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Detection Of Egg Types and States Using Image Processing and Deep Learning

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ABSTRACT

The utilization of computer vision and automation for monitoring and collecting eggs is crucial for enhancing labor productivity. Deep learning and computer vision techniques have been adopted by researchers and developers in diverse fields. This study proposes an efficient, lightweight network model based on YOLOv8. The model considers various egg categories and their states. Our methodology has three main stages. First, image preprocessing and augmentation are performed, including image cropping. Second, YOLOv8 detection algorithms are used. Finally, deep learning approaches enhance classification accuracy. A comparative analysis then evaluates algorithm performance in detection and classification across different criteria. Chicken, duck, and quail eggs, each in two states (intact and broken), were included in this study. High detection accuracy is achieved while reducing the model's parameter count and computational load. The method lowers deployment expenses and improves suitability for robotic platforms. The study identifies a classification model to categorize six egg types by state. The CNN model's performance is evaluated against Random Forest, K-Nearest Neighbors (KNN), and ResNet50. The dataset was split into training, validation, and test sets. Analysis of the experimental results reveals that the Convolutional Neural Network (CNN) performs similarly to other models. However, the CNN model stands out for its lightweight architecture, minimal parameter count, and rapid performance. For raw images, the prediction capabilities of the proposed method reach 97% in egg categories and 94% in egg condition.

Keywords: Egg classification, yolo v8, deep learning, convolutional neural network.

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Introduction

Nutritional requirements have increased as the global population has grown. Also in recent years, egg demand has grown. To prepare for issues such as fraud or mislabeling, informing people about egg quality is essential (Sehirli and Arslan, 2022). Both consumers and businesses are concerned about egg safety and quality (Nasiri et al., 2020). The production value of laying hens diminishes due to faulty eggs. This is especially true in cage-free systems, where floor eggs are common (Yang et al., 2023). According to Liu et al. (2023) egg size is essential for consumer satisfaction and helps determine quality ratings. In their research utilizes single-view metodology and deep learning to measure the major and minor axes of eggs (Liu et al., 2023). Image-based approaches for crack detection are limited since each crack must be unique (Wu et al., 2018). Also backlighting causes black areas on the eggshell, making crack detection harder. In their research, a new machine vision approach for crack detection was introduced (Bao et al., 2019).

Nowadays, human visual inspection remains the main method for egg grading. Inspectors check eggshells for internal irregularities, such as blood or meat stains, and for external defects, such as cracks and contamination. High-speed grading machines can process 10,000 eggs per lane, creating a bottleneck for human inspection. Recent studies focus on optical and mechanical methods to automate eggshell fracture detection (Nakamura and Katayama, 2000). Deep learning extracts features and performs classification, a process called feature learning. It modifies weights through backpropagation and error adjustment to allow the classifier to use important features often missed by humans (Shin et al., 2016).

Bao G et al. (2019) proposed a method for detecting eggshell cracks with computer vision. Their goal was to identify small cracks hidden by dark spots in images. To boost crack visibility, they applied a negative LOG (Gaussian Laplacian) filter and used other techniques to lessen noise. Despite the challenge, the system achieved a 92.5% detection rate. Pasco Sánchez J. M. et al. (2023) developed a system to classify poultry eggs by physical features such as size and shape. This improved sorting efficiency and reduced manual inspection. They used computer vision and deep learning, including convolutional neural networks, for model training. The VGG19 model achieved 97.33% accuracy. Milovanovic B et al. (2021) evaluated a computer vision system against a Minolta colorimeter for measuring eggshell, yolk, and white color in five egg types: chicken, goose, duck, quail, and turkey. The study compared the computer vision system (CVS) and the colorimeter measurements. CVS accuracy ranged from 75% to 100%, while the colorimeter showed larger discrepancies from actual sample colors.

YOLOv8 used in the study, was introduced by Ultralytics on January 10, 2023, building on the YOLOv5 model for object detection and classification. Ultralytics improved YOLOv8 to be more efficient and user-friendly. The model comes in several sizes for different needs. YOLOv8n is efficient and fits limited computational power or real-time demands. YOLOv8s balances speed and accuracy. YOLOv8m offers a middle ground with higher accuracy and moderate computational cost. YOLOv8l is larger and prioritizes accuracy over speed. YOLOv8x is the largest, reaching maximum accuracy for applications with large computational resources. These variations help users optimize for speed, accuracy, and available resources (G. G. Casas et al., 2023). In the study, all models of YOLOv8 were applied to the training set and their performances were compared.

Material and Method

This study involves the training and assessment of deep learning models, YOLO and CNN, utilizing Google Colab Pro on a computer equipped with an Intel® Core™ i5-5300U CPU operating at 2.30GHz, running Windows 10 Pro 64-bit.

Information on creating the dataset, performing pre-processing, preparing training/validation/test sets, YOLO/CNN models and performance metrics are provided in detail below.

The Data Sets

The data sets for the suggested models comprise photos of various egg kinds and conditions. In this research, we employed the dataset derived from multiple sources:

1.Samples of chicken egg images (intact and broken) were collected from the Kaggle website, which contains 7,392 images. Of this dataset, 472 samples were selected (Abdullahkhanuet22, n.d.; Gauravduttakiit,n.d).

2. The duck egg image samples (intact and broken) contain 7,337 images collected from the Kaggle website. The number of images selected from this dataset is 746 (Abdullahkhanuet22, n.d.; Gauravduttakiit, n.d.).

3. Samples of quail egg images (intact and broken) were collected from the Roboflow website, which contains 2071 images. The number of samples selected from this dataset is 45 (Roboflow, n.d.). The values of the data set used are given in Table 1.

Table 1. Egg data set

Eggs	Sample dataset raw images	Sample dataset processed images
Training	1263	842
Validation	388	384
Test	245	243

Preprocessing of The Data Sets

Before pre-processing, 1263 training, 388 validation, and 245 test images were used in the dataset. After pre-processing, 842 training, 384 validation, and 243 test images were used. Table 1 shows the image count for each egg type.

CNN Models

The egg model consists of the following steps:

Step 1: Preprocessing the dataset (intact and broken chicken, duck, and quail eggs).

Step 2: Split the datasets into 70% for the "training" set (used to teach the model), 20% for the "validation" set (used to tune model parameters), and 10% for the "testing" set (used to evaluate model performance).

Step 3: Train and test the YOLO V8 model to detect the object "egg". Use the CNN model and algorithm ("ResNet50") and some algorithms in machine learning ("knn", "random forest") for classification.

Step 4: Evaluate and save the models.

Using multitask learning to classify egg type and condition in a single model as sharing a layer between the tasks improves accuracy. This is faster and simpler than training two separate models.

The Convolutional Neural Network (CNN) was created to categorize pictures of eggs by condition and type. All photos in the dataset were resized to 128 x 128 pixels and split into "training," "validation," and "test" sets. Using the ImageDataGenerator program, data augmentation methods such as rescaling, zooming, and horizontal flipping were applied to enhance generalization and reduce overfitting.

Two convolutional layers (Conv2D) and max pooling (MaxPooling2D) were used in the network architecture to extract hierarchical image features. Using the ReLU activation function, the first convolutional layer had 64 filters, and the second had 128. After the feature maps were flattened into a one-dimensional vector using a flattening layer, a fully connected dense layer with 256 neurons was added. A dropout layer (rate = 0.5) was added before the output layers to reduce overfitting. Figure 1 contains the flow chart of the steps followed in this study.

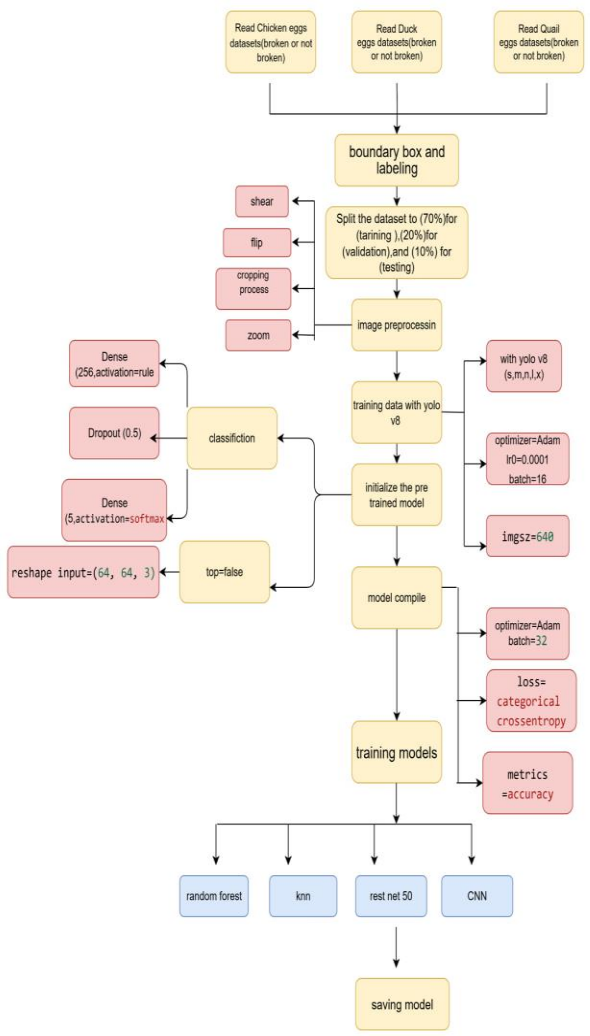

Figure 1. Training of three CNN models on six egg types.

Performance Measures and Validation

Precision, accuracy, recall, and F-Score are commonly employed to assess model execution in classification tasks. These values are computed using Equations (1-4) (İnik & Turan, 2018).

$$Accuracy \; = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1 - Score \; = \frac{2 * Precision * Recall}{Precission + Recall} \tag{4}$$

In instances of uneven class distribution within a dataset, it is essential to evaluate the F1-Score metric in conjunction with accuracy for comparative analysis. Also, it is necessary to evaluate both precision and recall to thoroughly assess a model's efficacy. (Kaya et al., 2023).

Results

This section defines the performance assessment of the CNN models for each egg type and condition. The accuracy rate serves as a standard for assessing each model's performance in recognition tasks.

Training YOLOv8 Models Raw Images

With the best mAP@0.5 (0.8763) and a competitive mAP@0.5:0.95 (0.7863), the YOLOv8x model outperforms the other YOLOv8 models in terms of precision (0.8523) and recall (0.7967), yielding a fitness score of 0.7953. Likewise, the YOLOv8m model has the best mAP@0.5 (0.8823), balanced precision (0.7953) and recall (0.7838), and the highest overall fitness score (0.8008). However, the YOLOv8s model has the highest recall (0.9325), which makes it especially good at identifying a variety of objects, even though its precision (0.7553) isn't as high as that of other models. Despite being the lightest model, YOLOv8n achieves a respectable mAP@0.5 (0.7642) and maintains competitive precision (0.7831) and recall (0.715). Although the YOLOv8l model's mAP@0.5:0.95 (0.7314) and fitness score (0.7398) are marginally lower than those of YOLOv8m and YOLOv8x, it nevertheless exhibits a balanced trade-off between precision (0.8111) and recall (0.8256). Overall, the findings show that larger models like YOLOv8m and YOLOv8x deliver better, more balanced detection performance across assessment measures, while smaller models like YOLOv8n and YOLOv8s offer competitive accuracy with faster inference. The training results obtained using raw images from YOLOv8 models are given in Table 2.

Training YOLOv8 Models Processed Images

The YOLOv8x model, which has the highest fitness score (0.8153), mAP@0.5 (0.8153), and mAP@0.5:0.95 (0.8153), outperforms the other YOLOv8 models in Table X in terms of balance and performance across all metrics. In a similar vein, the YOLOv8l model, although somewhat lower in precision (0.6385), demonstrates its efficacy for precise detection with a high mAP@0.5 (0.8043) and a consistent mAP@0.5:0.95 (0.8042). While its precision (0.6201) is lower than that of other models, the YOLOv8m model has the highest recall (0.898), demonstrating its strong ability to recognize the majority of items. The YOLOv8s model, on the other hand, has a fitness score of 0.6478 and reasonable precision (0.7813) and recall (0.5531), making it a more portable yet competitive choice. The YOLOv8n model, on the other hand, has a rather good precision (0.7326) but the lowest recall (0.1567) and the weakest overall results across mAP and fitness. Overall, the results show that the larger models, especially YOLOv8x and YOLOv8l, frequently outperform in terms of accuracy and balanced detection, making them more appropriate for applications needing high precision and reliability, even though smaller models like YOLOv8n and YOLOv8s are more computationally efficient. The training results of YOLOv8 models using processed images are given in Table 3.

Table 2. Training results of YOLOv8 models using raw images

Types of yolo v8	Precision	Recall	mAP@0.5	mAP@0.5:0.95	Fitness
Yolo v8 n	0.7831	0.715	0.7642	0.6897	0.6972
Yolo v8 s	0.7553	0.9325	0.8570	0.7840	0.7913
Yolo v8 m	0.7953	0.7838	0.8823	0.7917	0.8008
Yolo v8 l	0.8111	0.8256	0.8159	0.7314	0.7398
Yolo v8 x	0.8523	0.7967	0.8763	0.7863	0.7953

Table 3. Training results of YOLOv8 models using preprocessed images

Types of yolo v8	Precision	Recall	mAP@0.5	mAP@0.5:0.95	Fitness
Yolo v8 n	0.7326	0.1567	0.4111	0.3737	0.3774
Yolo v8 s	0.7813	0.5531	0.6618	0.6462	0.6478
Yolo v8 m	0.6201	0.898	0.7677	0.7655	0.7657
Yolo v8 l	0.6385	0.7744	0.8043	0.8042	0.8042
Yolo v8 x	0.671	0.7392	0.8153	0.8153	0.8153

The ResNet50 Classification

The ResNet50 model's classification performance during pre-processing demonstrates exceptionally high accuracy across the various egg types. Quail eggs had the best classification performance, as indicated in Table 4 (a), with flawless F1-scores of 1.00 for precision, recall, and F1-score. With a flawless F1-score of 1.00, duck eggs likewise show outstanding results. With an F1-score of 0.99, the chicken eggs come in second, demonstrating dependable, consistent recognition. The model's good generalization is confirmed by the overall egg type classification accuracy of 0.99. In terms of egg condition, the intact eggs perform marginally worse with a f1-score of 0.95, whilst the damaged eggs obtain a strong f1-score of 0.97. For egg condition, the total classification accuracy is 0.96. The classification performance substantially improves after applying the processing stage, especially for detecting egg conditions. Quail eggs continue to perform well, as shown in Table 4 (b), with a f1-score of 0.96, whilst duck eggs attain an almost flawless f1-score of 0.99. Additionally, chicken eggs do exceptionally well, with a f1-score of 0.98. The model's stability across many categories is confirmed by the overall classification accuracy for egg types, which stays around 0.99. The advantages are even more pronounced for egg condition. While the intact eggs likewise record a very high f1-score of 0.99, the damaged eggs attain a perfect f1-score of 1.00. After processing, the overall classification accuracy for condition detection is 1.00, indicating perfect performance. The values are given in Table 4.

The classification results are displayed as confusion matrices for both egg type and condition, in Figures 2 and 3.

Table 4. Resnet50 classification

a			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	1.00	0.99	0.99
Duck	0.99	1.00	1.00
Quail	1.00	1.00	1.00
Accuracy	0.99		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Broken	1.00	0.94	0.97
Intact	0.90	1.00	0.95
Accuracy	0.96		
b			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.98	0.99	0.98
Duck	0.99	0.99	0.99
Quail	1.00	0.92	0.96
Accuracy	0.99		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Intact	0.99	1.00	0.99
Broken	1.00	0.99	1.00
Accuracy	1.00		

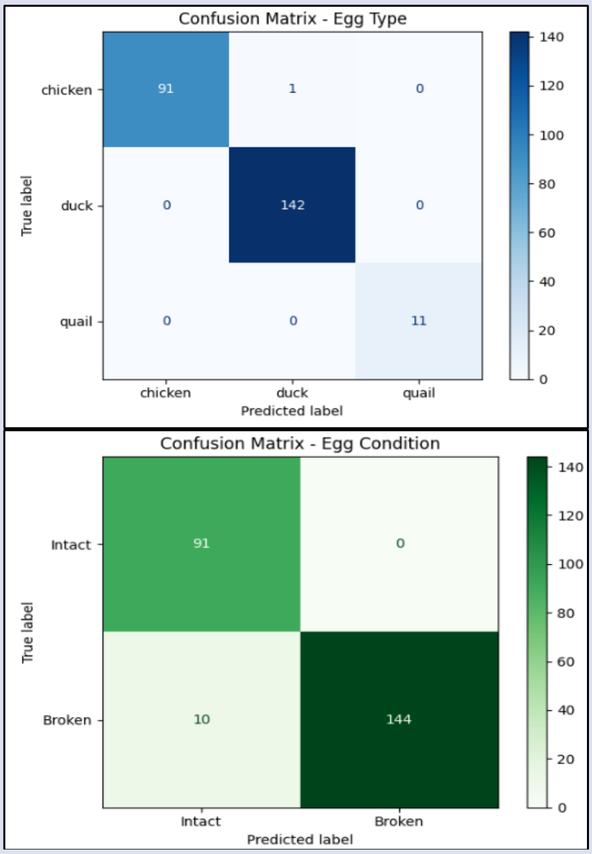

Figure 2. The ResNet50 Classification for raw images

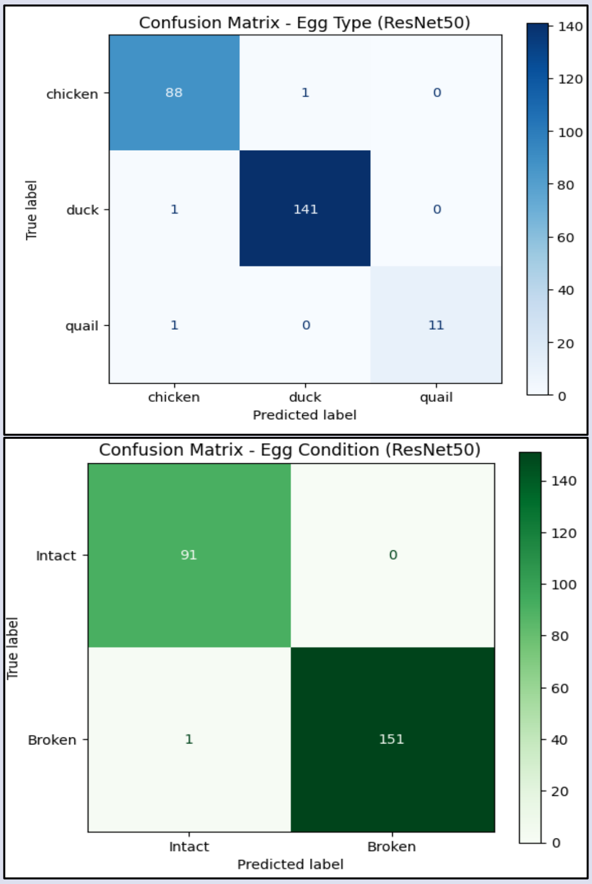

Figure 3. The ResNet50 Classification for processed images

The Random Forest Classification

Table 5 (a) demonstrates that the Random Forest model performs well in classification throughout the pre-processing phase. With a F1-score of 0.96 for egg type categorization, duck eggs perform best, closely followed by chicken eggs with a F1-score of 0.92. With an F1-score of 0.78, quail eggs, on the other hand, show the lowest classification accuracy of all the types, suggesting considerable difficulty in identifying this category. The model performs quite well, as evidenced by the overall egg type classification accuracy of 0.93. Both intact and damaged eggs yield almost flawless classification results for egg condition. In addition to the damaged eggs, the intact eggs also receive a f1-score of 0.99. The Random Forest model's excellent ability to differentiate between intact and broken eggs is confirmed by its overall classification accuracy of 0.99 for egg condition. According to Table 5(b), the Random Forest model exhibits consistent results after processing, with no discernible change from the pre-processing phase. With a f1-score of 0.96, duck eggs continue to be the best-performing category for classifying egg types. Chicken eggs come in second with a f1-score of 0.92. Once more, the Quail eggs do worse, with a f1-score of 0.78. The model's consistent performance before and after processing is demonstrated by the egg type classification accuracy, which remains at 0.93. The outcomes are the same as those from the pre-processing step for classifying egg conditions. With f1-scores of 0.99 apiece, intact and damaged eggs both continue to function exceptionally well. Regardless of the processing step, the Random Forest model's robustness in condition detection is confirmed by the overall classification accuracy for egg condition, which is kept at 0.99. The values are given in Table 5.

The classification results are displayed as confusion matrices for both egg type and condition, in Figures 4 and 5.

Table 5. Random Forest Classification

a			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.92	0.91	0.92
Duck	0.96	0.96	0.96
Quail	0.75	0.82	0.78
Accuracy	0.93		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Intact	1.00	0.98	0.99
Broken	0.99	1.00	0.99
Accuracy	0.99		
b			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.92	0.88	0.90
Duck	0.90	0.96	0.93
Quail	1.00	0.50	0.67
Accuracy	0.91		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Broken	1.00	0.98	0.99
Intact	0.99	1.00	0.99
Accuracy	0.99		

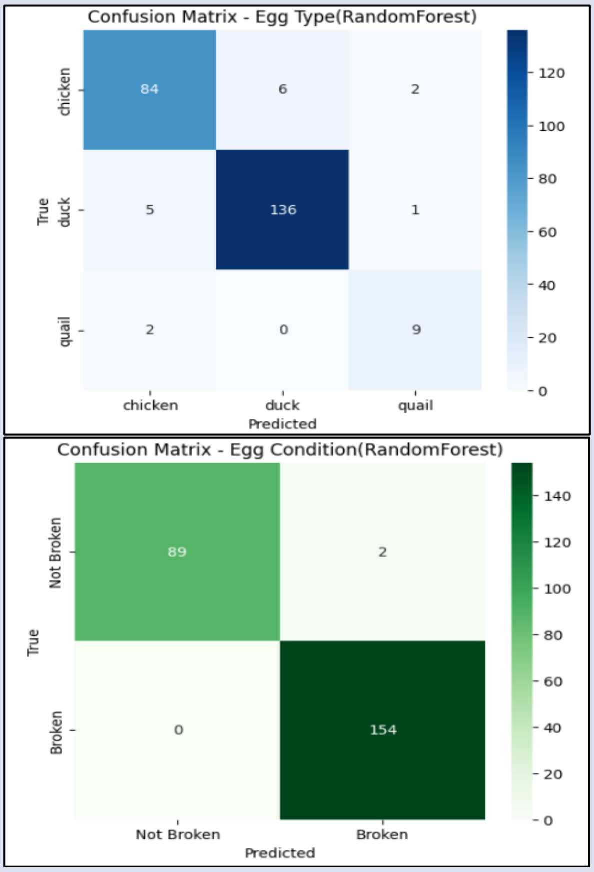

Figure 4. The Random Forest Classification for raw images

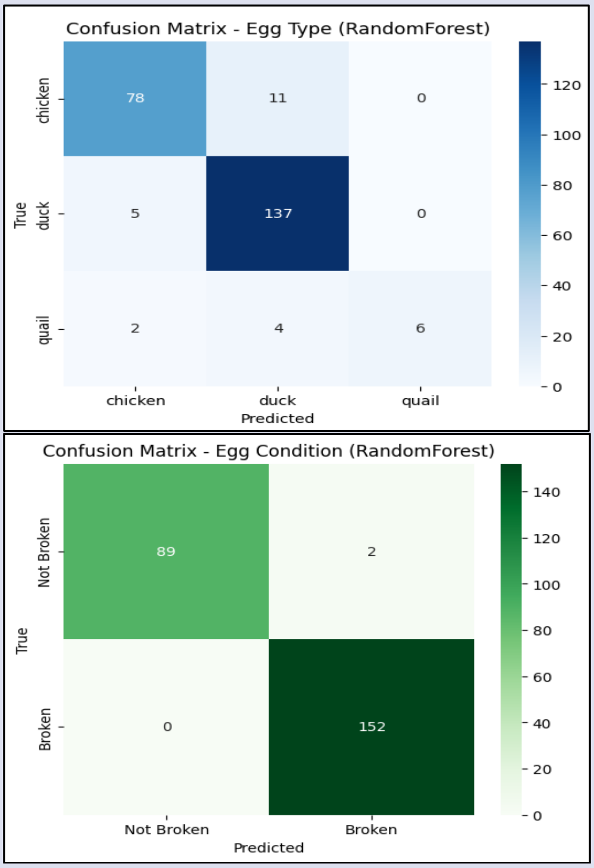

Figure 5. The Random Forest Classification for processed images

K-Nearest Neighbors (KNN) Classification

The KNN classifier performs well across egg types during pre-processing. With a f1-score of 0.94, duck eggs have the best classification performance, followed by chicken eggs with a f1-score of 0.90, as indicated by Table 6 (a), which shows consistent accuracy. However, the lower f1-score of 0.80 for quail eggs indicates some challenges in accurately classifying this kind. The KNN model's ability to distinguish between species is demonstrated by the overall classification accuracy of 0.92 for egg type detection. The performance of egg condition categorization is excellent. With an F1-score of 0.99, intact eggs have a perfect recall of 1.00, and damaged eggs have a perfect precision of 1.00. The KNN model exhibits near-perfect identification and reliability for this task, as evidenced by its overall classification accuracy of 0.99 for condition detection. For several egg types, the KNN model's classification performance declines somewhat after processing, as indicated by Table 6(b), with a f1-score of 0.90. Duck eggs continue to have a strong recognition ability, whereas chicken eggs have a f1-score of 0.85. With a f1-score of just 0.67. Since post-processing did not enhance species-level recognition in this instance, the total classification accuracy for egg type detection drops marginally to 0.88. On the other hand, after processing, the classification of egg state remains consistently high. With f1-scores of 0.98 and 0.99, respectively, intact and damaged eggs both perform well. Regardless of the processing method, the KNN model's overall classification accuracy for condition detection remains 0.99, demonstrating its stability and robustness in distinguishing between intact and damaged eggs. The values are given in Table 6.

The classification results are displayed as confusion matrices for both egg type and condition, in Figures 6 and 7.

Table 6. K-Nearest Neighbors (KNN) classification

a			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.95	0.86	0.90
Duck	0.92	0.96	0.94
Quail	0.71	0.91	0.80
Accuracy	0.92		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Intact	0.98	1.00	0.99
Broken	1.00	0.99	0.99
Accuracy	0.99		
b			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.90	0.81	0.85
Duck	0.86	0.95	0.90
Quail	1.00	0.50	0.67
Accuracy	0.88		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Intact	0.99	0.98	0.98
Broken	0.99	0.99	0.99
Accuracy	0.99		

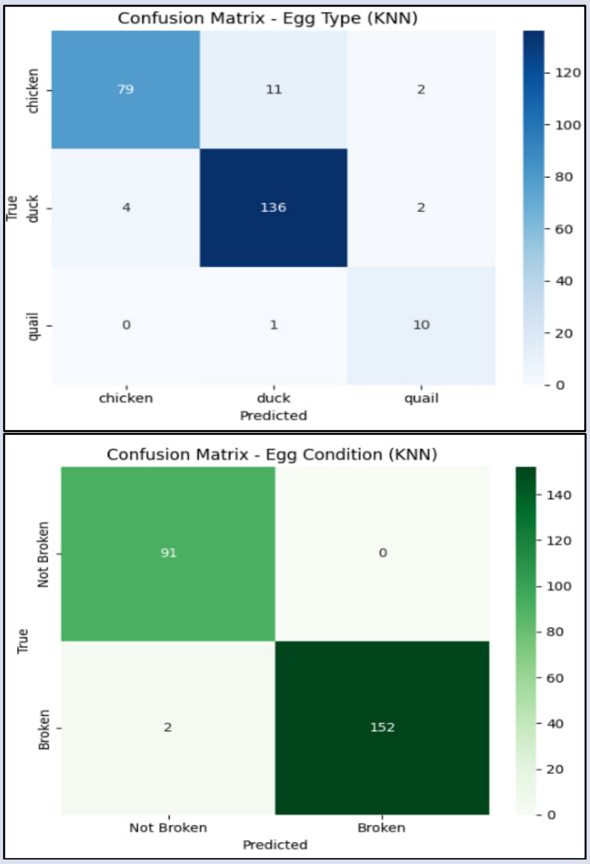

Figure 6. K-Nearest Neighbors (KNN) Classification for raw images

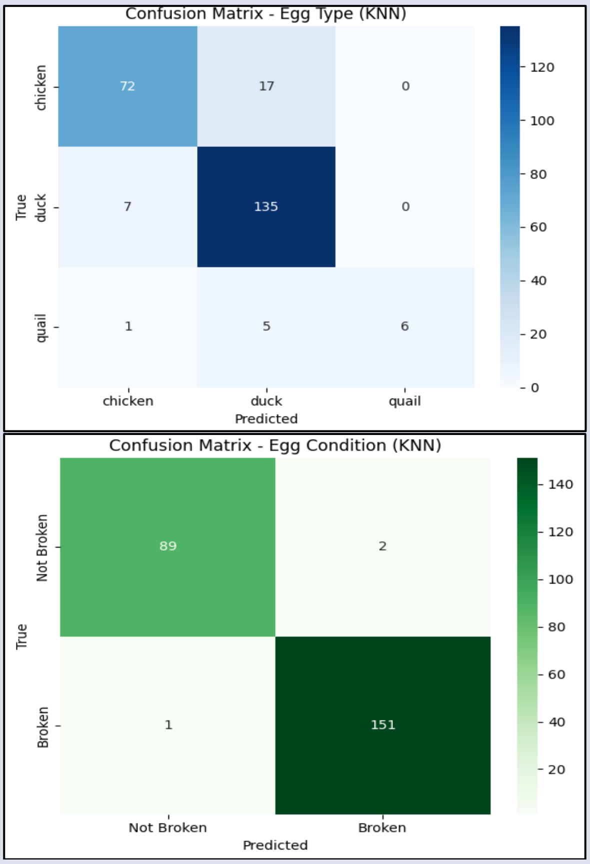

Figure 7. K-Nearest Neighbors (KNN) Classification for processed images

The CNN Classification

The CNN model performs well at categorizing all egg types during the pre-processing phase. Quail eggs exhibit immaculate recognition of this category, as demonstrated in Table 7 (a), where precision, recall, and f1-score all equal 1.00. With a f1-score of 0.98, duck eggs likewise show outstanding categorization. Chicken eggs come in second with a f1-score of 0.96. With an overall egg type classification accuracy of 0.97, very strong detection skills are demonstrated. Due to a few small misclassifications, the intact eggs receive a slightly lower F1-score of 0.92 than the damaged eggs, which receive an F1-score of 0.95. The CNN model reliably distinguishes between broken and intact eggs prior to processing, with an overall classification accuracy of 0.94 for condition detection. As shown in Table 7(b), the CNN model continues to perform well after processing, with only minor changes across categories. With a f1-score of 0.96 for egg type categorization, quail eggs continue to perform well, but less well than the flawless recognition attained prior to processing. The F1-score for chicken eggs is 0.92, but the F1-score for duck eggs is 0.95. Despite a modest decline to 0.94, the overall accuracy for egg type remains strong, indicating strong categorization abilities. Performance changes depending on the condition of the egg rather than during the pre-processing phase. The damaged eggs have a lower F1-score of 0.81, whereas the intact eggs have a higher F1-score of 0.96. The model performs well after processing; however, it struggles to reliably distinguish between damaged and intact eggs, as evidenced by an overall condition classification accuracy of 0.93. The values are given in Table 7.

The classification results are displayed as confusion matrices for both egg type and condition, in Figures 8 and 9. Table 8 presents the classification performance of different models (YOLOv8, CNN, Random Forest, KNN, and ResNet50) before and after preprocessing (cropping).

Table 7. CNN model classification

a			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.97	0.96	0.96
Duck	0.97	0.98	0.98
Quail	1.00	1.00	1.00
Accuracy	0.97		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Broken	0.93	0.97	0.95
Intact	0.95	0.90	0.92
Accuracy	0.94		
b			
Classification Report – Type			
	Precision	**Recall**	**f1-score**
Chicken	0.92	0.91	0.92
Duck	0.94	0.96	0.95
Quail	1.00	0.92	0.96
Accuracy	0.94		
Classification Report – Egg Condition			
	Precision	**Recall**	**f1-score**
Broken	0.81	0.81	0.81
Intact	0.96	0.96	0.96
Accuracy	0.93		

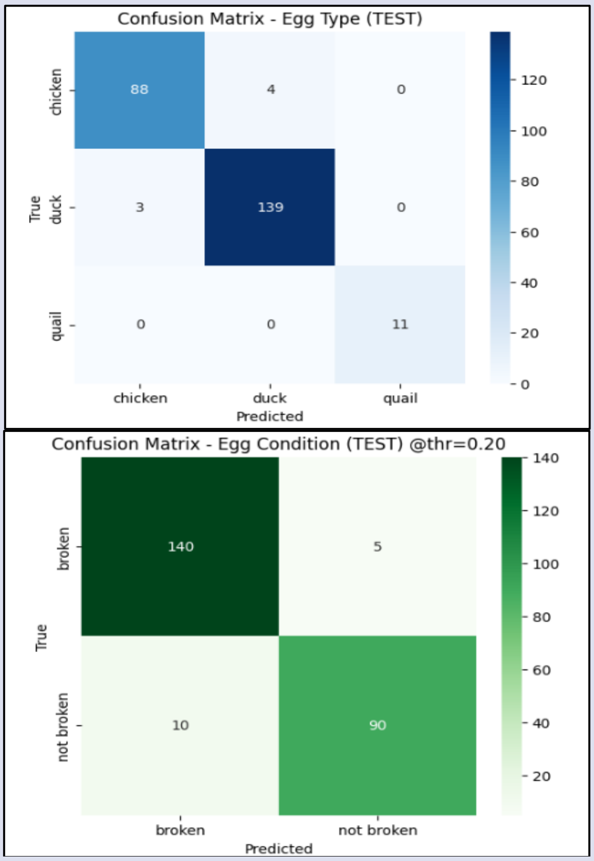

Figure 8. CNN Classification for raw images

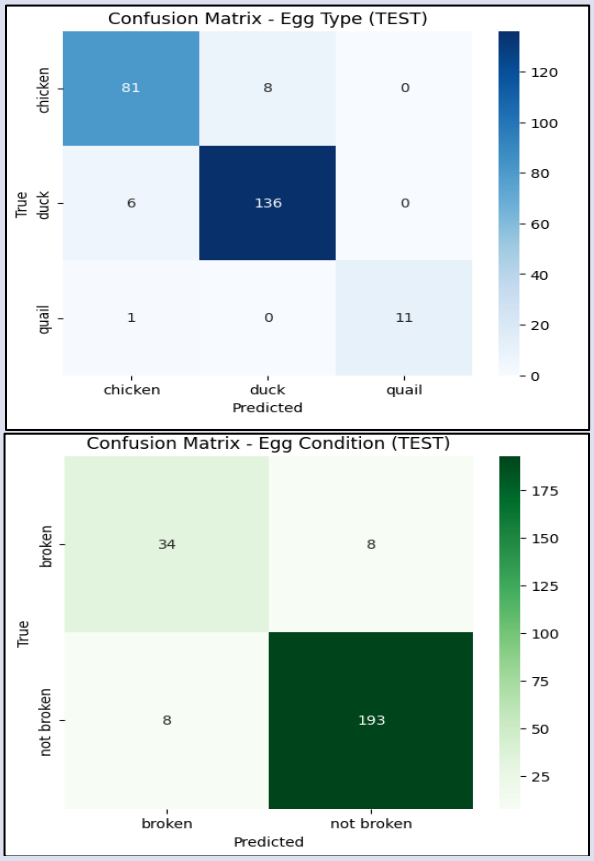

Figure 9. CNN Classification for processed images

Table 8. Comparison Results

Recommended Method	Before processing (cropping)	Chicken Duck Quail	CNN model	94% (condition) / 97% (type)
			Random Forest	99% (condition) / 93% (type)
			The K-Nearest Neighbors (KNN)	99% (condition) / 92% (type)
			ResNet50	96%(condition) / 99% (type)
Recommended Method	After processing (cropping)	Chicken Duck Quail	CNN model	93%(condition) / 94% (type)
			Random Forest	99% (condition) / 91% (type)
			The K-Nearest Neighbors (KNN)	99% (condition) / 88% (type)
			ResNet50	100% (condition) / 99% (type)

Discussion

Eggs offer many benefits for humans and are considered a complete source of protein. Therefore, their quality should be recognized. To classify egg type and status, a new dataset containing 1,896 samples from these types (chicken eggs, duck eggs, and quail eggs) was created. After processing (trimming), the dataset was reduced to 1,469. In this study, before processing (cropping), three deep learning and machine learning models were used for training, validation, and testing.

Upon comparison with prior research (Li et al., 2020), it was observed that the Common Objects in Context (COCO) dataset was used, yielding accuracies of 91.9%-100%. A Faster Region-based Convolutional Neural Network (Faster R-CNN) was employed to classify eggs (Huang et al., 2023), achieving 96.4% accuracy in classifying broken eggs, using the enhanced YOLOv5 in their research. The data was acquired through photographic capture using a camera (Datta et al., 2019). The researchers achieved 75% accuracy and used the Faster Region-based Convolutional Neural Network (R-CNN) algorithm to analyze chicken eggs (Sánchez et al., 2023). Sánchez et al. (2023) employed VGG19 and achieved a remarkable 97.33% accuracy on brown chicken eggs. (Brasil et al., 2021) employed PLSDA and SVMC to assess the quality of quail eggs, achieving an accuracy of 80%.

Comparison With Previous Studies

This section compares the effectiveness and results of the proposed methodology with previous research on egg type and status identification. Table 9 provides a comparative summary of proposed methodologies and alternative approaches from different years and authors.

Table 9. Comparisons with Previous Studies

Author's	Dataset	Eggs	Models	Accuracy
(Li et al., 2020)	Common Objects in Context (COCO) dataset	ground eggs	faster region-based CNN (faster R-CNN)	91.9%–100%
(Huang et al., 2023)	photo was taken with a camera	broken egg	improved YOLOv5	96.4%
(Datta et al., 2019)	photo was taken with a camera	Cracked Chicken Eggs	Faster Region based Convolutional Neural Network (R-CNN)	75%
(Sánchez et al., 2023)	used from a local farm	brown chicken eggs	VGG19	97.33%
(Brasil et al., 2021)	sourced from local farms	Quail egg quality	PLSDA and SVMC	80%
Recommended Method	Images sourced from Kaggle and Roboflow websites	Quail, Chicken, Duck Eggs (broken/intact)	CNN	97%

Conclusion

This study focused on identifying egg types and their health status. YOLO V8 egg detection, Random Forest, K-Nearest Neighbors (KNN), and ResNet50 deep learning models were used for egg type and health control. Furthermore, the dataset was applied to deep learning models both without and with preprocessing, and the results were compared. Three different egg types (chicken eggs, duck eggs, quail eggs) and two different conditions (intact and broken) were considered in the study.

The results obtained without preprocessing the dataset: Accuracy scores for classifying egg types were 97% for CNN Models, 93% for Random Forest, 92% for KNN, and 99% for ResNet50. Accuracy scores for classifying eggs (broken or intact) were 94% for CNN Models, 99% for Random Forest, 99% for KNN, and 96% for ResNet50. The results obtained after pre-processing the data set are as follows: The models' egg type classification accuracy scores are 94% for CNN Models, 91% for Random Forest, 88% for KNN and 99% for ResNet50. The egg condition classification accuracy scores are 93% for CNN Models, 99% for Random Forest, 99% for KNN and 100% for ResNet50.

Recommendations For Future Work

Some potential future directions for this study are as follows:

1. The new model (CNN) can be applied to different datasets.

2. Other convolutional neural network models (except "Random Forest," "K-Nearest Neighbors (KNN)," and "ResNet50") can be used on the egg dataset to classify egg status and type.

3. It would be useful to evaluate the proposed method on larger and more diverse datasets to verify its generalizability and applicability to real-world settings.

4. New parameters can be added to improve the performance of the CNN model for egg type datasets and others.

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