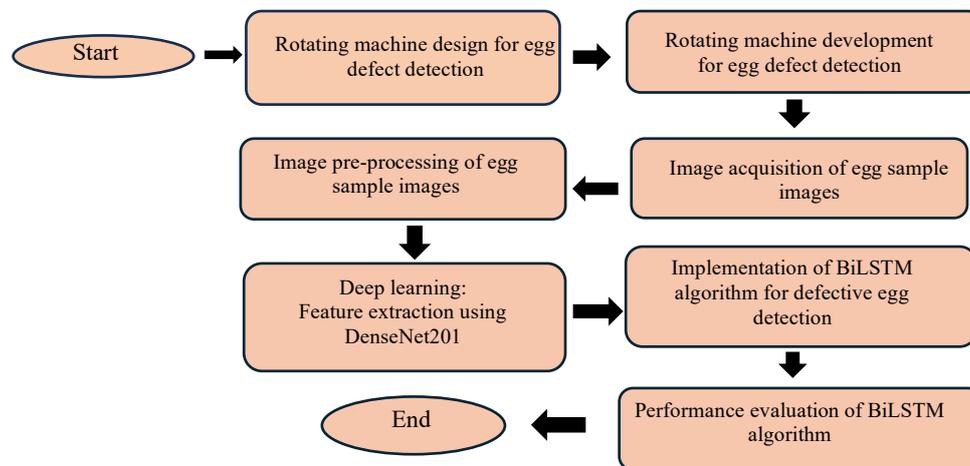
Fig. 1 *Project framework flowchart of BiLSTM implementation for egg defect classification*

3.2 Machine Vision System

The machine vision system was developed to identify intact, cracked, bloodstained, and dirty eggs. Its primary component is the image acquisition module, which integrates a deep learning model with a continuously rotating mechanism. The operational sequence is as follows: a digital camera is placed at the center of the egg vial tray, and upon system activation, eggs undergo automatic rotation, with images captured at 4-second intervals.

A total of 400 eggs were used, with 100 eggs each for dirty, bloodstained, cracked, and intact egg assessments. Each egg was captured from six distinct angles, resulting in 2400 images with a resolution of 224 × 224 pixels.

3.3 Image Acquisition and Pre-processing System

The image acquisition system (Fig. 2) features an egg vial tray with an incorporated continuous rotation system to fully expose egg surfaces (Fig. 3).
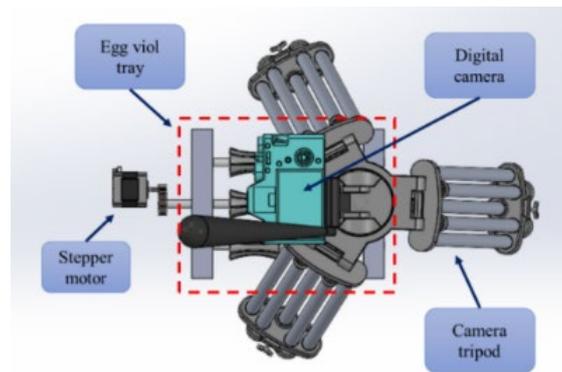
Fig. 2 *Image acquisition system*
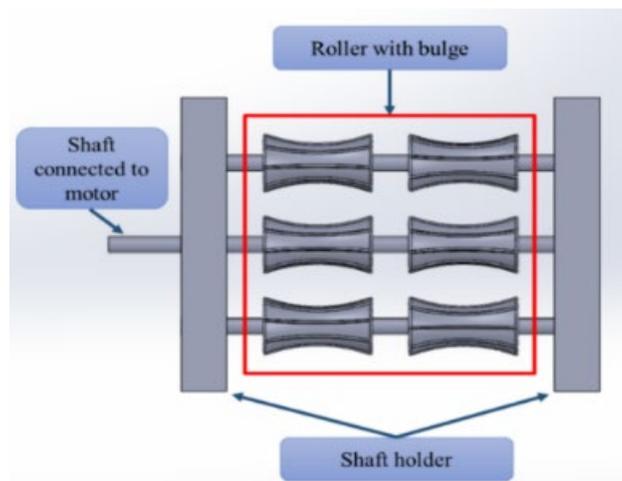
Fig. 3 *Egg vial tray*

The system includes a 2.5–3.0 rpm stepper motor and a hardware mechanism accommodating four eggs, linked to the motor. The motor completes one revolution every 20 seconds, enabling automated image capture at 0, 4, 8, 12, 16, and 20 seconds. A Fujifilm X-T100 camera, with a 24-megapixel CMOS sensor and 4K/15p video capability, was positioned 60cm vertically above the tray. Egg defect detection was performed using deep learning mechanisms, leveraging multi-layered neural networks. DenseNet201, a pre-trained CNN, was applied for deep feature extraction, while a BiLSTM network identified and classified these characteristics into defect types and grades.

3.4 Feature Extraction Using DenseNet201

This study employs DenseNet201 architecture [22]. DenseNet201 features direct forward connections between all layers, using bottleneck structures and pooling layers as transition layers to enhance model efficiency and reduce complexity. With 806 connections and 709 layers, it encompasses approximately 20 million parameters within its 201-depth design. Trained on the ImageNet dataset, DenseNet201 demonstrates proficiency in diverse object classification.

A key part of the model is the Dense Block, which plays an important role in improving how information flows between layers. Each Dense Block includes Batch Normalization (BN), a Rectified Linear Unit (ReLU), and a 3×3 Convolution (Conv) layer. In this study, DenseNet201 was initialized with ImageNet-pretrained weights. During training, only the fully connected layer was trained on our dataset. Upon completion of training, the extracted feature of the fully connected layer is as the input of BiLSTM, producing a 256-dimensional feature vector. This vector captures fine-grained details of the egg samples, offering a rich and informative representation for accurate classification. The extracted 256-dimensional feature vector from DenseNet201 is then directly passed into the BiLSTM for classification task without additional normalization. This is because the output of the DenseNet201 feature extraction layer is already in a numerically stable range due to the internal normalization operations (Batch Normalization and activation functions) applied throughout the network.

3.5 Classification of Defective Egg Using BiLSTM

Long-Short Term Memory (LSTM), proposed by Hochreiter and Schmidhuber [23], addressed the gradient problem in Recurrent Neural Network (RNN) architectures and has undergone significant refinement. The architecture comprises a cell unit and three gates. The input, forget, and output.

LSTM networks are sequentially interconnected, with each subsequent neural network having a distinct structure. Information is added, removed, and stored within the cell. BiLSTM introduces a bidirectional flow of information, training two LSTM networks with parallel layers operating in both forward and backward directions. The ultimate output is an amalgamation of the outputs from these two layers [24, 25]. Fig. 4 compares LSTM and BiLSTM architecture, and Fig. 5 depicts the BiLSTM architecture
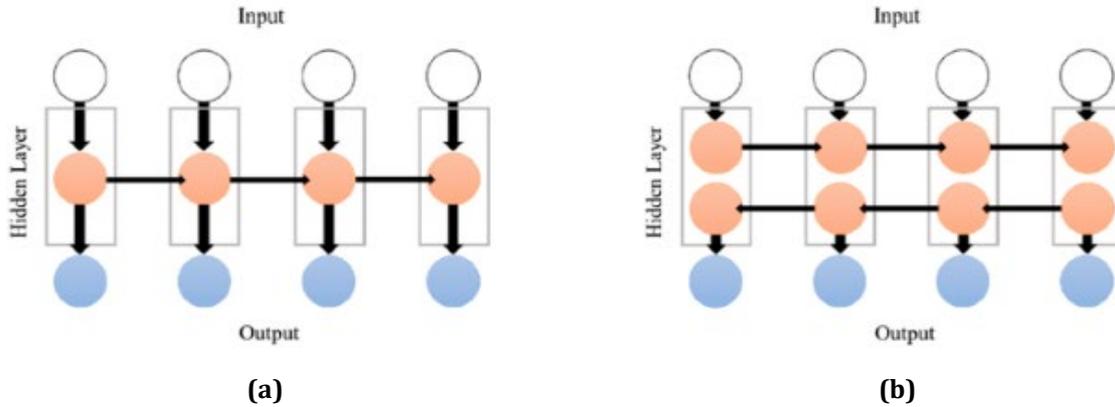

(a)   **(b)**

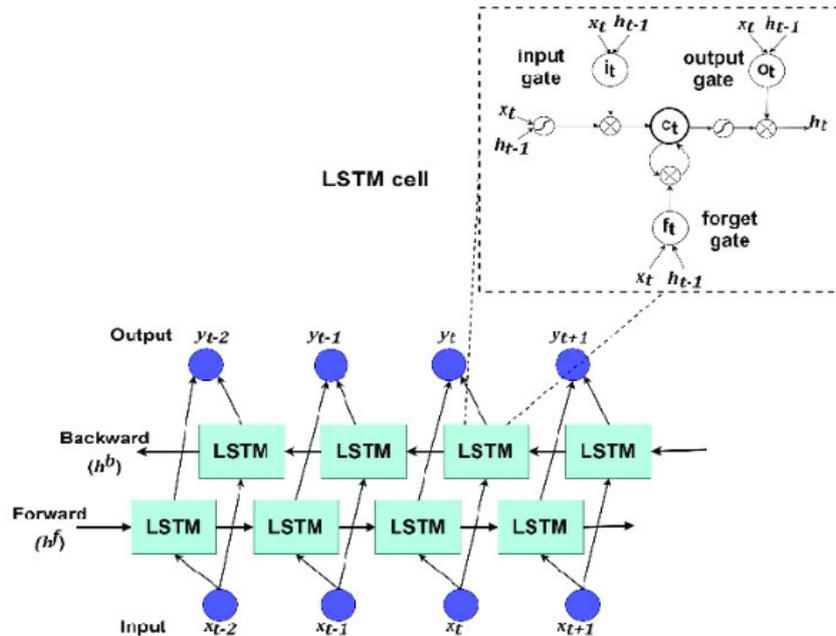**Fig. 4** *LSTM (a); and BiLSTM (b) architecture structures [19]*

Fig. 5 *Architecture of BiLSTM [26]*

Within BiLSTM architecture, the forward $\left(h_t^f\right)$ and backward hidden layer $\left(h_t^b\right)$ as shown in process the input vector x_t. The forward layer processes in ascending order, where t takes values from (t=1 to T) while the backward hidden layer, h_t^b, operates in descending order, with t ranging from T to 1. The ultimate output, y_t, is derived by integrating the outcomes of both h_t^f and h_t^b [26], as shown in Equations (1) to (3):

$$h_t^f = tanh\left(W_{xh}^f x_t + W_{hh}^f h_{t-1}^f + b_h^f\right) \tag{1}$$

$$h_t^b = tanh\left(W_{xh}^b x_t + W_{hh}^b h_{t+1}^b + b_h^b\right) \tag{2}$$

$$y_t = W_{hy}^f h_t^f + W_{hh}^b h_t^b + b_y \tag{3}$$

The Adaptive Moment Estimation (ADAM) optimization solver was frequently selected due to its superior performance and efficiency in training deep learning models. In contrast to traditional gradient descent methods, ADAM amalgamated the benefits of two prominent extensions of stochastic gradient descent (SGD) and RMSProp (Root Mean Square Propagation) to offer an adaptive learning rate. This integration rendered ADAM exceptionally effective and resilient for training complex neural networks. The default parameter setting was fine-tuned to achieve the best performance. The parameter setting applied is shown in Table 1.

Table 1 *Training parameters and values of proposed defect classification model*

Parameter	Values
Optimization Algorithm	ADAM
Initial Learn Rate	0.001
Gradient Threshold Method	12norm
Gradient Threshold	1
L2 regularization	0.0001

3.6 Evaluation Metrics

The confusion matrix (Fig. 6) delineates the classification model's performance, including True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).
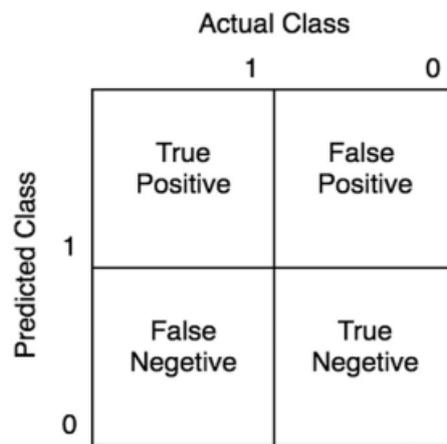
Fig. 6 *Confusion matrix*

The classifiers underwent performance evaluation utilizing precision, accuracy, recall, specificity and F1 score as the key metrics. The mathematical formulations for these measures are expressed in Equations (4) to (8) [20]:

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{5}$$

$$Recall = \frac{TP}{TP + FN} \qquad (6)$$

$$Specificity = \frac{TN}{TN + FP} \qquad (7)$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \qquad (8)$$

Accuracy signifies the ratio of correctly predicted instances to total predictions. Precision (positive predictive value) represents the fraction of positive predictions among total predicted positives. Recall denotes the fraction of positive predictions relative to overall actual positive instances. F1-score is the harmonic mean of precision and recall.

4. Results And Discussion

4.1 Fabrication of Simple System for Defective Eggs Detection

The first step in this study was to fabricate a simple rotating system capable of acquiring six images of egg samples from various angles. The rotating apparatus, shown in Fig. 7, utilizes a concave roller configuration to maximize contact area and frictional force for secure egg gripping. A gear transmission mechanism transfers torque from a motor shaft to an intermediate shaft, initiating egg rotation. Unhindered rotation of ancillary shafts facilitates the transmission of frictional force, optimizing torque transfer and minimizing power consumption.
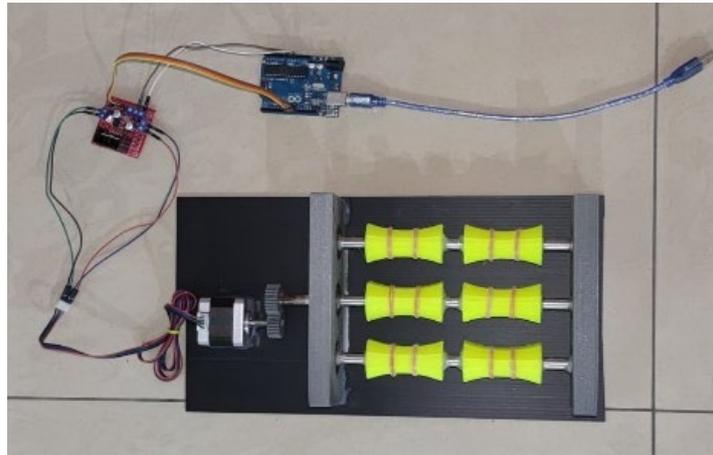
Fig. 7 *Rotating machine fabricated*

The system comprises an egg vial tray for stable egg holding, a stepper motor for precise rotation, and an Arduino controller for motor operation. The Arduino instructs the motor to rotate and pause at 4-second intervals, allowing high-quality image acquisition from multiple perspectives (Fig. 8). This automated process enhances accuracy and consistency in egg inspection.
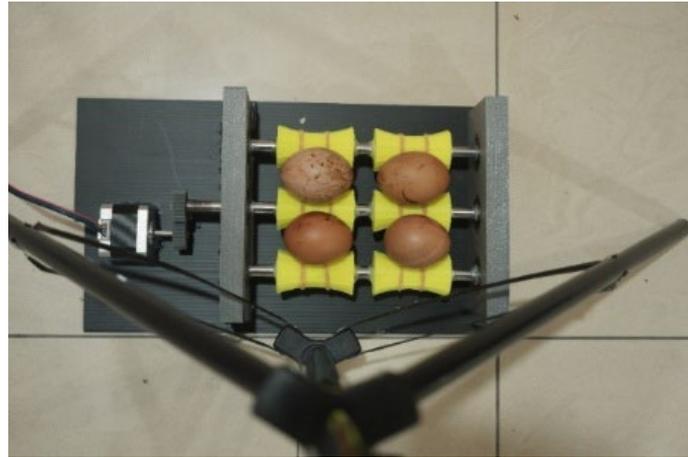
**Fig. 8** *Image obtained using the designed rotating system*

4.2 Analysis of Egg Defect Detection Using Deep Learning

Following image acquisition with the Fujifilm X-T100 camera, egg defect detection was performed using BiLSTM model in Matlab R2024a on a personal laptop with a GeForce GTX 1060 Ti GPU and 8 GB of RAM. A total of 400 images (100 per defect type, Table 2) were collected.

Table 2 *Number of images for each defect type*

Type of Defect	Number of Image
Bloodstained	100
Cracked	100
Dirt	100
Intact	100

Since six images were taken for each egg, the total dataset comprised 2400 images. 80% (1920 images) were used for training, and 20% (480 images) for testing. Raw images (Figure 8) underwent cropping to isolate individual eggs (Figure 9).
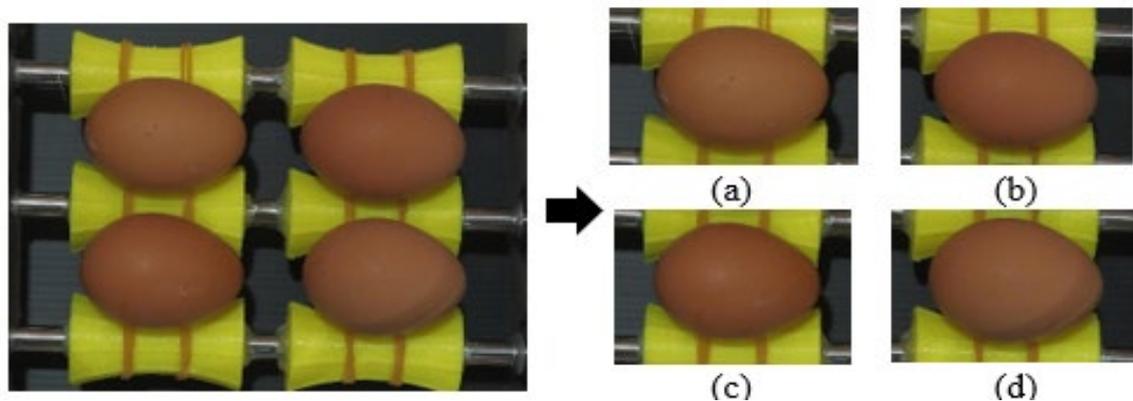

Fig. 9 *Cropping from raw image to individual egg*

Deep features extracted from individual egg images using DenseNet201 were directly used as input for the BiLSTM model. The BiLSTM model's performance was evaluated (Table 3) using recall, specificity, precision, F1-score and accuracy.

Table 3 *Performance evaluation of BiLSTM model for defect detection*

	Defect type	Predicted				Recall	Specificity	Precision	F1	Accuracy
		Bloodstained	Cracked	Dirty	Intact					
Actual	Blood stained	120	0	0	0	1	1	1	1	0.9771
	Cracked	0	109	0	0	1	0.9704	0.9080	0.9518	
	Dirty	0	1	120	0	0.9920	1	1	0.9960	
	Intact	0	10	0	120	0.9230	1	1	0.9600	
					Average	0.9788	0.9926	0.9770	0.9770	

The model achieved perfect recall for bloodstained and cracked eggs (100%), and 99.20% for dirty eggs, but misclassified 1 egg as dirty and 10 eggs as intact out of 120 cracked egg samples. This resulted in a lower recall of 99.20% for dirty eggs, mainly due to variations in egg sample positioning during rotational imaging (Fig.10). Different angles could obscure cracks, leading to misinterpretation of the defects.

(a)   **(b)**
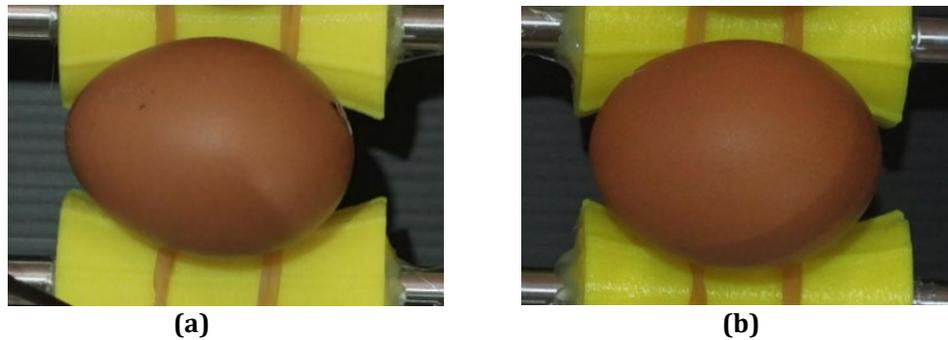
Fig. 10 *Cracked egg images that are misclassified as dirt (a); and intact (b)*

The misclassifications impacted specificity (0.9704) and precision (0.9080) for cracked eggs. Despite this, the model achieved an average recall of 0.9788, specificity of 0.9926, precision of 0.9770, F1-score of 0.9770, and overall accuracy of 0.9771, indicating high classification efficiency.

The proposed DenseNet–BiLSTM framework demonstrates strong potential for industrial deployment. Once trained, the model processes each image in a few milliseconds, enabling high-throughput inspection suitable for conveyor-based sorting lines. Because the model relies on compact 256-dimensional feature representations, it is computationally lightweight and can be scaled to larger datasets or integrated into embedded vision systems with minimal hardware requirements.

4.3 Egg Defect Detection Comparison Between BiLSTM Model and Existing Models

Table 4 compares the proposed BiLSTM model's performance against existing research. The BiLSTM achieved 97.71% accuracy, competitive but fell short of perfect accuracies by SVM [17], SMI-CNN-BiLSTM [19], EfficientNet [21], and HEDIT [26].

Table 4 *Defect detection comparison of proposed model with existing research*

Research	Algorithm	Detection type				Accuracy
		Bloody	Cracked	Dirty	Intact	
Deng, Wang et al. (2010)	SVM	No	Yes	No	No	98.90%
Turkoglu (2021)	SMI-CNN-BiLSTM	Yes	Yes	Yes	Yes	99.17%
Botta, Gattam and Datta (2022)	CNN	No	Yes	No	No	95.38%
Liu, Wen et al. (2023)	EfficientNet	No	Yes	No	No	99.50%
Proposed model	BiLSTM	Yes	Yes	Yes	Yes	97.71%

Deng and Wang's research [17] extracted wavelet-based features for signal characteristics. Turkoglu's SMI-CNN-BiLSTM model [19] used ensemble techniques. Liu and Wen's study [21] focused on transfer learning with EfficientNet. While Chen and Hsu [26] proposed HEDIT for precise egg defect detection using hyperspectral imaging.

The BiLSTM model differentiates itself by specializing in sequential data processing and temporal dependency capture. BiLSTM networks excel in tasks requiring context over time, such as natural language processing and time series analysis.Each model's efficacy depends on its strengths and task requirements, emphasizing suitable architecture selection.

5. Conclusion and Recommendations

5.1 Conclusion

This study sets out to develop an egg defect detection system using advanced technologies. The first goal was to design a simple rotating device powered by a stepper motor and controlled via an Arduino system. This setup ensured precise positioning of each egg for image capture and helped automate the inspection process, resulting in consistent and reliable data collection.

The second goal was to apply machine vision and deep learning to detect egg defects. This was accomplished through a system that captured high-quality images, applied pre-processing techniques, and then used a BiLSTM network to analyse the data for fast and accurate classification. Compared to traditional methods, this approach significantly improved both efficiency and accuracy.

The BiLSTM model achieved impressive performance, with an accuracy rate of 97.71% in classifying defects. Overall, the study demonstrates how combining advanced machine vision, deep learning, and practical hardware solutions can create a robust and efficient system for egg defect detection.

5.2 Recommendations

While the BiLSTM architecture showed promising results, there are several limitations and challenges that need to be addressed.

Fine Cracks visibility: Detecting fine cracks can be difficult due to changes in visibility at different rotation angles. This limitation contributes to the 9.2% misclassification rate observed for cracked eggs. To improve detection, using high-resolution cameras could provide clearer, more detailed images, making it easier to distinguish cracks from the background or other visual noise.

Dirt-Like Defects and Misclassification: Some defects closely resemble dirt, especially under certain lighting conditions, which can lead to misclassifications. Ensuring better control over environmental factors during image capture is essential. In addition, applying image pre-processing techniques such as contrast enhancement and noise reduction can help clarify image features and reduce errors.

Limited Image Samples: A relatively small number of image samples limited the model's performance and increased the risk of overfitting. To address this, the dataset should be expanded by collecting more images or using data augmentation techniques. Another effective strategy is to use transfer learning, applying pre-trained models that have already been learned from large and diverse datasets to improve performance and generalization.

The current image acquisition system operates offline and lacks real-time functionality. For future work, the system can be further enhanced by integrating real-time image capture using high-speed cameras and edge computing devices. These IoT devices would enable immediate defect detection, faster decision-making, and improved efficiency. Lightweight models on edge devices could reduce latency and eliminate dependence on cloud processing. Although implementing real-time hardware and algorithms requires initial investment, modern advances make it feasible and cost-effective. A real-time feedback loop would support proactive sorting, reduce waste, enhance automation, and allow the system to adapt dynamically to changing production conditions.

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Conflict of Interest

All authors declare that there is no conflict of interest regarding the publication of this paper.

Author Contribution

*The authors confirm contribution to the paper as follows: **Conceptualization, Methodology, software**: Pauline Ong, Cheng Kit Cheong; **Formal analysis:** Pauline Ong, Jia Hang Wu, Rexca Jamit; **Data collection & curation:** Cheng Kit Cheong; **Analysis and interpretation of results:** Pauline Ong, Jia Hang Wu, Rexca Jamit; **Draft manuscript preparation:** Jia Hang Wu, Rexca Jamit. All authors reviewed the results and approved the final version of the manuscript.*

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