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Deep learning-based assessment of egg quality: freshness and shell integrity detection

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Abstract:
Assessment of egg quality is a critical operation in the food industry to promote consumer safety and nutritional quality as well as preventing economic losses that are a direct result of spoilt products. Traditional ways of assessing the quality of eggs usually involve manual inspection that is subjective and demanding of labour as well as susceptible to human error. The most recent progress in computer vision and deep learning allows creating automated, non-invasive methods of identifying defects in eggs and assessing the quality of their shells.
The study uses the Good and Bad Eggs Identification Image Dataset of Mendeley Data, which has 1,000 high-resolution images of eggs and 6,000 augmented images created by transformation (flips, rotations, and brightness/contrast manipulation). The dataset records some important external characteristics of eggs such as shell texture, shape, color, and visible defects, thus, it is very appropriate in the defect classification and integrity detection processes.
Taking advantage of convolutional neural networks (CNNs) and transfer learning methods in Python through Google Colab, the present research will develop and test an automatic system that can differentiate between a good quality and a defective egg with high precision. This project results will also aid the development of intelligent-based food quality monitoring systems which can offer a scalable and more dependable solution to the issue of real-time monitoring of egg quality used in industry.

Keywords: Include at least 5 keywords or phrases.

I. INTRODUCTION

Evaluation of egg quality is crucial for food safety, nutritional value, and reducing economic losses from contaminated eggs (Zahir & Akhter, 2025). Due to their high perishability, eggs are prone to freshness degradation and microbial risks such as Salmonella (Mafe, et al., 2024). Traditional methods like candling and manual inspection are widely used but are subjective, labor-intensive, and prone to errors, making them unsuitable for large-scale industrial use (Nukala, et al., 2026; Ahmed & Milani, 2025).
Recent advancements focus on non-destructive sensing technologies such as near-infrared (NIR), hyperspectral imaging, and electronic noses, which can effectively assess freshness and detect spoilage (Zhang, et al., 2025; Ong, et al., 2025; Rabehi, et al., 2024). However, these methods are often expensive, complex, and computationally demanding, limiting practical adoption (Rabehi, et al., 2024).

Computer vision and AI, particularly deep learning and CNNs, offer a cost-effective, fast, and non-invasive alternative for egg quality assessment. CNNs have shown strong performance in agricultural tasks by automatically learning visual features like shape and texture, improving accuracy and consistency (Fan, et al., 2025; Ding, et al., 2025).
Despite this, research on deep learning for egg quality remains limited due to the lack of large annotated datasets (Zhang, et al., 2023). The availability of datasets like the Good and Bad Eggs Identification

Dataset, along with augmentation techniques and transfer learning (e.g., VGG, ResNet, Inception), has improved model performance and reduced training complexity (Hernández-García, et al., 2024).
With increasing demand for real-time quality monitoring, AI-based systems can enable automated egg classification in production lines, improving consistency and food safety. Future integration with multimodal sensing can further enhance accuracy and scalability for industrial applications.

A. Research Problem

Ensuring egg quality is essential for food safety, consumer health, and reducing economic losses. Traditional methods like manual inspection and candling are time-consuming, subjective, and unsuitable for large-scale industrial use (Zhang, et al., 2023). Although computer vision and deep learning have shown success in food inspection, their application in egg freshness and shell integrity remains limited (Olagunju, et al., 2025). Therefore, there is a need for an automated, accurate, and scalable system to classify eggs using external features, enabling reliable and real-time processing.

B. Problem Statement

Eggs are widely consumed but highly perishable, making them prone to quality degradation and microbial risks like Salmonella, leading to health hazards and economic losses (Mafe, et al., 2024). Traditional methods such as candling and manual inspection are subjective, labor-intensive, and unsuitable for large-scale operations, while destructive methods cause wastage (Loffredi, et al., 2021; Yu, et al., 2025).
Although CNN-based deep learning has shown strong performance in food inspection, its application to egg quality is limited due to lack of datasets, standardization, and high computational requirements (Alharthi, et al., 2025). Techniques like transfer learning and augmentation can address these challenges (Mahmoud, et al., 2024; Li, et al., 2025).
Therefore, there is a need for a non-invasive, accurate, and scalable deep learning system to classify eggs based on shell features, enabling real-time industrial use while reducing manual errors and improving food safety.

C. Objectives

The primary objective of this study is to develop and evaluate a CNN-based deep learning model to classify eggs as good or defective using external shell characteristics such as shape, texture, color, and cracks.
The study also aims to apply transfer learning techniques using pre-trained models like VGG, ResNet, and EfficientNet to improve classification accuracy while reducing computational cost and training time. Additionally, image preprocessing and augmentation methods such as flipping, rotation, and contrast adjustment will be used to enhance model robustness and prevent overfitting.
Furthermore, the developed model will be evaluated using performance metrics including accuracy, precision, recall, and F1-score, and compared with traditional manual inspection methods. The research also explores the feasibility of integrating the model into real-time industrial egg grading systems. Finally, the study aims to extend the proposed framework to other food quality inspection applications using similar deep learning approaches.

D. Research Gaps

There is limited application of deep learning in egg quality evaluation, as most studies focus on other agricultural products, leaving egg freshness and shell defect detection underexplored (Ali & Hashim, 2024). Additionally, the use of transfer learning for egg classification has not been sufficiently studied, despite its potential to reduce data and computational requirements while maintaining high accuracy (Alrawahneh, et al., 2026).
Furthermore, there is a lack of standardized methods for image preprocessing and augmentation, and existing research does not clearly identify the most effective techniques for improving model performance

(Aini, et al., 2025). There is also insufficient benchmarking between deep learning models and traditional manual inspection methods, making it unclear whether automated systems consistently outperform human evaluation (Faisal, et al., 2025).
Finally, limited research has explored the real-time industrial implementation of these models, particularly in terms of scalability, speed, and cost-effectiveness in practical egg grading systems (Akkoyun, et al., 2025).

II. LITERATURE REVIEW

Ong et al. (2025) proposed hyperspectral imaging combined with deep learning and distance correlation for nondestructive egg freshness prediction, achieving high accuracy with reduced wavelengths and good generalization. However, high cost, complex calibration, and scalability issues limit industrial adoption.
Patil & N. Patil (2025) used NIR spectroscopy with chemometric models (PLS-R, PLS-DA) to predict egg freshness and classify quality, achieving high accuracy (>95%). Despite effectiveness, high cost, calibration complexity, and environmental sensitivity remain challenges.

Olufemi et al. (2025) developed an integrated framework combining HACCP, QMRA, IoT, and AI to manage microbial risks like Salmonella in egg supply chains, improving safety and traceability. However, high cost, data requirements, and implementation complexity limit adoption.
Gao et al. (2025) reviewed traditional and non-destructive egg freshness evaluation methods, highlighting high accuracy of spectroscopy, imaging, and sensor fusion approaches (>90%). Limitations include high cost, environmental sensitivity, and lack of standardization.

Crivei et al. (2025) proposed a comprehensive risk and hazard analysis framework for egg sorting and packing based on GFSI standards, improving safety and traceability. However, high implementation cost and operational complexity restrict use in small-scale systems.
Olagunju et al. (2025) reviewed machine learning with nondestructive sensing for food quality, showing >90% accuracy in many applications, especially with CNNs. Challenges include high computational cost, limited datasets, and lack of standardization.
Sheidaee & Bazyar (2025) applied machine vision and feature extraction to improve destructive egg quality assessment, achieving higher accuracy and consistency. However, it remains destructive and unsuitable for real-time large-scale use.

Denli et al. (2025) used electronic nose sensors and machine learning to detect freshness changes in boiled eggs, achieving >98% accuracy. Limitations include small dataset size and sensitivity to environmental conditions.
Atwa et al. (2024) reviewed non-destructive technologies like NIR, HSI, and E-nose, showing >96% accuracy in freshness detection. However, high cost, slow processing, and limited capability for some quality parameters remain issues.

Sheidaee & Bazyar (2024) enhanced destructive egg quality testing using machine vision and ML models (SVM, ANN), improving accuracy and reducing human error. However, the method still requires breaking eggs and controlled conditions.
Wu et al. (2025) developed an automated machine vision system with robotics for real-time egg monitoring in poultry farms, improving detection accuracy and reducing manual effort. Limitations include dependence on controlled conditions and high infrastructure requirements.
Nivasini et al. (2024) proposed a hybrid CNN-SVM model using thermal imaging for egg freshness classification, achieving high accuracy and reliability. However, performance depends on environmental conditions and limited dataset size.

Ahmed et al. (2024) reviewed hyperspectral imaging applications in the egg industry, showing high accuracy in quality assessment and hatchery monitoring. Challenges include high cost, data complexity, and lack of standardization.

Akowuah et al. (2023) used spectral fingerprinting with chemometric models to classify freshness and predict laying date with >90% accuracy. However, environmental sensitivity and small datasets limit generalization.

Ahmed et al. (2023) reviewed optical sensing technologies (Vis/NIR, HSI, Raman) for egg quality, highlighting high accuracy and automation potential. Limitations include high cost, calibration complexity, and scalability issues.

Nakaguchi & Ahamed (2022) used thermal imaging with deep learning for non-destructive freshness detection, achieving >90% accuracy. However, environmental sensitivity and limited dataset restrict broader applicability.

Patila & Patil (2022) reviewed egg freshness detection techniques, showing AI-based methods achieving 90–97% accuracy. However, high cost, environmental sensitivity, and lack of standard systems limit industrial adoption.

Yogeswari et al. (2024) reviewed metabolomics for poultry quality assessment, showing high accuracy in detecting freshness and spoilage. However, high cost, complex instrumentation, and lack of standardization limit practical use.

Han et al. (2022) developed a VIS-NIR spectroscopy-based model for egg sorting, achieving >90% classification accuracy. Limitations include sensitivity to shell properties, small datasets, and high equipment cost.

III. PROPOSED FLOW OF THE RESEARCH

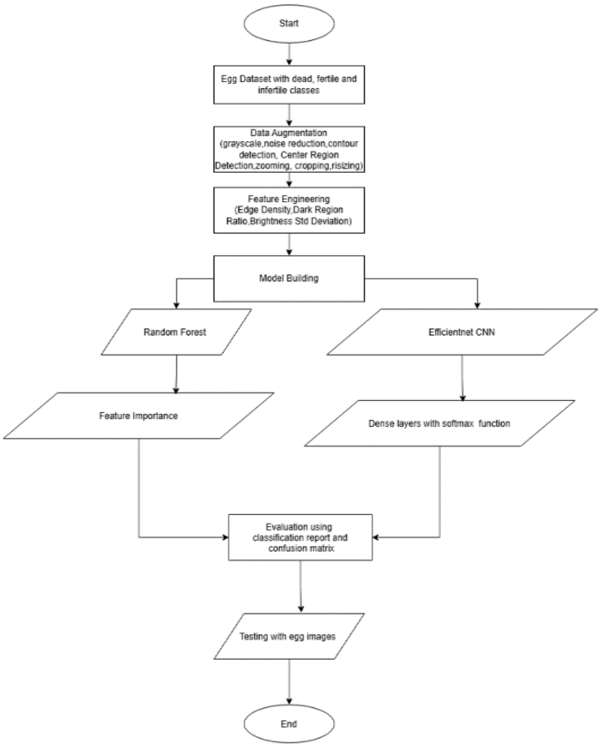

Fig 1: Proposed Flow of the Research

The system classifies eggs into dead, fertile, and infertile using image-based analysis. Images are first preprocessed through grayscale conversion, noise reduction, cropping, and resizing to enhance quality and consistency. Feature engineering extracts key visual attributes such as edge density, brightness variation, and texture patterns. Two models are then applied: a Random Forest classifier for structured feature analysis and an EfficientNet-based CNN for automatic feature learning. Model performance is evaluated using metrics like accuracy, precision, recall, and confusion matrix, and validated on unseen images to ensure real-world applicability.

IV. IMPLEMENTATION

A. Dataset

The dataset consists of 1000 original egg images capturing variations in shell texture, color, and defects, along with 6000 augmented images. Augmentation techniques such as flipping, rotation, brightness/contrast adjustment, shear transformation, and noise addition improve model robustness and generalization. This dataset supports the development of reliable AI-based egg classification systems for practical industrial applications.

B. Dataset Description

The study uses the Chicken Egg Analysis Dataset from Kaggle, consisting of egg images classified into three categories: dead, infertile, and fertile. The dataset is designed for image classification tasks and enables deep learning models, especially CNNs, to identify egg quality and internal condition based on visual patterns such as embryo development and structural features.

The dataset contains a total of 3420 images, with 1140 images in each class, ensuring a balanced distribution. This balanced structure helps prevent bias during training and improves model accuracy, stability, and generalization when applied to unseen data. The dataset is publicly available on Kaggle and is commonly used for research in computer vision, agriculture, and poultry applications.

The data is organized in a folder-based structure where each class (dead, infertile, fertile) is stored in separate directories. This format allows deep learning frameworks like TensorFlow and PyTorch to automatically assign labels based on folder names, simplifying data loading and training processes. Dataset verification confirmed equal image distribution across all classes, ensuring reliability for model development.

All images are in RGB format (JPG) and capture internal egg structures, making them suitable for three-class classification. The images contain key visual features such as texture, brightness, and internal patterns, which help models distinguish between different egg conditions.

Each class shows distinct visual characteristics: dead eggs appear darker with abnormal internal structures, infertile eggs show uniform interiors without embryo patterns, and fertile eggs display visible embryo development and structural variations. These differences allow CNN models to learn and accurately classify eggs based on internal visual features.

C. Data Pre-processing

Data preprocessing is a critical step in improving image quality and ensuring accurate deep learning performance, as raw images often contain noise, lighting variations, and irrelevant background details. In this study, multiple preprocessing techniques are applied to enhance images and focus only on meaningful egg features. These include grayscale conversion, thresholding, noise reduction, contour detection, and region isolation, which collectively standardize the data, remove unwanted variations, and highlight important visual patterns for effective model learning.

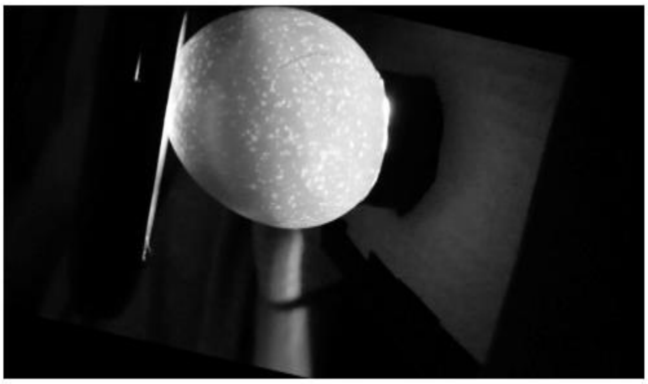

Fig 2: grayscale Thresholding

Initially, images are converted from RGB to grayscale to simplify computation and emphasize intensity-based features such as edges and internal structures. Thresholding is then applied to segment the egg from the background by converting the image into a binary form, making object boundaries clearer. Noise reduction techniques like Gaussian and median filtering are used to remove random pixel variations while preserving important structural details, improving edge detection and segmentation accuracy.

Fig 3: Noise Reduction

Contour detection is performed to identify the egg boundary, where the largest contour is selected as the region of interest. This is followed by egg region isolation, which removes unnecessary background and ensures that only the egg is analyzed. Further refinement is done using center region extraction to focus on the most informative part of the egg, where key features related to quality and fertility are present. Cropping and zooming enhance this region, allowing the model to capture fine visual patterns such as texture and internal variations.

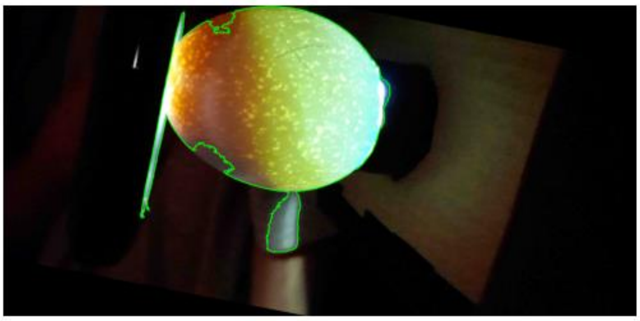

Fig 4: contour Detection

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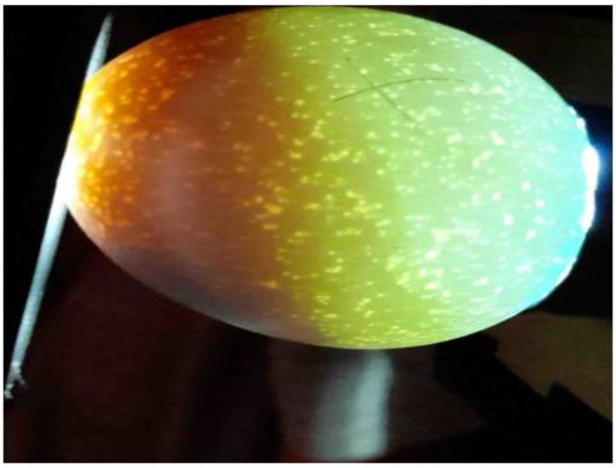

Fig 5: Egg Region Isolation

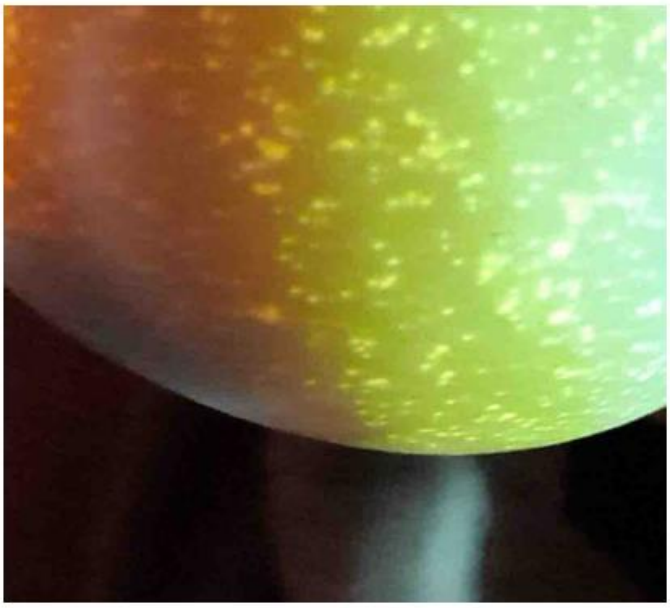

Fig 6: Center region isolation

All processed images are then resized to a standard size of 224×224 pixels to ensure compatibility with CNN architectures and improve computational efficiency. Pixel normalization is applied to scale values between 0 and 1, stabilizing training and improving convergence. These steps ensure uniformity across the dataset and optimize it for deep learning models.

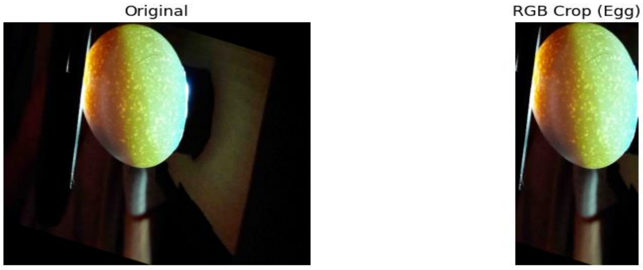

Fig 6: Resizing the image

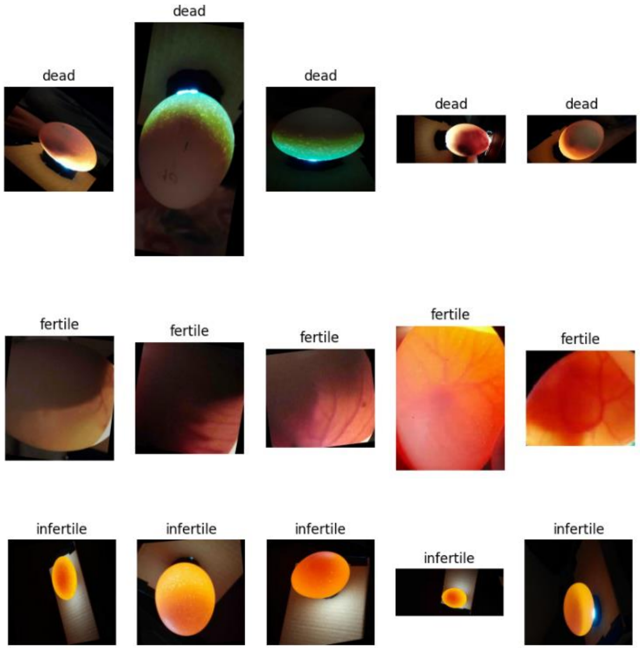

Fig 7: Processed images

Overall, the preprocessing pipeline transforms raw images into clean, consistent, and feature-rich inputs, significantly improving model accuracy, generalization, and reliability. By removing noise, enhancing key features, and isolating the egg region, the system ensures that the model learns only relevant patterns, leading to better classification performance in real-world scenarios.

Feature Extraction and Feature Analysis

Feature extraction is a crucial step in converting egg images into meaningful numerical data that can be used for classification. Instead of using raw pixel values, key features such as brightness, texture, and structural patterns are extracted to represent egg characteristics. In this study, four main features—mean brightness, brightness standard deviation, dark region ratio, and edge density—are used to capture internal egg properties and differentiate between dead, infertile, and fertile eggs.

Mean brightness represents overall light intensity, indicating egg transparency, while brightness standard deviation captures variation in intensity, reflecting internal complexity such as embryo development. The dark region ratio measures the proportion of darker areas caused by internal structures or damage, and edge density identifies structural boundaries using edge detection, indicating texture complexity. These features collectively describe both intensity and structural variations in egg images.

Analysis of these features shows clear differences among egg types: fertile eggs exhibit moderate brightness, higher variation, and increased edge density due to embryo structures; infertile eggs show uniform brightness with low variation and fewer edges; and dead eggs often have higher dark regions and irregular patterns. Feature relationships, such as the correlation between brightness and dark regions or edge density and variation, further help in distinguishing egg classes.

Overall, feature extraction reduces data complexity, improves model interpretability, and enhances classification performance by focusing on relevant visual patterns. These extracted features serve as effective inputs for machine learning and deep learning models, enabling accurate and reliable egg classification.

D. Deep Learning Model Architecture and Training Pipeline

The deep learning model is developed using a Convolutional Neural Network (CNN) to classify egg images into dead, infertile, and fertile categories by automatically learning visual patterns such as texture, brightness, and internal structures. Unlike traditional methods, CNNs extract hierarchical features directly from images, enabling accurate and efficient classification without manual feature design.

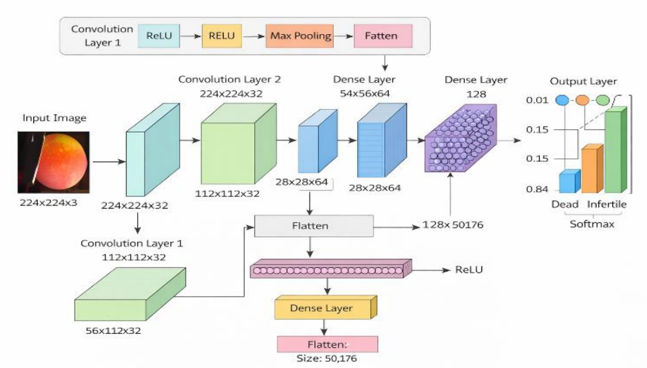

Fig 8: Architecture of CNN

The workflow includes dataset loading, preprocessing, feature preparation, model building, training, validation, and evaluation. Processed images are fed into the CNN, which consists of convolutional layers for feature extraction, ReLU activation for non-linearity, and pooling layers for dimensionality reduction. These layers capture both low-level features (edges, textures) and high-level patterns (internal egg structures), enabling effective classification.

The feature maps are flattened and passed through fully connected layers, where learned features are combined to generate predictions. The output layer uses a Softmax function to classify images into three categories. The model is trained using categorical cross-entropy loss and optimized with the Adam optimizer, ensuring stable and efficient learning. Training is performed in multiple epochs with batch processing, allowing the model to progressively improve its performance.

Table1- Model Summary Table (EfficientNetB0)

Layer Type	**Output Shape**	**Description**
Input Layer	(160, 160, 3)	Resized RGB image input
EfficientNetB0 (Base)	(None, 5, 5, 1280)	Pre-trained feature extractor (ImageNet weights, top removed)
Global Average Pooling	(None, 1280)	Reduces spatial dimensions
Batch Normalization	(None, 1280)	Normalizes activations for stability
Dense Layer (ReLU)	(None, 128)	Learns high-level features
Dropout (0.5)	(None, 128)	Prevents overfitting
Output Layer (Softmax)	(None, 3)	Multi-class classification (dead, fertile, infertile)

Table 2- Model Strategy

Stage	**Description**
Feature Extraction	Base model frozen, only top layers trained
Fine-Tuning	Last 50–60 layers unfrozen for performance improvement
Data Augmentation	Rotation, zoom, horizontal flip applied
Model Saving	Best model saved using validation accuracy

Model validation is conducted during training to monitor generalization and prevent overfitting, while evaluation metrics such as accuracy, precision, recall, and F1-score assess classification performance. A confusion matrix provides insight into prediction errors, and training curves (accuracy and loss) help analyze learning behavior.
Overall, the CNN-based architecture, combined with a structured training pipeline, enables reliable and scalable egg classification by effectively learning visual features and delivering high accuracy in real-world applications.

V. RESULTS AND OBSERVATIONS

The trained CNN model was evaluated using multiple metrics including accuracy, loss, precision, recall, and F1-score to assess its performance in classifying eggs into dead, fertile, and infertile categories. The model was trained using Adam optimizer, categorical cross-entropy loss, batch size of 32, image size 160×160, and trained for 5 initial epochs followed by 10 fine-tuning epochs with learning rates of 0.001 and 0.00001.

Table 3- Training Configuration

Parameter	Value
Optimizer	Adam
Loss Function	Categorical Cross entropy
Metrics	Accuracy
Batch Size	32
Image Size	160 × 160
Epochs (Phase 1)	5
Epochs (Fine-tune)	10
Learning Rate	0.001 (initial), 0.00001 (fine-tuning)

Training and validation accuracy increased steadily, with both curves closely aligned, indicating minimal overfitting. The final validation accuracy reached approximately **96%**, demonstrating strong classification capability.

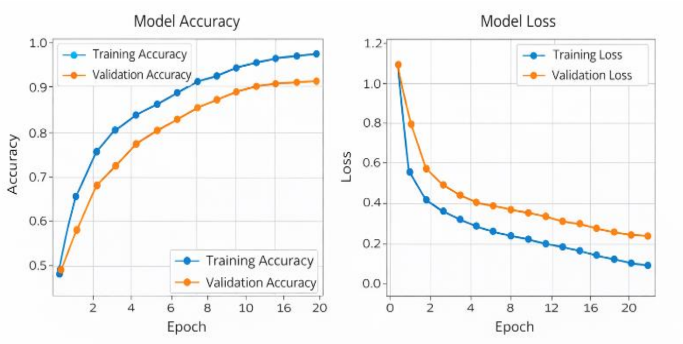

Fig 9: Model Accuracy and Loss

Training and validation loss consistently decreased across epochs, showing stable convergence without significant fluctuation or overfitting. The classification report further confirms strong performance across all classes: dead eggs achieved **precision 0.98, recall 0.94, F1-score 0.96 (266 samples)**; fertile eggs achieved **precision 0.97, recall 0.97, F1-score 0.97 (280 samples)**; and infertile eggs achieved **precision 0.93, recall 0.97, F1-score 0.95 (259 samples)**. The overall accuracy, macro average, and weighted average were all **0.96**, indicating consistent performance across categories.

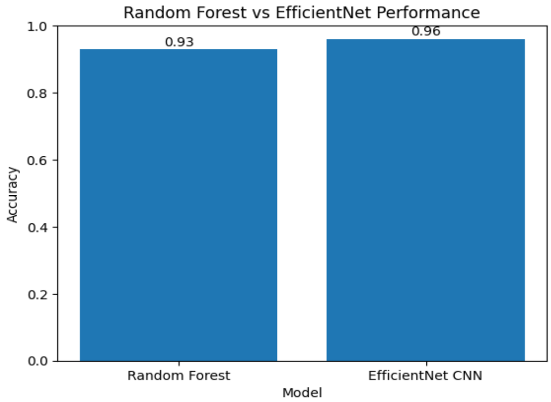

Fig 10: Comparison of Random Forest and EfficientNet Model Accuracy

Precision analysis shows highly reliable predictions, especially for dead (0.98) and fertile (0.97) eggs, while slightly lower precision for infertile eggs (0.93) suggests minor misclassification due to visual similarity. Recall values remain high across all classes (dead: 0.94, fertile: 0.97, infertile: 0.97), indicating effective detection of true cases. The F1-scores (dead: 0.96, fertile: 0.97, infertile: 0.95) confirm balanced performance between precision and recall. Balanced support values (266, 280, 259) ensure unbiased evaluation.

The overall model accuracy of **96%** highlights the effectiveness of the CNN-based EfficientNet approach, which outperformed the Random Forest model by better capturing complex spatial and texture features. Preprocessing techniques such as grayscale conversion, thresholding, contour detection, and region isolation significantly improved feature clarity, while the combination of brightness and edge-based features enhanced classification. Overall, the model demonstrates high accuracy, stability, and reliability, making it suitable for real-world automated egg quality assessment.

VI. CONCLUSIONS

Egg quality is critical for food safety and economic stability, but traditional methods like manual inspection and candling are subjective, labor-intensive, and unsuitable for large-scale industrial use. This study addressed these limitations by proposing a deep learning-based automated system using CNNs for egg classification. The system leverages computer vision to extract visual features such as texture, brightness, and structural patterns, enabling accurate classification of eggs into dead, infertile, and fertile categories.

A robust dataset with augmentation techniques (flipping, rotation, brightness, and contrast adjustments) was used to improve generalization. Extensive preprocessing, including grayscale conversion, thresholding, noise reduction, contour detection, region isolation, cropping, resizing, and normalization, ensured high-quality inputs by removing noise and focusing on relevant egg features. The CNN architecture, trained using Adam optimizer and categorical cross-entropy loss, effectively learned hierarchical visual patterns without manual feature engineering.

The model achieved strong performance with an overall accuracy of approximately 96%, along with high precision, recall, and F1-scores across all egg classes. Training and validation curves showed stable convergence with minimal overfitting, confirming good generalization on unseen data. These results demonstrate the effectiveness of combining preprocessing, data augmentation, and deep learning for reliable egg classification.

The proposed system offers significant practical advantages, including non-invasive, fast, and automated egg quality assessment, reducing human error and enabling real-time industrial implementation. Overall, this work highlights the potential of AI-driven solutions in improving efficiency, accuracy, and consistency in the poultry industry. Future work can focus on expanding datasets, integrating multimodal sensing, and deploying lightweight models for real-time industrial applications..

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