Comparison of InceptionResNetV2 Method with PCA-based KNN and LDA-based KNN for Cracked Egg Classification Based on Eggshell Images

Bima Aviandi Wiguna[1*], Dwiza Riana[2]

[1,2]Faculty of Computer Science, Nusa Mandiri University, Jakarta, Indonesia
E-mail: [1*]14230007@nusamandiri.ac.id, [2]dwiza@nusamandiri.ac.id

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Abstract

This study compares the performance of the InceptionResNetV2 method with K-Nearest Neighbors (KNN) based on Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for classifying cracked eggs based on eggshell images. Cracked egg classification plays a vital role in the food industry, particularly in product sorting and quality control processes. Traditional manual inspection methods are often inconsistent and inaccurate, necessitating automated image-based approaches to improve efficiency and reliability. In this study, egg images were processed using standard image preprocessing techniques, followed by dimensionality reduction using PCA and LDA, and classification using KNN. The results were then compared to a transfer learning approach using the InceptionResNetV2 architecture from TensorFlow Hub. Performance evaluation showed that the InceptionResNetV2 model achieved the highest accuracy in detecting cracked eggs, while KNN combined with LDA also produced competitive results with the advantage of lower model complexity. These findings contribute to the development of efficient and accurate image-based classification systems using artificial intelligence and highlight the potential of such systems for broader applications in image-based quality control in various domains.

Keywords: Cracked Egg Classification, Eggshell Image, PCA, LDA, K-Nearest Neighbors, InceptionResNetV2, Transfer Learning.

I. INTRODUCTION

Egg classification based on eggshell images is crucial in the food industry, particularly for maintaining standard quality and efficient sorting processes. The ability to distinguish between different types of eggs, such as chicken, duck, or those that are cracked or empty, provides a common basis for sorting procedures. However, traditional manual inspection methods are time-consuming and prone to subjective errors, which can affect the quality of production [1], [2].

With the advancement of technology, digital image processing techniques have become widely used in the development of automated classification systems. These systems can consistently and efficiently extract and analyze visual features from images [3], [4]. One of the essential steps in image classification is dimensionality reduction, which helps to simplify the feature data while improving classification performance.

Principal Component Analysis (PCA) is known for its ability to filter key features from high-dimensional data, while Linear Discriminant Analysis (LDA) is designed to maximize the separation between classes within the data [7], [8]. Both methods have proven to be effective in various image classification research, including applications in agriculture and food technology [9], [10].

This study focuses on comparing two classification methods: PCA-KNN and LDA-KNN, to assess which approach yields better classification results for eggs based on their shell condition whether intact, cracked, or empty. The K-Nearest Neighbors (KNN) algorithm was chosen for its simplicity and its ability to leverage feature reduction results for distance-based classification [5].

Additionally, image processing techniques such as grayscale conversion, edge detection, and visual enhancement through histogram equalization are applied to ensure that the extracted features are representative before moving to the classification stage.

On the other hand, deep learning-based approaches, particularly using the InceptionResNetV2 architecture, have demonstrated high performance in various image classification tasks. InceptionResNetV2 combines the strengths of Inception and ResNet architectures, enabling deeper and more complex feature extraction. Previous studies have shown that this model is effective in detecting various objects and patterns in images, including those in agriculture and food industries [11].

Transfer learning with InceptionResNetV2 allows a model pre-trained on large datasets like ImageNet to be applied to specific classification tasks without requiring an extensive dataset. This approach not only reduces training time but also improves the model's accuracy in analyzing vital features in eggshell images. Research in agricultural fields has already demonstrated that this architecture can effectively detect object quality and condition based on image data [13], [14]. Meanwhile, in the medical and manufacturing domains, InceptionResNetV2 has also significantly enhanced classification performance [15], [16].

The goal of this research is to compare the performance of the InceptionResNetV2 method with PCA and LDA-based KNN methods in the classification of cracked eggs based on eggshell images. This study includes an evaluation of the accuracy, efficiency, and complexity of each method, aiming to identify the most effective approach for industrial food applications.

II. RELATED WORKS

This research references various approaches in image classification of eggs, specifically for detecting cracked eggs. Previously, methods such as KNN combined with PCA and LDA have been utilized for egg image classification, achieving varying results. Orcun [46] reported a performance of 95.29% accuracy using KNN without augmentation, while this study enhances those methods by incorporating data augmentation techniques and deep learning. The use of convolutional neural network models, particularly InceptionResNetV2, has also gained popularity due to its ability to recognize complex features within images.

III. RESEARCH METHODS

This research is divided into several stages, including dataset collection, preprocessing, training process, evaluation. The flow of these stages can be seen in Figure 1.

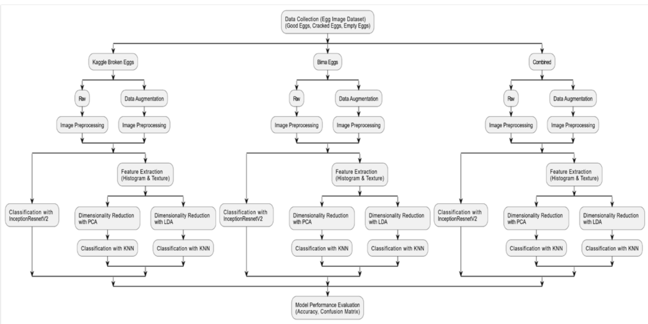


Figure 1. Activity diagram of egg classification methodology

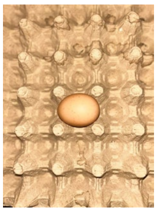
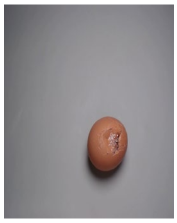
A. Data Collection

In this study, two primary datasets were used to develop and evaluate the egg classification models. The first dataset was obtained from Kaggle, consisting of a total of 569 images categorized into three classes: good eggs, cracked eggs, and empty eggs. These images were collected from diverse sources with variations in lighting, background, and egg orientation to enhance the robustness of the training process.

The second dataset consisted of 150 images collected manually from local sources, specifically Bima eggs, with an equal distribution across the three classes to maintain data balance. Both datasets underwent a preprocessing stage, including resizing all images to 299×299 pixels to ensure consistency across datasets and compatibility with CNN models.

A comparison between the Bima dataset and the Broken Eggs dataset is presented in Table 1. The table illustrates the classification of images into three primary categories: good, crack, and empty.

Tabel 1. Image Sample

No	*Dataset* Bima		
	Good	Crack	Empty
1			
	Dataset Broken Eggs		
	Good	Crack	Empty
2			

To strengthen the dataset and improve model performance, data augmentation techniques were applied, expanding the number of training images by a factor of ten. This process involved transformations such as rotation, flipping, and brightness adjustment, which helped increase variability and prevent overfitting.

After augmentation, the combined dataset contained a total of 6,325 images, which were then divided into training and testing sets with an 80:20 ratio. This comprehensive and diverse dataset provided a solid foundation for training deep learning models such as InceptionResNetV2, enabling the models to learn discriminative features robustly across different egg classes and conditions.

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B. Preprocessing

The preprocessing step is a crucial stage in preparing the image data before training and testing the classification models. In this study, all images from both the Kaggle dataset and Bima Eggs are resized to a standard dimension of 299×299 pixels to match the input requirements of the InceptionResNetV2 CNN model. This transformation ensures data consistency while maintaining the key features of the eggs, such as contours, textures, and cracks, which remain clearly visible after resizing. Additionally, the images undergo normalization through a rescaling layer, which adjusts pixel values to an optimal range for training, thereby accelerating convergence and enhancing the model's performance.

Furthermore, data augmentation techniques are applied to the training dataset to significantly increase the variety and quantity of data. This includes rotations, horizontal and vertical flipping, and brightness adjustments. By augmenting the data tenfold, the model is exposed to diverse visual conditions, making it more robust to variations that might be encountered in real-world data. Through comprehensive preprocessing, it is expected that the model can learn relevant features efficiently, resulting in accurate and consistent classification performance on new data.

C. Feature Extraction

Feature extraction is a critical step in the image classification process, where meaningful and representative features are derived from raw image data to facilitate effective learning by the model. In this study, two methods are utilized for feature extraction: manual features and deep learning-based features. The manual features involve dimensionality reduction techniques such as Principal Component Analysis and Linear Discriminant Analysis, combined with K-Nearest Neighbors classifiers. These methods analyze color, texture, and shape attributes extracted from the images to identify patterns that distinguish different egg categories.

In addition to manual feature extraction, deep learning approaches are employed using a pretrained convolutional neural network, InceptionResNetV2. This model automatically learns hierarchical and high-level features directly from the input images. The feature extractor from the pretrained network captures complex patterns such as cracks, contours, and textures of the eggs with high accuracy. The extracted features are then passed to dense layers which perform the classification task. This combination of manual and deep learning features aims to optimize the model's ability to differentiate between cracked eggs, whole eggs, and empty shells effectively, even in complex visual conditions.

D. Classification

Classification is the process of assigning input images into predefined categories based on the extracted features. In this research, various classification techniques are employed to distinguish between different types of eggs, such as cracked, intact, and empty shells. Traditional classifiers like K-Nearest Neighbors (KNN) are combined with feature reduction methods such as PCA and LDA to categorize eggs based on manual features. These classifiers rely on measuring the similarity between feature vectors, making them suitable for datasets with limited computational resources.

Alongside traditional methods, advanced deep learning models, particularly InceptionResNetV2, are used to perform classification directly on the image data. This model leverages a pretrained architecture to extract high-level features and then applies fully connected layers with softmax or sigmoid activation functions to output the probability of each class. This deep learning approach enables the system to learn complex visual patterns, such as subtle cracks or texture differences, that might be challenging to capture using manual features alone. The result is a highly accurate and robust classification system capable of handling variations in image quality and lighting conditions.

The effectiveness of each classification approach is evaluated based on metrics such as accuracy, precision, recall, and F1-score. These metrics provide insights into the models' ability to correctly identify each egg category, as well as their robustness against false positives and negatives. While traditional classifiers like PCA-KNN and LDA-KNN offer simplicity and speed, deep learning models like InceptionResNetV2 generally outperform them in terms of accuracy and generalization capabilities, especially on larger and more complex datasets. This comprehensive classification strategy ensures that the system can reliably distinguish egg types in various operational scenarios.

E. Evaluation

In the evaluation process, various performance metrics such as accuracy, precision, recall, and F1-score were measured to obtain a comprehensive understanding of the model's effectiveness in classifying egg images. The results demonstrate that the InceptionResNetV2 model achieved remarkably high accuracy, approaching 100% on the Bima and combined datasets, both with and without data augmentation. These findings confirm that this model is capable of recognizing complex visual features in egg images with exceptional precision, making it the preferred choice in this study.

In addition to overall performance metrics, confusion matrix analysis was used to assess the distribution of predictions relative to the true labels in the datasets. The results showed that the model performs nearly perfectly, accurately classifying classes such as empty, good, and cracked eggs. However, some minor misclassifications occurred, particularly between the good and cracked classes, especially in datasets with high variability and noise. This indicates a slight challenge in distinguishing features that are visually similar.

Overall, this evaluation demonstrates that deep learning techniques, specifically InceptionResNetV2, significantly outperform traditional methods like PCA-KNN and LDA-KNN. Its consistent and high performance across diverse scenarios underscores its suitability as a reliable solution for egg image classification tasks. These results provide a solid foundation for concluding the effectiveness of the proposed approach in this research.

IV. RESULTS AND DISCUSSIONS

A. Results of Image Resizing

Image resizing is an essential step in the data preprocessing stage to ensure that all images have uniform dimensions according to the model's requirements. In this study, images from the Kaggle and Bima datasets were resized from their original dimensions to 224×224 pixels to ensure compatibility with the input requirements of deep learning models, as well as for training the KNN model and other classification methods. This resizing process aimed to standardize the data, allowing the extracted features to remain consistent and accurate.

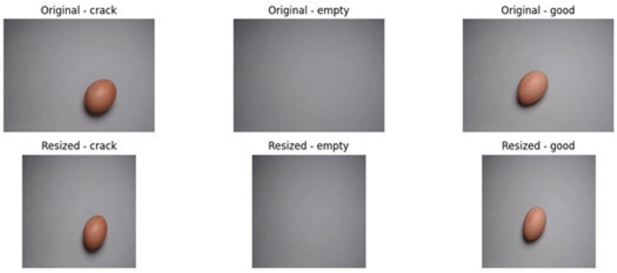

Figure 2. Resized images from the Kaggle dataset

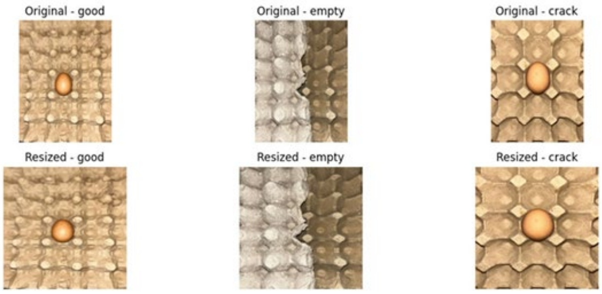

Figure 3. Resized images from the Bima dataset

The images demonstrate that the resizing process successfully preserves the sharpness and key features of the images, ensuring they remain suitable for feature extraction and subsequent model training.

B. Results of KNN

The K-Nearest Neighbors (KNN) model was tested under three schemes, utilizing PCA and LDA as feature extraction methods for the Kaggle dataset, the Bima dataset, and the combined dataset. The results showed that KNN performance varied considerably depending on the scheme and dataset. The highest accuracy achieved by KNN on the Kaggle dataset was approximately 91.89% using the LDA scheme with augmentation across three classes, while on the Bima dataset, the accuracy reached about 97.77% under the same conditions. The use of PCA tended to lower accuracy due to its less optimal feature representation compared to LDA.

Tabel 2. Model Accuracy Results of KNN

Dataset Type	Model	Accuracy Results			
		2 Class	Augment-ation	3 Class	Augment-ation
Dataset Kaggle	PCA-KNN	85.13	66.32	90.35	79.21
	LDA-KNN	90.54	76.86	97.36	85.13
Dataset Bima	PCA-KNN	100	81.66	96.66	97.03
	LDA-KNN	100	98.33	100	94.07
Dataset Combined	PCA-KNN	85.10	70.26	96.52	78.59
	LDA-KNN	88.29	69.07	92.36	78.67

These results indicate that KNN still has limitations in recognizing complex patterns and is sensitive to noise and data variations, making it less robust than deep learning architectures for the egg classification task.

C. Results of InceptionResnetV2

The testing outcomes reveal that the InceptionResNetV2 architecture offers considerable benefits when dealing with datasets exhibiting high variability. This model maintains almost perfect classification performance across diverse testing scenarios, demonstrating its robustness and reliability. Based on the data presented in Table 3, the accuracy of the InceptionResNetV2 model across different datasets and experimental conditions can be summarized clearly. The model shows exceptional performance on the Bima dataset, achieving an accuracy of 100% in all tested conditions. Whether using data with or without augmentation, and regardless of whether the classification task involves two or three categories, the model reliably recognizes the visual patterns inherent in the data. This consistency underscores its ability to effectively analyze relatively homogeneous data as well as more complex, combined datasets.

In contrast, the Kaggle dataset presents a slightly more challenging environment for the model. The accuracy for binary classification remained high at 94.11%, while the three-class classification achieved an accuracy of 96.29% in the absence of data augmentation. These figures indicate that the model performs admirably even with datasets that are more variable or less controlled. However, when data augmentation techniques were applied to the Kaggle dataset, there was a noticeable decline in accuracy to 88.88%.

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Tabel 3. Model Accuracy Results of InceptionResnetV2

Dataset Type	Model	Accuracy Results			
		2 Class	Augmentation	3 Class	Augmentation
Dataset Kaggle	Inception ResNet V2	94.11	94.11	96.29	88.88
Dataset Bima	Inception ResNet V2	100	100	100	100
Dataset Combined	Inception ResNet V2	100	100	98.61	98.61

Overall, the results reinforces the suitability of the InceptionResNetV2 as a powerful classifier for egg images. It excels particularly with clean, high-quality data, providing high levels of accuracy across different experimental conditions. The model's capacity to adapt and perform well even with varied datasets demonstrates its potential for broader application in image classification tasks involving similar types of data. Its robustness across diverse testing environments indicates that it can serve as a dependable approach for future research and practical implementations, especially in scenarios where data quality and consistency are critical factors.

D. Results of Confusion Matrix

The InceptionResNetV2 model without augmentation on the Kaggle dataset demonstrated excellent classification performance on the three-class dataset, as shown in Figure 4. The confusion matrix illustrates the model's ability to accurately recognize each egg image category with a high level of precision.

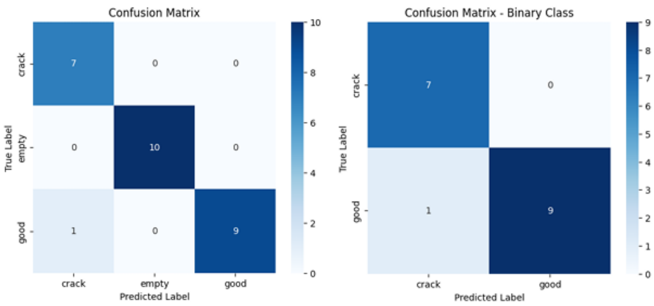

Figure 4. InceptionResNetV2 Results without Augmentation Kaggle Dataset

In the testing results, the model correctly classified all 10 empty egg images and 7 cracked egg images, with only one good egg image misclassified as cracked. This indicates that the model effectively recognizes visual patterns and achieves a high level of accuracy even without the use of data augmentation.

The InceptionResNetV2 model without augmentation on the Bima dataset demonstrated perfect classification performance on both the three class and two class datasets, as shown in Figure 5. The confusion matrix illustrates that the model successfully classified all test images correctly in every category.

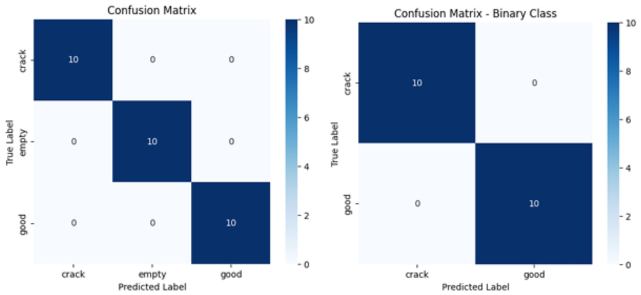

Figure 5. InceptionResNetV2 Results without Augmentation Bima Dataset

In the three class scenario, all images of cracked, empty, and good eggs each consisting of 10 samples were accurately identified, achieving 100% accuracy. Similarly, in the binary classification, the model flawlessly distinguished between cracked and good eggs without any misclassification. These results confirm the exceptional capability of the InceptionResNetV2 model in recognizing visual patterns and maintaining perfect accuracy even without the use of data augmentation.

The InceptionResNetV2 model without augmentation on the combined dataset demonstrated excellent classification performance for both three-class and binary-class scenarios, as illustrated in Figure 6. The confusion matrices show that the model was able to accurately classify most images across all categories.

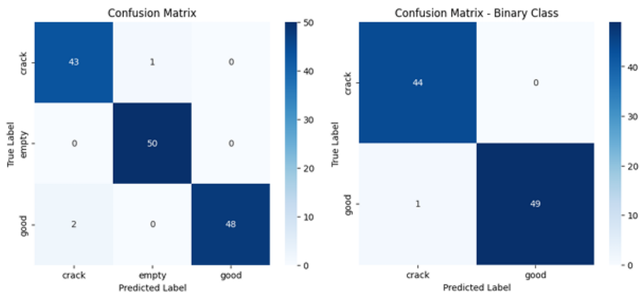

Figure 6. InceptionResNetV2 Results without Augmentation Combined Dataset

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In the three class configuration, the model correctly identified 43 cracked eggs, 50 empty eggs, and 48 good eggs, with only a few minor misclassifications one empty egg incorrectly predicted as cracked and two good eggs as cracked. Similarly, in the binary classification scenario, the model accurately distinguished 44 cracked eggs and 49 good eggs, with only one misclassification. These results indicate that the InceptionResNetV2 model maintains high accuracy and robustness even when handling a more diverse combined dataset without data augmentation.

V. CONCLUSIONS

This study successfully demonstrated the effectiveness of the InceptionResNetV2 deep learning model in classifying egg images into different categories such as empty, good, and cracked. The model consistently achieved high accuracy, reaching nearly 100% on the Bima and combined datasets, regardless of data augmentation. Its capability to learn and recognize complex patterns in high-resolution images highlights its advantage over traditional classical methods like PCA-KNN and LDA-KNN, which showed more variability and sensitivity to data noise and augmentation.

Furthermore, the results indicate that the InceptionResNetV2 model is highly reliable and suitable for practical implementation in automated egg quality inspection systems. Its strong generalization ability across different datasets reflects its robustness in various scenarios, including complex and diverse data conditions. Future research can explore expanding the dataset, experimenting with other lightweight models, and optimizing the network further to enhance classification accuracy and efficiency in real-world applications.

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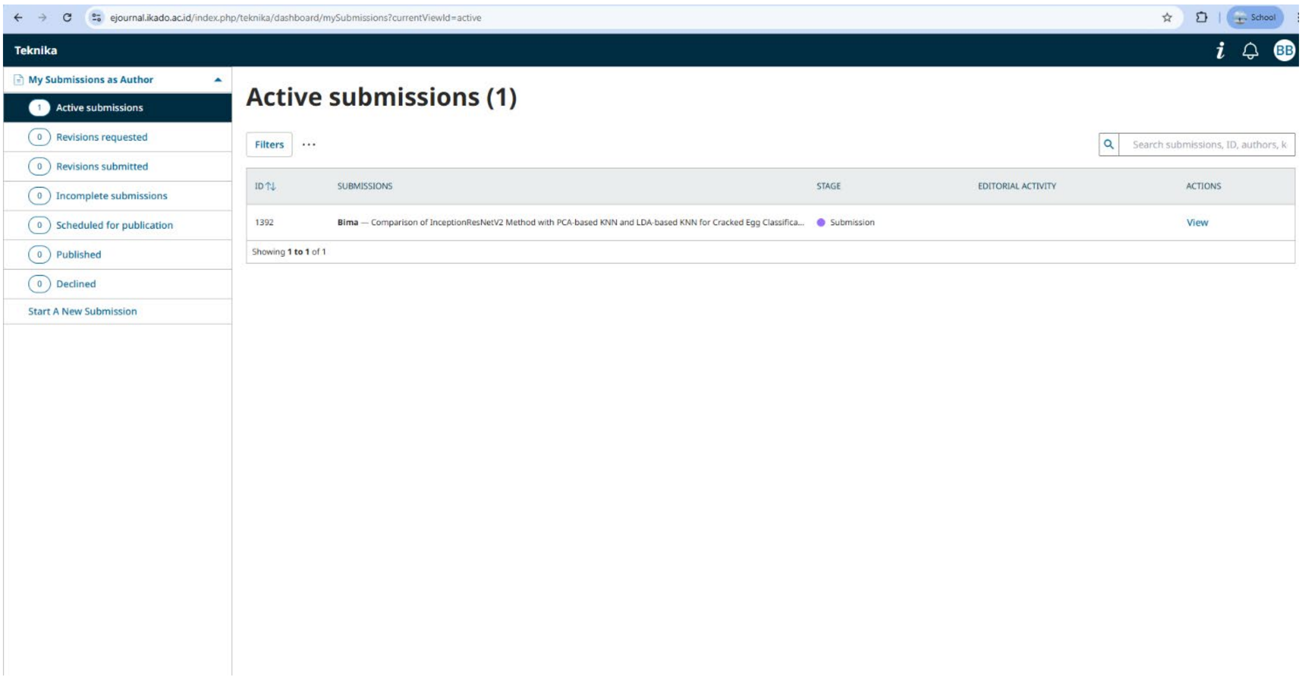

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Bima Aviandi Wiguna[1*], Dwiza Riana[2]

[1,2]Faculty of Computer Science, Nusa Mandiri University, Jakarta, Indonesia
E-mail: [1*]14230007@nusamandiri.ac.id, [2]dwiza@nusamandiri.ac.id

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Abstract

This study compares the performance of the InceptionResNetV2 method with K-Nearest Neighbors (KNN) based on Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) for classifying cracked eggs based on eggshell images. Cracked egg classification plays a vital role in the food industry, particularly in product sorting and quality control processes. Traditional manual inspection methods are often inconsistent and inaccurate, necessitating automated image-based approaches to improve efficiency and reliability. In this study, egg images were processed using standard image preprocessing techniques, followed by dimensionality reduction using PCA and LDA, and classification using KNN. The results were then compared to a transfer learning approach using the InceptionResNetV2 architecture from TensorFlow Hub. Performance evaluation showed that the InceptionResNetV2 model achieved the highest accuracy in detecting cracked eggs, while KNN combined with LDA also produced competitive results with the advantage of lower model complexity. These findings contribute to the development of efficient and accurate image-based classification systems using artificial intelligence and highlight the potential of such systems for broader applications in image-based quality control in various domains.

Keywords: Cracked Egg Classification, Eggshell Image, PCA, LDA, K-Nearest Neighbors, InceptionResNetV2, Transfer Learning.

I. INTRODUCTION

Egg classification based on eggshell images is crucial in the food industry, particularly for maintaining standard quality and efficient sorting processes. The ability to distinguish between different types of eggs, such as chicken, duck, or those that are cracked or empty, provides a common basis for sorting procedures. However, traditional manual inspection methods

This study focuses on comparing two classification methods: PCA-KNN and LDA-KNN, to assess which approach yields better classification results for eggs based on their shell condition whether intact, cracked, or empty. The K-Nearest Neighbors (KNN) algorithm was chosen for its simplicity and its ability to leverage feature reduction results for distance-based classification [5].

Additionally, image processing techniques such as