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Deep Learning-Based Egg Crack Detection: Benchmarking CNN, Resnet, and Xception Models

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Abstract— Egg grading and quality inspection have a crucial role in maintaining food safety and avoiding any economic losses in poultry rearing. Manual inspection of eggs for cracks cannot be very effective as this is a time-consuming, laborious, and erratic method, especially in scenarios where large quantities of eggs have to be inspected regularly. To deal with this problem, this manuscript proposes a framework for automatic crack detection of eggs using deep learning and image processing techniques. Images of eggs are taken, and appropriate preprocessing techniques are applied to these images to enhance the features of the egg shell surface. A classification system using Convolutional Neural Network (CNN) classifier, ResNet, and Xception models is designed to classify the eggs as normal or cracked eggs. An additional module using a YOLOv-based detection model to find the cracked location in eggs with a bounding box around the particular region of interest is also included. The suggested method is assessed using appropriate performance measures such as accuracy, precision, recall, and F1-score. Experimental study results showed that the recognition ability of the proposed transfer learning model is enhanced compared to the basic CNN, while the YOLOv model ensures fast localization of the cracks. Such a system ensures a non-destructive, economical, and automated method for smart poultry farms and the egg processing industry.

Index Terms— Egg inspection, Crack detection, Deep learning, CNN, ResNet, Xception, YOLOv, Computer vision.

I.INTRODUCTION

Eggs are one of the most popular and significant egg forms of poultry, and the quality aspect of eggs plays an important role in their consumption. Cracks in the eggs provide an opportunity for microorganisms to enter the eggs, resulting in contamination of the eggs [1]. Conventional methods of inspecting and testing of eggs involve visual observation, candling, and other related processes, which may not be efficient in terms of processing at high speeds due to the human judgment factor involved in the mechanisms of inspective candling of eggs [2].

Recently, advancements have been made in the field of computer vision, which enable the automatic quality evaluation of the products obtained from the agriculture industry. While common machine learning methods involve manual feature selection, as mentioned in reference [3], deep learning algorithms, especially the Convolutional Neural Networks (CNN), can effectively learn the features directly from the input images, as mentioned in reference [4]. Moreover, as mentioned in references [5] and [6], ResNet and Xception can be used effectively for the classification of cracked and uncracked eggshells.

However, classification algorithms are not capable of identifying the exact region of the cracked area on an eggshell. For classification, it is important to have localization of defects for real-time applications. Object detection algorithms can be effective for locating defects on an eggshell because they are capable of generating bounding boxes on objects, thus allowing for real-time defect detection [7].

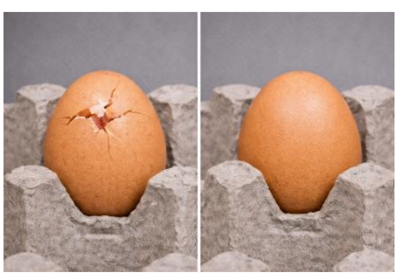

Fig. 1. Cracked (damaged) & normal egg samples

Object detection algorithms, particularly YOLO, are appropriate for real-time applications due to their high processing speed. This paper proposes an automatic crack detection approach for eggs using CNN classification models such as CNN, ResNet, and Xception in conjunction with the YOLO real-time object detection algorithm. While the classification models detect the crack state for the eggs in the image, the YOLO approach detects the crack location and the number of damaged eggs in real-time. The framework can be accessed using the proposed web application, which allows users to upload an image or use the camera to stream live video.

The aim of the proposed method is to increase the accuracy of inspection, reduce the working load, and create a cost-effective technique for poultry farms and the egg processing industry. For the evaluation of the models, metrics such as accuracy, precision, recall, and F1-score are used. A comparative analysis is also conducted to assess which of the models works best in the context of automatic egg quality evaluation.

II. RELATED WORK

The inspection of egg quality is a very important factor in the poultry processing industries due to the significance of egg quality with respect to the production of reliable food products. Eggs with cracks are identified with an elementary but highly dependent process of physical observation or candling, where a source of light illuminates the defective areas of the eggshell during inspection. This process is not very effective as the observation of a person grows tiresome and inconsistent with the increasing volume of the eggs that have to be inspected in an ongoing process.
Earlier intelligent systems utilize classical image processing for crack detection. Classical image processing involves execution of functions such as thresholding, filtering, and detection of contours based on grayscale value, shell texture, and discontinuity of edges. Although these systems decreased man-hours, there are difficulties involving variations in lighting, orientation of eggs, and background noise. Additionally, detection of small or hair crack patterns is problematic.

To achieve a better detection accuracy, learning-based classification techniques were proposed that were based on the extraction of learning-based features from the images of the eggs. These techniques were intended to classify the eggs as either defective or not defective in a better way based on the statistical features of the eggshells. This method showed higher performance with regard to the previously presented techniques; however, it was still labor-intensive with regard to the preprocessing operation.

Currently, with the recent advancements in the field of artificial intelligence, deep learning techniques have gained

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more popularity for performing visual inspections. Convolutional Neural Networks have the ability to learn features directly from images without the requirement of performing any handcrafted feature extraction. The image classification problem has achieved better results using the ResNet and Xception models of transfer learning.

In addition to that, object detection models are also investigated for not just classifying the eggs but also determining their defects. In that context, real-time detection models such as You Only Look Once (YOLO) allow the simultaneous detection and localization of defective regions. This detection can even draw bounding boxes around the defective region of the object so that damaged eggs are counted.

However, most of the existing works that addressed either classification or localization were performed separately. Yet an effective system that combines the process of classification, localization of cracks, and the process of monitoring was not achieved. Hence, the proposed work integrates the CNN-based classification with the use of ResNet and Xception approaches with the YOLO-new crack detection algorithm.

III. METHODOLOGY

The current section includes information on the complete working procedure of the suggested model of an automated egg crack detection system. The main purpose of this system is to identify whether an egg is damaged or non-damaged. Additionally, the suggested framework is directed towards detecting egg crack using bounding box detection. The suggested framework is based on several deep learning algorithms, including Convolutional Neural Network (CNN), ResNet, Xception, and YOLO. The complete workflow of the suggested system is depicted in Fig. 2.

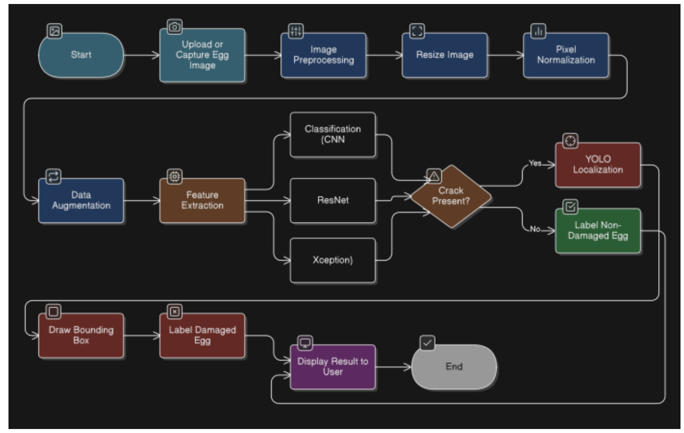

Fig. 2. Processing workflow of egg crack detection system

A. Image Acquisition and Dataset Preparation

It is a dataset of images of eggs captured in a variety of illumination conditions and from different angles of view. There are two classes in the dataset: damaged eggs and nondamaged eggs. Each image is labeled manually to ensure the correct ground truth classification.

These images are pre-processed before training to enhance the learning performance of the models. The steps undertaken for preprocessing include resizing, normalization, and noise reduction. All the images are brought to the same resolution for maintaining uniformity during training. The pixel values are normalized within a standard range so that the gradient updates become stable while training the model for optimal performance. Further, rotation, flipping, and brightness variations are other data augmentation methods applied to increase diversity in the dataset and prevent overfitting.

After preprocessing, the dataset is divided into training and testing sets. It is further used to learn model parameters in the training set and used for performance evaluation in the testing set.

B. Convolutional Neural Network (CNN)

A convolutional neural network (CNN) is adopted as the baseline model for egg crack classification, as CNNs automatically learn spatial features from images without manual feature extraction. The general architecture will include convolutional and activation layers, pooling layers, and then fully connected layers. Convolution layers extract visual patterns such as edges, texture variations, and crack

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structures on the surface of the eggshell. ReLU introduces non-linearity in most of them, while max-pooling reduces spatial dimensions and subsequently reduces computational complexity, preserving significant features. Extracted features are flattened and input to fully connected layers, and finally the Softmax output layer will predict the egg as either damaged or non-damaged. The architecture of CNN is shown in Fig. 3.

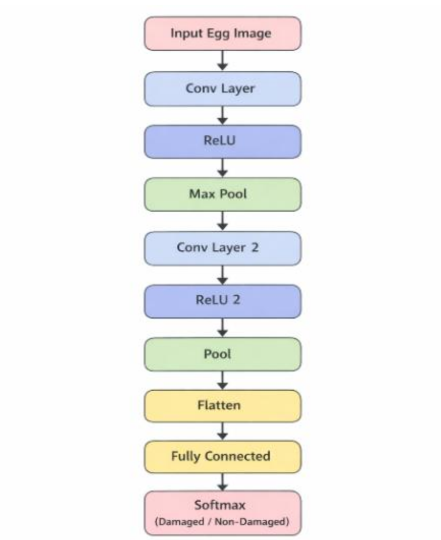

Fig. 3. Convolutional Neural Network used for egg classification.

C. Residual Network (ResNet)

Another challenge that deep CNNs often face is the vanishing gradient and degradation problems. In this regard, a residual network (ResNet) is used to address this problem. ResNet has introduced the skip (residual) connections that enable gradients to propagate directly across layers during training. These residual blocks ease feature propagation and allow the network to learn even deeper hierarchical representations of egg surface textures, including fine crack patterns. Therefore, the classification performance improves. The residual learning structure is represented in Fig. 4.

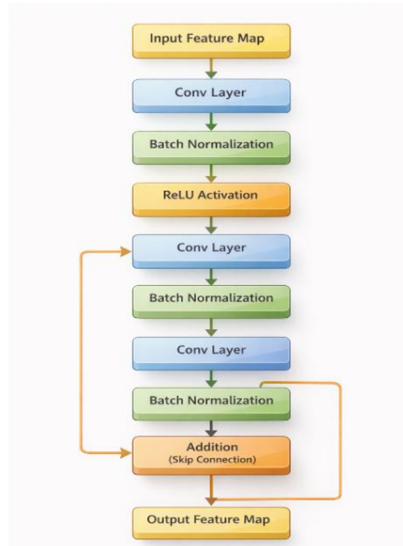

Fig. 4. Residual learning block with skip connection in ResNet.

D. Xception Network

Xception is a model that is based on depthwise separable convolution, which means that spatial filtering and channel filtering are performed separately using depthwise and pointwise convolutions. This structure reduces computational cost and enhances the ability of feature extraction. The model can effectively capture the subtle crack pattern and surface discontinuity, which enhances the generalization capability and classification accuracy compared to the standard CNN model. It can be summarized in Fig. 5:

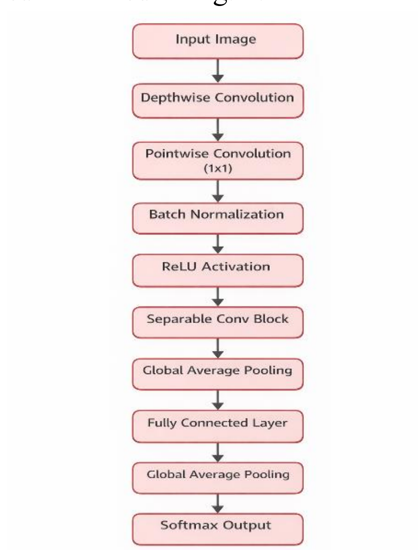

Fig. 5. Xception architecture based on depthwise separable convolution.

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E. YOLO Object Detection

In order to perform the crack localization task, the YOLO object detection algorithm is incorporated into the system. Unlike other classification models, the YOLO algorithm detects the exact position of the cracks using bounding box detection. The algorithm divides the image into grids and detects the bounding boxes, confidence, and class in parallel. Eggs with cracks detected by the algorithm are considered damaged, while the uncracked ones are considered non-damaged. The YOLO structure of the object detection algorithm is demonstrated in Fig. 6.

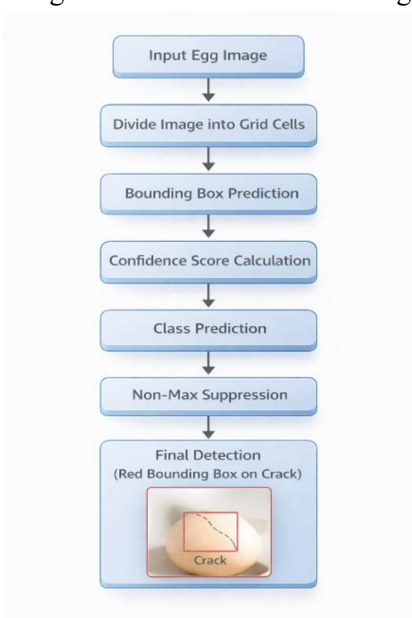

Fig. 6. YOLO-based crack localization and bounding box detection.

F. Prediction and Output Generation

During the test phase, the input image is passed through the models that have been previously trained. The classification models identify if the egg is damaged or non-damaged, while the YOLO model identifies areas with cracks in the egg. The output of the image processing will have the predicted class label with areas of cracks highlighted. In case no cracks are detected, the egg is considered non-damaged. This method can also find application in poultry farming.

IV. PERFORMANCE ANALYSIS

The egg crack detection system is tested for the accuracy of classification and the accuracy of egg crack localization. For testing, the dataset is divided into the training dataset and the testing dataset. In this case, the CNN, ResNet, Xception, and YOLO models are used for the binary classification task, while the image is viewed by the YOLO model.

A. Evaluation Metrics

The performance of the system is determined using various parameters, namely accuracy, precision of damaged eggs, recall of all cracked eggs, and F1-score, which represents the trade-off between precision and recall. The above parameters belong to the confusion matrix given in Fig. 7. The various elements of the confusion matrix consist of TP, TN, FP, and FN, with low values of FP and FN ensuring the inspection.

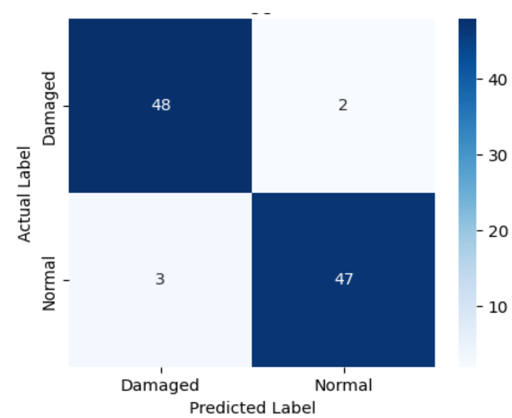

Fig. 7. Confusion Matrix of Damaged and Non-Damaged Egg Classification

B. Classification Performance

The accuracy curves for training and validation data describe the learning behavior of the classification models. As the number of epochs increases, accuracy is shown to converge properly without significant overfitting. This is validated by the close overlap between the training and validation accuracy curves, showing generalized performance for unknown images of eggs.

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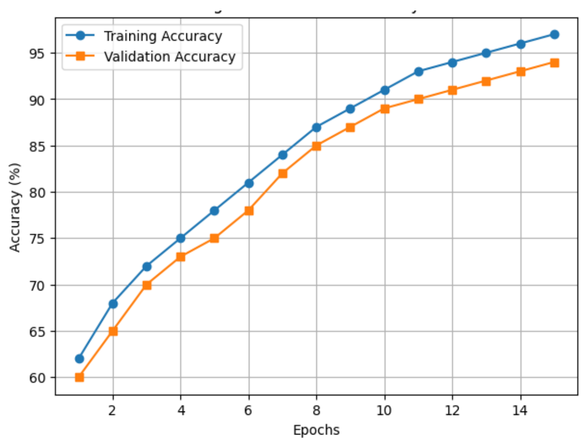

Fig. 8. Training & Validation Accuracy Curve

Performance metrics of CNN, ResNet, and Xception models, i.e., accuracy, precision, recall, and F1-score, are compared. The performance of the CNN model is the baseline, while the ResNet model enhances classification by recognizing deeper image features. The Xception model has the highest performance metrics for all three measures, showing its strongest potential for recognizing crack patterns.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
CNN	88.2	86.9	85.7	86.3
ResNet	93.4	92.1	91.8	91.9
Xception	96.1	95.4	95.8	95.6

Table I -- Performance Comparison of Models

C. Detection Performance Using YOLO

YOLO was used for real-time crack localization. Cracked eggs were highlighted with bounding boxes, whereas normal eggs showed no detection regions. The system accurately identifies even small cracks and provides visual confirmation of egg condition, as illustrated in Fig. 9.

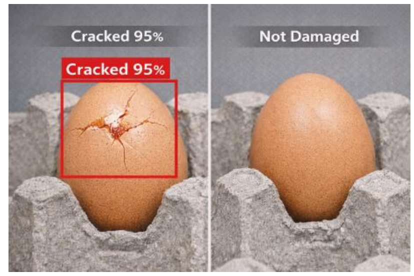

Fig. 9. YOLO Crack Detection Output

D. Overall System Performance

The performance of the entire system is evaluated using CNN, ResNet, and the Xception model, and is represented in terms of accuracy, precision, and F1-score, as shown in Fig. 10. It can be observed that although the performance of the CNN model is poor, the ResNet model is capable of achieving good performance by using the deeper architecture for classification. In addition, the Xception model indicates better performance in all aspects, significantly classifying the crack patterns.

The above results also validate that the deeper architectures enhance the reliability of the inspection task, and by using YOLO localization together, both classification and visual validation for the damaged eggs are achieved.

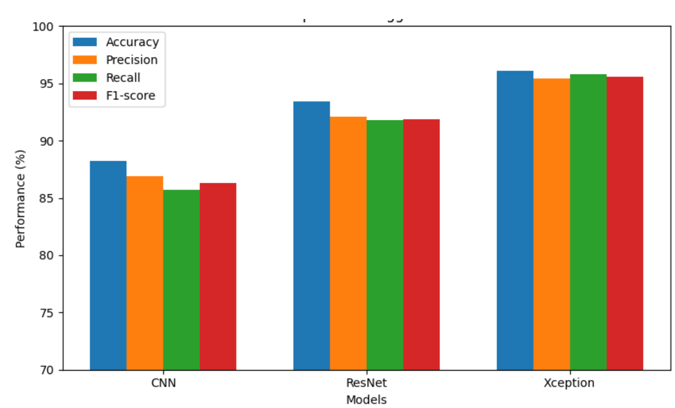

Fig. 10. Performance comparison of CNN, ResNet and Xception models

V. RESULTS AND DISCUSSION

These experimental results confirm that the proposed automated egg crack detection system with both classification and crack localization is effective. For the practical inspection test condition, egg images that had never been seen by the models were used for testing. Among them, some examples showed that the classification networks CNN, ResNet, and Xception could successfully classify damaged and non-damaged eggs. Meanwhile, it was observed that the YOLO model can provide localization on the crack regions on the eggshell.

The CNN is a strong baseline model that performs well in identifying obvious cracks but lacks strength in identifying thin or subtle cracks. The ResNet model enhanced the model's performance by learning deeper feature mappings using residual connections and minimizing the effects of misclassifications due to small surface details. The Xception model provides the most consistent results in the identification of fine details of cracks and micro-texture changes.

In terms of visualization, YOLO detection ensured a form of confirmation using bounding boxes to indicate crack locations. Crack-filled eggs were classified as damaged, while eggs without any cracks were classified as non-damaged. The detection results ensured that the system had accurately localized the eggs and had few false detection rates.

Overall, the integration of classification and object detection methods would be highly effective in making the efficiency of egg inspection systems. In this method, classification models are employed to identify whether the egg is defective or of good quality, and the YOLO model is used to visually verify the defect by pointing out the defective regions of the egg. This method is highly accurate and reliable since it not only identifies the egg but also indicates the regions where the defect exists. It also reduces the need for manual inspection, which in turn reduces the chances of defective eggs passing through the production line. Hence, this method is highly appropriate for automated poultry farms and large-scale egg production units.

VII. CONCLUSION

The proposed automated egg crack detection system utilizes non-destructive deep learning methods to assess the quality of the egg. In this paper, three classification models, namely CNN, ResNet, and Xception, are trained to classify damaged and undamaged eggs based on the texture and appearance of the eggshell surface. In addition to the classification task, the YOLO detection model is used to locate the position of the cracks on the egg surface.

Among the models tested, CNN is used as the baseline model. The ResNet model enhances the performance of the model by learning more detailed features from the egg images. The Xception model yields the best results, as it is able to detect very fine and irregular patterns of cracks, which are not easily noticeable. The YOLO model also marks the cracked areas using bounding boxes.

By combining classification and localization, the system increases inspection reliability and reduces manual effort and human error. The approach enables faster quality assessment and can be applied in poultry farms and egg processing industries for automated inspection.

In future work, the dataset can be expanded to include more variations in lighting and environmental conditions. The system can also be deployed on embedded or edge devices to support real-time operation in practical industrial environments.

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