Intelligent Methods in Engineering Sciences 3(1): 013-021, 2024

INTELLIGENT METHODS
IN ENGINEERING SCIENCES

https://www.imiens.org

International Open Access

March, 2024

e-ISSN 2979-9236

Research Article

https://doi.org/10.58190/imiens.2024.83

Automatic Classification and Detection of Faulty Packaging using Deep Learning Algorithms: A Study for Industrial Applications

Irem CATAL [a,*], ***Yavuz Selim TASPINAR*** [b]

[a] *Akinsoft, Konya, Turkiye*
[b] *Doganhisar Vocational School, Selcuk University, Konya, Turkiye*

ARTICLE INFO

Article history:
Received 07 January 2024
Accepted 25 March 2024

Keywords:
classification,
deep learning,
faulty, industry,
object detection

ABSTRACT

In order to market the product to the consumer with the correct methods and to increase the reliability and sustainability of the brand in many stages from the production stage to the launch of the product in the national and international environment, to prevent faulty problems that may be encountered, the project will classify the packages with computer vision within the framework of deep learning algorithms and detect faulty packages. Studies have been carried out in this direction with the aim of saving labor and time, reducing the margin of error and increasing efficiency. In the study, a total of 3000 images, 1000 from each class, were used in three classes of fruit juice boxes called "Flawless", "Pressed" and "Stained" to ensure the image distribution ratio according to classes. In the study, training and testing of the model was carried out using the YoloV8 object detection algorithm. In addition, in order to make comparisons, SqueezeNet and IncepptionV3 classification models were trained and tested using images. Values of 99.5% for mAP50 and 97.9% for mAP50-95 were obtained from the YoloV8 model. 100% classification success was achieved from the SqueezeNet model and 99.9% classification success was achieved from the InceptionV3 model. The performance results obtained from the tests of the models were analyzed and evaluated, and then real-time testing was carried out. The accuracy of the study was evaluated by taking real-time images of the juice boxes moving on the conveyor with a camera. It is thought that the system created as a result of the study can be used in the industrial field.

1. INTRODUCTION

Packaging refers to protective products made of any material used to transport, protect, store and sell products during their delivery to the consumer. Packaging for food products has become a concept that appeals to consumers' emotions and is effective in their purchasing decisions, rather than just being a factor that preserves the product and prevents it from spoiling. Packaging, which plays the role of a salesperson, is the first factor that establishes contact with the consumer and conveys the message that the producer wants to convey to the consumer. In this context, it is seen as an important marketing activity that promotes the product, and thanks to this function, it is important in terms of guiding the consumer and helping him make a decision. Image processing techniques and deep learning algorithms are among the fast and reliable methods for determining product quality and defects. Song et al. proposed an anti-noise feature descriptor called local binary models (AECLBP) to improve the detection rate of defects in products. They showed that their proposed approach improves the defect recognition performance under the influence of feature variations of intra-class changes, illumination and grayscale changes [1]. Bulnes et al. They emphasized the importance of early detection of errors or defects, improving product quality and reducing the economic impact resulting from the disposal of defective products. The authors propose a method to detect a specific type of defects that may arise during the production of materials: periodic defects. Such defects are very harmful because they can create many surface defects. Since the time available to perform the detection of these defects may be limited, it is crucial to consume as little time as possible [2]. In their study, Zhang, Jiang, and Li found that as PCB becomes increasingly complex, cosmetic defect detection tasks become more difficult than before. They demonstrated all the processes of the PCB cosmetic defect detection system. First of all, an original PCB is scanned into an automatic optical inspection (AOI) system, then the AOI system can select images with suspected defects using simple and crude algorithms such as image comparison [3]. Sensors may seem like a minor aspect of IoT in particular, but they have the potential to change the way certain industries operate [4]. It shows the

*** Corresponding Author:** ytaspinar@selcuk.edu.tr

sensor's huge impact on the industry. Various industries are now integrating sensors into product packaging. Packaging machines are equipped with sensors and tagged [5]. Packaging can be an integral part of complete operational improvement. In particular, the application of sensors in product packaging has brought great benefits for both manufacturers and customers [6]. Sensors for beverage packaging are not always electronic. Devices; They can also be in the form of an indicator that shows Color change occurs when the beverage state changes [7]. Budiarti et al. proposed a size detection model to detect the size of melon fruit. They used YoloV4 as the object detection model. They obtained an F1 Score of 84.47% with their proposed model [8]. Rowick B. Legaspi et al. detected whiteflies and fruit flies in images of fruits collected with Raspberry pi. They have also developed both desktop and web-based applications to process images. They achieved 83.07% classification accuracy in their study using YOLOv3 [9]. Siricharoen et al. used Mask R-CNN in their study to grade fruit maturity. They increased a small dataset with a new data augmentation method. As a result of their experiments, they achieved classification success of up to 99.20% [10]. The motivation of the study was created by considering the following problems. These problems:

• Packaging is warped, stained, dents, etc. Putting it on the market without being classified as such affects the sustainability of the product in the market.

• Products with packaging errors reaching consumers may cause negative feedback. As a result, it may cause damage to the reputation of the manufacturer's brand.

• Labor intensity and limited time during production and distribution cause the margin of error to be high.

• With all these, there is a danger that the manufacturing company and the product will not be marketed correctly in the national and international markets, their sustainability will be low and they will fall behind in the competitive environment in the market.

The contributions of this study based on these problems to the literature are as follows:

• Necessary object detection methods will be developed to detect damaged products in the industrial field, thus contributing to the correct marketing of products.

• Workforce and time will be used in the most efficient way.

• The project will contribute to the development of artificial intelligence applications in many areas, increasing the efficiency of production distribution activities in many areas with correct classification methods and minimizing the margin of error.

• The damaged product will be detected at the factory and will be prevented from reaching intermediary companies and consumers, thus preserving the reputation of the brand.

• Due to the success of the proposed models and the low cost of the system, it will be usable by every manufacturer.

• Widespread use can be achieved by developing a system that can be modified for every sector and product.

With this study, it is aimed to minimize the negative effects that occur during the production and distribution stages of packaging and to pave the way for exports by efficiently reducing the labor force in production and distribution and by classifying the packages correctly. In addition, by preventing defective products from reaching the consumer, complaints will be reduced and the reputation of the manufacturer's brand will be protected.

The rest of the article is planned as follows: in the second section, information about the dataset used in the study is given. Additionally, information about the YoloV8 model, SqueezeNet model, and InceptionV3 model used is given. Explanations of the performance metrics required to measure the performance of the models are also given in this section. In the third section, the experimental results obtained from the study are given. In the last section, general results and recommendations from the study are given.

2. Materials and Methods

In this section, information is given about the dataset used in the study, YoloV8 model, SqueezeNet model, InceptionV3 model and performance metrics.

2.1. Dataset

The dataset used in the study was downloaded from kaggle.com [11]. In the study, the focus was on fruit juice boxes and a dataset containing a total of 3000 images was used in this context. These images represent three different states of juice boxes: “Flawless”, “Pressed”, “Stained”. In order to be able to use it in the YoloV8 model, the data was meticulously labeled and the condition of each juice box was determined. This labeling process is critical for the model to learn correctly. Accurately determining the condition of each juice box allows the model to produce reliable and accurate results. After the labeling process is completed, data augmentation such as blur (up to 2.5 pixels) and noise (up to 1.99% of pixels) is performed to produce 3 outputs per training samples to better adapt the model to real-world conditions, increase the generalization ability of the model and prevent overfitting. techniques have been applied. Thanks to these techniques, 5876 images with added blur and noise were obtained from the original 3000 images. Data augmentation is important to increase the model's ability to generalize to new and unseen data. In addition to data augmentation, different transformations were applied to the existing data set. For example, the data set was diversified by using techniques such as rotation, reflection and perspective transformations. In this way, the model was able to recognize juice boxes from various angles and positions. The resulting extended dataset was divided into three parts to evaluate the performance of the model: training set 88% (5157 images), validation set 8% (479 images) and testing set 4% (240 images). This partitioning is standard practice for measuring the success of the model during and after its training. Additionally, the homogeneous distribution of each set allows an accurate assessment of the overall performance of the model. During the preparation of the images for model training, each image was corrected with automatic orientation and resized to a resolution of 640x640 pixels. These operations ensure that the model processes all images with the same size and orientation, increasing the consistency and efficiency of the training process. Cross validation method was used to train SqueezeNet and InceptionV3 models. k value was determined as 10.

2.2. Convolutional Neural Network

CNN is a deep learning model used in object detection, pattern recognition and image classification problems. There are different layers in the CNN structure. End-to-end classification operations can be performed with convolutional, pooling, activation and fully connected layers [12, 13]. Convolution is the layer where feature extraction from the image is performed. Feature maps are taken as output from this layer. Pooling layer is used to get rid of data confusion in feature maps. This layer reduces the size of feature maps. Activation layers ensure that the data is kept within a certain range. Classification of feature maps is performed with the fully connected layer. The number of layers in the CNN may vary depending on the problem [14, 15].

2.3. YoloV8

Compared to previous versions of YOLOv8, the advances made in object detection have marked a significant milestone. These advances are of great importance to researchers and application developers, as YOLOv8 offers higher accuracy and processing speed, improving the reliability and performance of object detection applications. In particular, there are many studies and test reports that YOLOv8 provides higher accuracy and processing speed than previous versions. These features offer significant advantages in applications that require fast response, such as real-time object detection. This description provides basic information about the development of YOLOv8, highlighting the important contributions of the model in the field of object detection [16]. In training the YoloV8 model, the optimizer SGD was set as a learning rate of 0.01.

2.4. SqueezeNet

SqueezeNet is a deep convolutional neural network architecture that is significantly smaller in size and has fewer parameters than AlexNet. This architecture includes compression and expansion (squeeze-and-excitation) modules and requires fewer computational resources than traditionally larger and more complex models. This increases usability in resource-limited environments such as mobile devices [17]. While SqueezeNet exhibits high performance in feature extraction tasks, it offers advantages in training and distribution processes thanks to its smaller model size and light weight. Therefore, SqueezeNet can be considered an attractive option for deep learning-based tasks, especially considering the application requirements and resource constraints [18, 19]. In training the SqueezeNet model, the activation function was determined as ReLU, the solver as Adam, and the iteration as 200.

2.5. InceptionV3

InceptionV3 is a deep learning model designed by Google and trained on the ImageNet dataset. InceptionV3, the third version of the Inception architecture, has a more complex and deeper structure than previous versions. The architecture of the model is defined by a complex Inception module, which includes parallel convolution layers and scale-to-scale connections [20]. This structure enables features to be extracted more effectively at different scales and facilitates the learning process of deeper networks. InceptionV3 stands out for its high accuracy and generalization performance and is often used in various tasks such as visual recognition, object detection and classification. Additionally, with techniques such as transfer learning and fine-tuning, the model can be adapted to different applications [21]. In training the InceptionV3 model, the activation function was determined as ReLU, the solver as Adam, and the iteration as 200.

2.6. Confusion Matrix and Performance Metrics

Confusion matrix, a tool used to evaluate the performance of classification models, is a table showing the relationship between actual and predicted classes [22]. This matrix represents the actual classes in the rows and the predicted classes in the columns. It contains four main cells: True Positive (TP - true positive), False Positive (FP - false positive), True Negative (TN - true negative) and False Negative (FN - false negative) [23]. Combinations of these cells indicate how accurately or incorrectly the model predicts classes. Confusion matrix is used to analyze the performance of the model in more detail and calculate different performance metrics. Metrics such as precision, recall, F1 score and accuracy can be calculated through the confusion matrix [24]. The confusion matrix is shown in Figure 1.

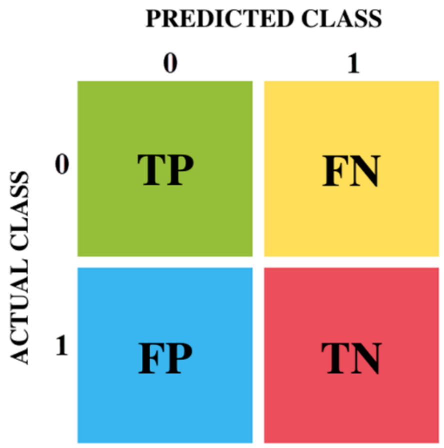

Figure 1. Confusion matrix

Accuracy is the ratio of a model's correct predictions to the total number of samples. Mathematically, it is calculated as the ratio of correctly predicted samples to the total number of samples [18]. However, it can be misleading in unbalanced class distributions. For example, if one of the classes has many more examples than the other, the model can have a high accuracy rate even without making correct predictions. Precision shows the ratio of samples predicted as positive to samples that are actually positive. That is, it is the ratio of the model's true positive predictions to all positive predictions. Precision is important when preventing false positives is important. For example, false positive results in medical diagnoses can have serious consequences. Recall shows the ratio of true positive predictions to true positives. That is, it is the ratio of positive examples correctly predicted by the model to all true positive examples. Responsiveness is important in situations where we don't want to miss how many of a class. For example, the sensitivity of a medical test allows true positive patients to be accurately recognized. F1 score is the harmonic mean of precision and sensitivity. It provides a more balanced performance measurement in unbalanced class distributions [25]. A high F1 score indicates that both sensitivity and sensitivity are high. The F1 score shows how close sensitivity and sensitivity are to each other. These metrics are commonly used to evaluate model performance and can be used together to understand how effective a model is. mAP50 (Mean Average Precision) is a metric by which average precision (AP) is calculated, but with an IoU (Intersection over Union) threshold corresponding to 0.5, which is a limiting threshold used in object detection. IoU measures the ratio of the area between the predicted object box and the actual object box. mAP50 refers to average sensitivity below the 0.5 IoU threshold and is often used in standard object detection tasks. mAP95 (Mean Average Precision) is a metric where the average precision is calculated under a threshold of 0.95 IoU. This metric measures the model's ability to detect objects more precisely by using a stricter threshold. It is especially preferred in object detection tasks that require high accuracy [26]. The formulas of the performance metrics used in the study are given in Table 1.

Table 1. Performance metrics formulas

Metric	Formula
Precision	TP / (TP + FP)
Recall	TP / (TP + FN)
F1 Score	2 * (Precision * Recall) / (Precision + Recall)
Accuracy	(TP + TN) / (TP + TN + FP + FN)

Both metrics are calculated separately for multiple classes and then averaged to represent overall performance. These metrics are used to understand how object detection models perform against different requirements and measure the model's ability to detect objects at different sensitivities.

3. Experimental Results

YoloV8 model was used to detect objects in the images. SqueezeNet and InceptionV3 models were used to classify the images. The results obtained were compared. Python programming language was used to code the models. The flow chart of experimental studies is given in Figure 2.

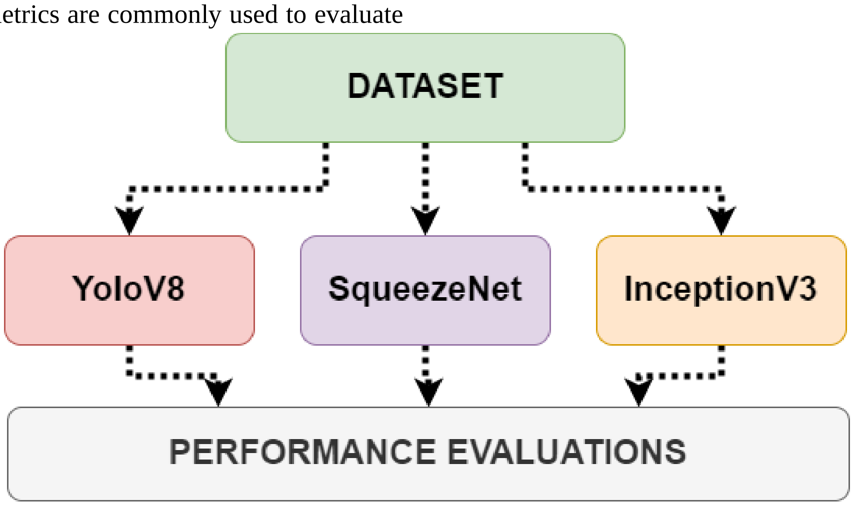

Figure 2. Flow chart of study

3.1. YoloV8 Results

The training process was carried out for 25 epochs and 14 iterations in each epoch using the YOLOv8 algorithm, and this process took 1,212 hours. The model has 168 layers and 111,267,745 parameters and is trained on Tesla T4 GPU. The performance of the model on the validation set is quite impressive, with mAP50 ranging from 99.5% to 97.5% and mAP50-95 ranging from 97.5% to 97.9%. These high success rates show that the model can recognize different object classes with high accuracy. As a result of the studies, a high-accuracy object recognition model that can be used in real-world applications has been developed. The data and metrics obtained during and after training the model will pave the way for further research and development. The graphs obtained from the training and testing of the YoloV8 model are given in Figure 3.

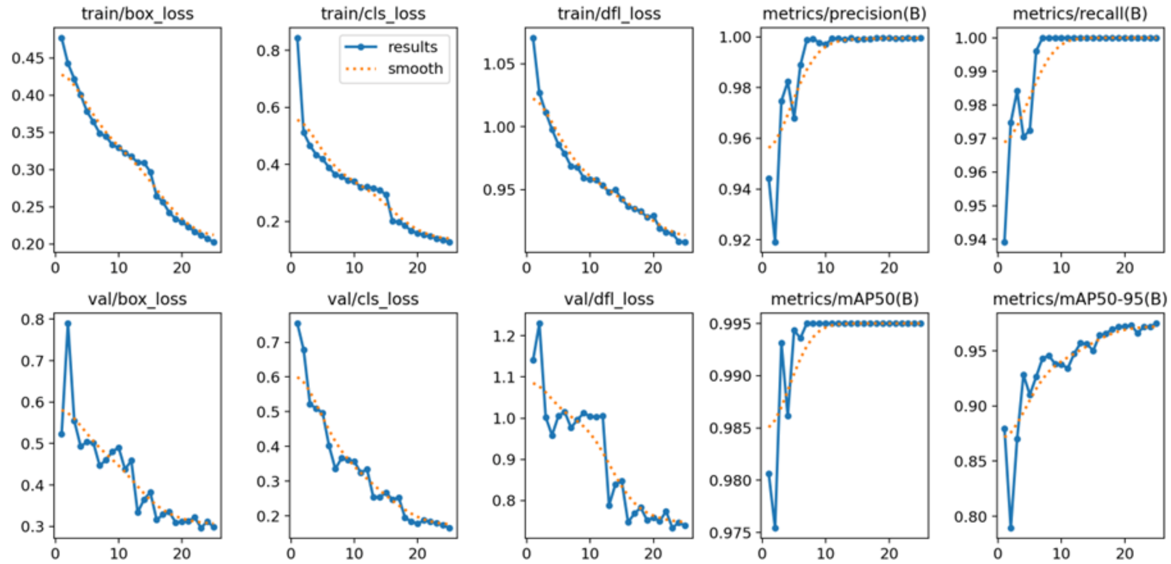

Figure 3. YoloV8 train and test charts

The fact that the 'train box loss' and 'validation box loss' values obtained during the training and validation stages are approximately zero shows that the object detection and recognition model developed within the scope of the study makes bounding box predictions with high accuracy. These results indicate that our model was effectively trained on real-world data and successfully detected, framed and classified objects.

A low 'train box loss' value indicates that our model is quite competent in learning the location and size of objects in the training data set. This shows that our model correctly detects objects in the training data and draws appropriate bounding boxes. However, it is important to evaluate whether this success is also replicated in real-world scenarios and on independent test datasets.

The low value of 'cls loss' (classification loss) for classification accuracy indicates that our model labeled objects with the correct classes during training. In the study, values of cls loss close to zero indicate that the model can distinguish different objects with high precision and produces reliable results in the classification task.

Dfl_loss is a customized loss function used to evaluate how effectively the model learns during training and its accuracy on complex tasks. Low values of this function indicate that the learning process of our model was successful and it was able to synthesize the features of the boxes with high accuracy. Figure 4 shows the visual results obtained from the YoloV8 model.

Figure 4. YoloV8 results

The real-time detection ability of the model was tested on various juice box images. The attached image shows that the model detected juice boxes labeled 'flawless' and 'crushed' with high accuracy, and predicted confidence scores on each classified object. The model achieved a very high confidence score of 1.0% when detecting different states of the boxes, which indicates the reliability of the classification and the accuracy of the model. These outputs were used to evaluate how effective the model was at object detection on the specific classes it was trained on and how it performed in real-world scenarios.

3.2. SqueezeNet and InceptionV3 Results

Confusion matrices of the SqueezeNet model are given in Figure 5, and the confusion matrices of the InceptionV3 model are given in Figure 6.

Actual \ Predicted	FLAWLESS	PRESSED	STAINED	Σ
FLAWLESS	1000	0	0	1000
PRESSED	0	1000	0	1000
STAINED	0	0	1000	1000
Σ	1000	1000	1000	3000

Figure 5. Confusion matrix of SqueezeNet model

It is quite impressive that the SqueezeNet model achieved 100% classification success based on confusion matrix data. The confusion matrix details the relationship between the model's actual and predicted classes. In this case, it means that the model predicts all classes correctly. That is, the model did not make any type of incorrect predictions for each class. Accurate classification performance means that the model can fully identify each class and does not experience confusion between different classes. This shows that the model has fully learned and can distinguish the features and patterns of each class. 100% classification success means that the model has learned the training data perfectly and successfully applied this learning on the test data. This result shows that the model works in a high quality and reliable manner. In general, the 100% classification success of the SqueezeNet model can be considered an extremely positive indicator in terms of the reliability and performance of the model. This shows that the model can be used effectively in many applications and provides confidence with a high level of accuracy.

Actual \ Predicted	FLAWLESS	PRESSED	STAINED	Σ
FLAWLESS	999	0	1	1000
PRESSED	1	999	0	1000
STAINED	0	0	1000	1000
Σ	1000	999	1001	3000

Figure 6. Confusion matrix of InceptionV3 model

It is quite impressive that the InceptionV3 model achieved 99.9% classification success based on confusion matrix data. The confusion matrix details the relationship between the model's actual and predicted classes. In this case, it means that the model predicts almost all classes correctly overall. However, it could still possibly have made incorrect predictions in some rare cases. The 99.9% classification success indicates that the model has an overall high level of accuracy. This indicates that the model learned the training data quite well and successfully applied this learning on the test data. The model's ability to make accurate predictions in most cases indicates that it performs reliably and can perform good classification overall. 99.9% classification success means that the model demonstrates high precision and sensitivity in most cases. This shows that the model is capable of correctly identifying positive and negative classes, and the number of false positives and negatives is quite low. As a result, the 99.9% classification success of the InceptionV3 model indicates that it is a generally reliable and effective model. However, due to the possibility of any incorrect predictions, the model may always need to be carefully evaluated and improved where necessary. Performance metrics for SqueezeNet and InceptionV3 models are given in Table 2.

Table 2. Performance metrics of SqueezeNet and InceptionV3 model

	Accuracy (%)	Precision	Recall	F1 Score
SqueezeNet	100	1	1	1
InceptionV3	99.9	0.99	0.99	0.99

The fact that the SqueezeNet model achieved 100% success indicates that it has excellent classification performance. This means that the model correctly classified all the test data, meaning it made no incorrect predictions. Additionally, the precision, recall and F1 Score values are all 1, indicating that the model has excellent precision and sensitivity for each class. This indicates that the model did not make any type of errors in the classification task and correctly identified each class. On the other hand, the InceptionV3 model achieved 99.9% success, meaning it correctly classified almost all test data. This represents a very high performance, but slightly lower than the SqueezeNet model. Precision, recall and F1 Score values of 0.99 also indicate a high performance, but are slightly lower than SqueezeNet. This indicates that the model may make minor errors in some cases, but overall it has a high level of accuracy and consistency. Both models show high performance, but the fact that SqueezeNet achieves 100% success and has excellent precision, recall and F1 Score values shows that this model is more reliable and perfect. However, both models can be used and preferred depending on specific situations and requirements.

4. Conclusions

The results of the YoloV8 model look quite remarkable. The mAP50 value is 99.5%, indicating that the model detects almost all objects with 99.5% accuracy. This highlights that the model has an overall high level of accuracy and can successfully identify a variety of objects. The high mAP50 value indicates that the model performs extremely reliably in the object detection task. The mAP50-95 value of 97.9% is also quite impressive. This value shows that the model generally detects objects with 97.9% accuracy and achieves this at different IoU (Intersection over Union) thresholds. That is, it shows that the model can effectively detect objects in varying conditions and sizes. This indicates that the model can perform reliably on a wide range of object detection tasks and in various scenarios. These results show that the YoloV8 model exhibits high-quality performance in the field of object detection and can be used effectively in real-world applications. However, as with any model, it is important to carefully examine the results obtained and improve them where necessary. This could help the model succeed in a wider range of applications and further improve its performance.

The fact that the SqueezeNet model achieved 100% classification success is quite impressive and represents excellent performance. This means that the model classifies all the test data exactly correctly; So he didn't make any wrong predictions. 100% classification success indicates that the model was trained comprehensively and effectively and completely learned the patterns in the test data. This result strongly indicates the model's ability to accurately identify each class and highlights that it exhibits outstanding classification performance overall. On the other hand, it is quite remarkable that the InceptionV3 model achieved 99.9% classification success. This means that the model usually classified all test data correctly, but in rare cases it may still have made incorrect predictions. The 99.9% classification success indicates that the model has an overall high level of accuracy and works reliably in most cases. The high classification success of both models indicates that they were robustly trained and successfully applied on test data. These results confirm that SqueezeNet and InceptionV3 models are powerful models capable of reliable and high-quality classification. The YoloV8 model was most likely to work as it was the most current Yolo model in the literature. New updated models have emerged that can achieve higher results using the same data. Advanced CNN models with more layers instead of SqueezeNet and InceptionV3 models can increase their separation accuracy.

Image processing technology can make significant contributions to production processes in detecting faulty packaging boxes. This innovation enables quick and precise identification of damaged or defective packaging, optimizing quality control processes and saving time and costs on the production line. Additionally, early detection of faulty products increases customer satisfaction and reduces recall costs. Image processing-based systems provide manufacturers with a more reliable and effective quality control solution while minimizing human errors and subjective evaluations. However, in order for this technology to be implemented effectively, it is necessary to provide appropriate training data, select the correct algorithms and update the systems regularly. It is also critical to provide appropriate infrastructure and resources so that it can be seamlessly integrated into operational processes.

Acknowledgments

This article was extracted from the project numbered 1919B012221683 carried out within the scope of TUBITAK 2209/A UNIVERSITY STUDENTS RESEARCH PROJECTS SUPPORT PROGRAM.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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