Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2, 1528-1543
2025
Publisher: Learning Gate
DOI: 10.55214/25768484.v9i2.4802

Classification of pineapple ripeness using YOLOv8 and convolutional neural networks under varied environmental conditions

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Abstract: Proper fruit harvesting timing is crucial in agriculture to ensure optimal product quality. Particularly, manually determining fruit ripeness requires significant time and expertise from farmers. Inaccuracies in harvest timing often lead to resource wastage and lower crop quality. Simultaneously, advancements in image-based classification technology offer promising solutions to address these challenges. Convolutional Neural Networks (CNN) are powerful deep learning architectures effective in recognizing complex patterns in image data, enabling high-accuracy visual information processing. YOLOv8 (You Only Look Once version 8) represents a recent implementation of object detection algorithms renowned for its ability to swiftly and accurately detect objects in real-time. Many studies have used limited data under controlled conditions. Additionally, there is a lack of research exploring how YOLOv8 and CNN models can be adapted to various environmental conditions, such as natural lighting and diverse backgrounds. This study proposes the integration of CNN with YOLOv8 to autonomously classify fruit ripeness stages, specifically focusing on pineapples. This method facilitates automated detection and classification of fruit ripeness, thereby enhancing harvest management efficiency for farmers. Performance testing of the YOLOv8 system yielded promising results with a mean Average Precision (mAP) of 88.5%, Precision of 78.4%, and Recall of 84.2%. These findings affirm the system's capability to consistently and accurately assess pineapple ripeness across various field conditions. By harnessing CNN and YOLOv8 technologies, we introduce an innovative approach to fruit harvesting management applicable in modern agricultural practices.
Keywords: *Classification, Convolutional Neural Network, Pineapple, YOLOv8.*

1. Introduction

Effective identification of fruit ripeness is crucial in modern agriculture to optimize harvest timing and ensure high-quality produce. Manual assessment of fruit ripeness is labor-intensive and prone to inconsistencies, leading to inefficiencies in resource management and market readiness. In pineapple cultivation, determining the optimal harvest time directly impacts yield, fruit quality, and economic returns. Environmental factors such as temperature, humidity, and soil conditions, alongside agricultural practices like irrigation and fertilization, significantly influence pineapple development and ripening. Variability in ripeness stages affects fruit flavor, texture, and nutritional content, influencing consumer preferences and market acceptance. Improper timing of harvest can result in premature or overripe fruits, leading to financial losses for farmers and processors. The challenges in accurately assessing fruit ripeness manually are manifold. Firstly, subjective judgment in visual assessment can vary widely among individuals, leading to inconsistent results. Secondly, the process is time-consuming

History: Received: 23 December 2024; Revised: 27 January 2025; Accepted: 29 January 2025; Published: 15 February 2025
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and labor-intensive, particularly in large-scale agricultural operations. Thirdly, factors such as variations in fruit size, shape, and external appearance can further complicate accurate ripeness assessment, necessitating more objective and efficient methodologies.

Recent advancements in image processing technologies have revolutionized fruit ripeness assessment. These systems leverage digital imaging and machine learning algorithms to automate the analysis of fruit characteristics. By capturing and analyzing digital images, these technologies can detect subtle differences in color, texture, and size indicative of ripeness stages [1]. This automation enhances accuracy, efficiency, and consistency in fruit grading and sorting processes, thereby improving overall productivity and market competitiveness. A variety of machine learning algorithms have been applied to fruit ripeness assessment, including Support Vector Machines (SVM), Random Forests, and Convolutional Neural Networks (CNN). CNNs have emerged as particularly effective in image-based tasks due to their ability to extract intricate features directly from pixel data. CNN-based methods enhance accuracy such as in robotics localization with AMCL+CNN and in skin cancer detection using GoogLeNet, achieving superior results in both applications [2, 3]. This capability allows CNNs to robustly classify complex patterns in fruit images, enhancing accuracy and adaptability across different fruit types and environmental conditions [4]. CNNs offer significant advantages in fruit ripeness classification due to their hierarchical architecture and feature extraction capabilities. These networks excel in handling large datasets and learning complex patterns, making them well-suited for real-time applications in agricultural settings [5]. YOLOv8 represents a cutting-edge approach in object detection, known for its real-time capabilities and high accuracy in identifying and classifying objects within images. Integrating YOLOv8 with CNNs enhances the speed and precision of fruit ripeness assessment, enabling rapid detection and classification of ripeness stages in pineapples and other fruits [6]. Implementation of CNN as part of deep learning continues to evolve in various research studies for detecting digital image [7, 8].

Several studies have explored YOLO's real-time object detection and classification capabilities for fruit ripeness assessment. YOLOv8, known for its high-speed processing and accuracy, has been successfully implemented for detecting and classifying fruits across various ripeness stages. For instance, research Wang [9] leveraged YOLOv8 to automate fruit ripeness detection, testing the model on a dataset labelled by ripeness stage. The study highlighted YOLOv8's accuracy and real-time processing as beneficial for agricultural applications, helping optimize harvest timing and reduce waste. Another study Patel [10] directly compared YOLO's performance to CNNs, finding that while CNNs were accurate, YOLO's speed and real-time feedback made it more suitable for immediate agricultural applications. Research Li and Chen [11] specifically applied YOLOv8 to classify pineapple ripeness, demonstrating the model's effectiveness in distinguishing between various ripeness stages, which underscores YOLOv8's utility in practical agricultural processes like sorting and quality control. Additionally, studies by Wang and Zhang [12] further emphasized YOLOv8's efficiency and accuracy in fruit ripeness assessment, proposing that YOLOv8 can significantly enhance automation in agriculture, thus supporting sustainable harvesting practices.

Another study Reddy and Reddy [13] proposed a similar hybrid model, combining YOLOv8 for locating fruits and CNN for classifying ripeness. This model achieved an accuracy of 95%, supporting effective harvesting and post-harvest processes by reducing waste and improving crop quality. Research on mango ripeness detection [14] also illustrated the benefits of merging YOLO's real-time detection with CNN's feature extraction, which showed promising results for practical applications in agriculture. Furthermore, studies such as Wang [15] on strawberry classification used YOLOv8+ with CNN to capture fine details, demonstrating the integrated model's ability to adapt to complex environmental variations.

Several studies have applied YOLOv8 and CNN specifically for classifying the ripeness of various fruits under diverse conditions, including pineapples. For example, research by Li and Chen [11] focused on training YOLOv8 to classify pineapple ripeness stages, achieving high accuracy across different ripeness levels, which validates YOLOv8's potential for use in quality control and efficient

Edelweiss Applied Science and Technology
ISSN: 2576-8484
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sorting in pineapple production. Additional research Kumar [16] extended the application of YOLOv8 to other fruits, underscoring the model's ability to handle datasets curated for distinct ripeness stages. The use of YOLOv8 and CNN combined in specialized contexts such as mango ripeness detection [14] and cherry ripeness assessment [17] further highlights the effectiveness of these models in specific agricultural applications, enhancing precision and robustness in real-world scenarios.

Addressing the limitations of controlled environments in agricultural applications, some studies focused on improving YOLOv8 and CNN adaptability to real-world conditions, including variations in lighting and background complexity. For instance, Xiao, et al. [18] developed an enhanced YOLOv8 model that demonstrated superior speed and accuracy under variable conditions, incorporating modules such as CSP and C2f for lightweight processing. Another study You [17] introduced an improved YOLOv8 with attention mechanisms to enhance detection in natural cherry fruit environments, achieving precision rates over 98%. Research by Wang [15] also adapted YOLOv8 for strawberry detection using Focal-EIOU loss to boost performance under diverse environmental conditions. These enhancements underscore the ongoing need to refine YOLO and CNN models to meet the dynamic requirements of agricultural settings, ultimately increasing their robustness and applicability.

Despite the significant advancements in the application of machine learning algorithms, particularly YOLOv8 and Convolutional Neural Networks (CNNs), for fruit ripeness classification, many existing studies have primarily utilized datasets that are limited in scope and collected under highly controlled conditions. These controlled environments do not accurately reflect the variability and challenges present in real-world agricultural settings. Moreover, there is a notable deficiency in research dedicated to investigating how these models can be effectively adapted to function under diverse environmental conditions. This includes factors such as varying natural lighting, which can affect image quality, and heterogeneous backgrounds that can introduce noise and complicate the detection and classification processes. Addressing these gaps is essential to develop robust, adaptable, and practical solutions for automated fruit ripeness assessment that can be reliably deployed in dynamic agricultural environments.

While significant progress has been made in applying machine learning techniques, such as YOLOv8 and Convolutional Neural Networks (CNNs), to the classification of fruit ripeness, many studies have relied on limited datasets collected in controlled environments. These controlled settings fail to represent the complexities and variability of real-world agricultural conditions. Furthermore, there is a lack of comprehensive research exploring the adaptation of these models to diverse environmental factors, including variations in natural lighting and complex, variable backgrounds. This gap highlights the need for further investigation to enhance the robustness and versatility of these models, ensuring their effectiveness in practical, real-world applications within the agricultural industry.

Based on various studies recommending increased use of YOLOv8 for fruit ripeness classification through CNN, this research also developed the algorithm to determine the ripeness level of pineapples. This study aims to develop and evaluate a pineapple ripeness classification system using CNN with YOLOv8. The research focuses on enhancing the efficiency of harvest operations, improving quality control measures, and reducing losses associated with improper timing. The outcomes of this research are expected to optimize pineapple production practices, mitigate economic losses due to suboptimal harvest timing, and strengthen the competitiveness of farmers in local and global markets. By advancing automated ripeness assessment techniques, the study contributes to sustainable agriculture practices and food security, ensuring consistent supply of high-quality produce.

2. Research Method

2.1. Data Collection

This research involves data collection, preprocessing, modeling, and testing, applying the YOLOv8 algorithm for object detection and CNN for classification on an annotated pineapple photo dataset with four ripeness labels, evaluated across 50 epochs. Data collection was conducted through field observations and interviews with pineapple farmers in Kotamobagu, resulting in a dataset of 592 photos

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labeled as Unripe, Half-Ripe, Ripe, and Overripe. Specifically, the dataset included 150 images of Unripe, 150 of Half-Ripe, 150 of Ripe, and 142 of Overripe pineapples. Each image was taken in a resolution of 1920x1080 pixels under varying environmental conditions to represent diverse real-world settings, including different lighting conditions and angles. The images were captured with a high-resolution DSLR camera to ensure quality. Data augmentation techniques such as rotation (up to 30°), horizontal flipping, cropping, and scaling were applied to enhance the dataset, increasing the diversity of training samples. This resulted in a post-augmentation dataset size of over 1,200 images, providing a robust foundation for model learning.

Labeling criteria for pineapple ripeness included various visual indicators. Unripe pineapples had dark green skin, a hard texture, no sweet aroma, and prominent eyes. Half-Ripe pineapples showed a transition from green to yellow skin, a slightly soft texture, a faint sweet aroma, and slightly flattened eyes. Ripe pineapples were mostly yellow-skinned, with a soft texture, a strong sweet aroma, and nearly flat eyes. Overripe pineapples had yellow to yellow-brown skin, a very soft texture, a strong sweet aroma with possible fermentation hints, and fully flattened or sunken eyes. These labels were validated through expert analysis to maintain labeling consistency.

The data collected had high quality and represented a diversity of environmental conditions, which was important for the machine learning model. The use of data augmentation techniques effectively expanded the dataset and added additional variations that helped the model learn better. Experience from previous research showed that datasets of similar size had yielded adequate results for similar tasks. Additionally, the evaluation and validation of the model were well-conducted with this dataset, ensuring the model did not overfit. Computational efficiency was also an important consideration, as a dataset of this size allowed model training to be carried out with limited resources. Therefore, the 592 manually labeled photos provided adequate representation for each stage of pineapple ripeness necessary for a reliable learning model.

The dataset was divided into three subsets to facilitate effective training, validation, and testing. The largest portion, 486 images, was allocated to the Training Set to enable the model to learn and recognize visual patterns for each ripeness stage. To evaluate model performance during training and fine-tune its parameters, 70 images were set aside for validation. This Validation Set assists in monitoring accuracy and adjusting the training process to prevent overfitting. The Test Set of 36 images was used for unbiased model performance evaluation, confirming its capability to detect and classify pineapple ripeness in real-world scenarios. This systematic dataset division enhances the model's reliability and effectiveness.

2.2. Modelling Process

Data modeling used CNNs for deep learning classification. YOLOv8, which uses CNN as its backbone, processes images to detect objects in one stage, making it faster than traditional two-stage models [19]. YOLOv8 was employed for object detection, while CNN handled classification. YOLOv8 detects the object in the image, and CNN classifies its ripeness stage. Testing evaluated the model's accuracy in identifying pineapple ripeness using metrics such as Mean Average Precision (mAP), Precision, Recall, and F1-Score. Performance metrics such as mAP, Precision, Recall, and F1-Score are utilized in this study to measure the accuracy and balance of YOLOv8 and CNN models in identifying pineapple ripeness from images. These metrics provide an objective evaluation of the models' precision, detection capabilities, and reliability in this task. Figure 1 shows the workflow stages of the program implementing YOLOv8 detection and CNN classification.

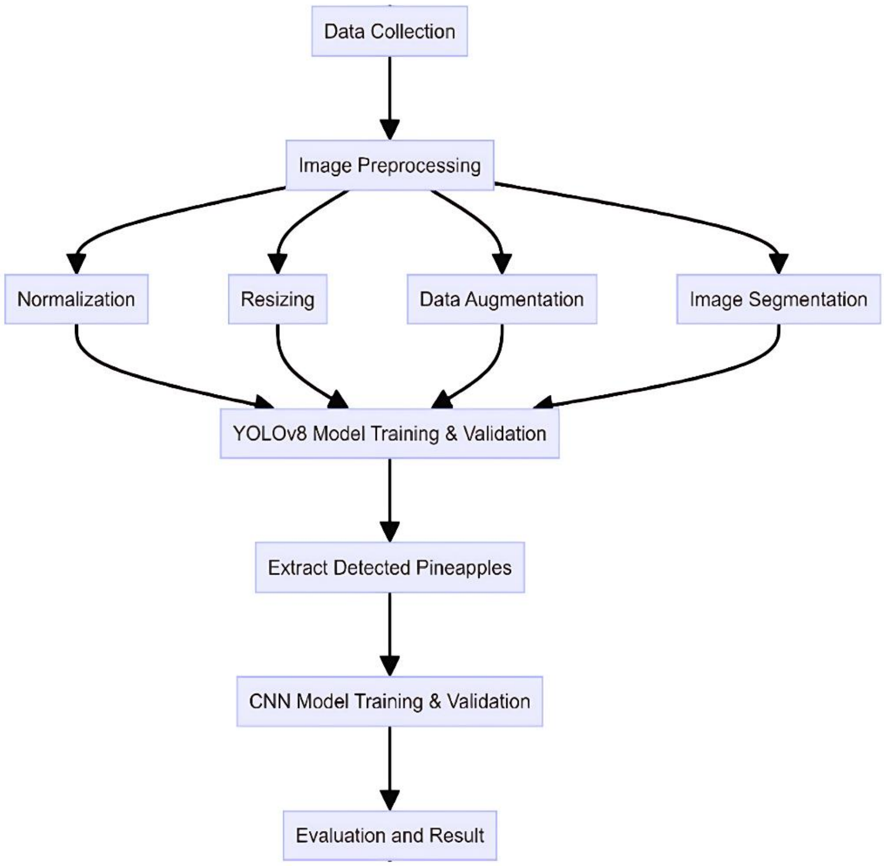

Figure 1.
Program flowchart.

Based on Figure 1, the process begins with data collection, where images of pineapples at various ripeness stages are gathered along with related metadata, such as lighting conditions and angles. This step ensures a diverse and representative dataset. Next, the images undergo preprocessing, which includes several sub-processes to enhance their quality and usability. Normalization adjusts the pixel values of the images to a standard range, such as [0, 1] or [-1, 1], which helps stabilize the training process and improve model convergence. Resizing ensures all images are of uniform size, consistent with the requirements of the YOLOv8 model, which is crucial for neural network training. Data augmentation applies transformations such as rotation (up to 30°), flipping, cropping, and scaling to the images, increasing the diversity of the training dataset and reducing overfitting by simulating variations. Optionally, image segmentation isolates the regions of interest (the pineapples), depending on the quality of the images and the specific requirements of the YOLOv8 model. With preprocessed data, the YOLOv8 model undergoes training and validation. The dataset is split into training and validation sets, and the YOLOv8 model is trained to detect pineapples in the images. Model validation ensures accurate pineapple detection. Detected pineapples are then extracted using the bounding boxes predicted by the YOLOv8 model, cropping the relevant regions from the images. These cropped images are preprocessed, if necessary, tailored to the CNN model's requirements. The CNN architecture included three convolutional layers for feature extraction, each followed by 2x2 max-pooling layers to reduce spatial dimensions. Two fully connected layers perform final classification. The model trained for 50 epochs with a learning rate of 0.001. This architecture supports high-speed classification across various ripeness classes, integrating well with YOLOv8's efficient detection process.

In this study, To train data using Roboflow and Pycharm with Ultralytics YOLOv8. A CNN with convolutional and pooling layers was employed alongside the YOLOv8 architecture, known for its superior object detection performance. The CNN model integrated features such as Feature Pyramid Networks (FPN) for multi-scale object detection. YOLOv8 excels in efficiency by performing object detection in a single pass through the network, making it suitable for applications requiring rapid and accurate object detection in images. The model is continually refined with optimizations aimed at improving speed and accuracy, maintaining its relevance across various real-world scenarios.

YOLOv8 is an object detection model that builds upon the principles of previous YOLO versions but with improvements in accuracy and efficiency. In the YOLOv8 stages, there are several calculation steps, including bounding box prediction, confidence score, class prediction, and loss function. In the bounding box prediction, each grid cell predicts B bounding boxes and confidence scores for those boxes. A bounding box is defined by:

$$Bounding\ Box = (x, y, w, h) \qquad (1)$$

Where (x, y) is the center of the box relative to the bounds of the grid cell, and w and h are the width and height of the box relative to the entire image. In the confidence score, each bounding box has a confidence score that reflects the probability that the box contains an object and the accuracy of the bounding box. The confidence score is defined as:

$$Confidence = P\ (Object) x\ IOU_{pred,truth} \qquad (2)$$

Where $P(Object)$ is the probability of an object being present in the box and $IOU_{pred,truth}$ is the Intersection over Union between the predicted box and the ground truth box. In the class prediction, each grid cell also predicts C conditional class probabilities. The final prediction score for each class is:

$$Class\ Score = P(\ Object) x\ Confidence \qquad (3)$$

Where $P(\ Object)$ is the conditional class probability given that an object is present. The YOLO loss function combines classification loss, localization loss (error between predicted bounding box and ground truth), and confidence loss (objectness score):

$$\begin{aligned} Loss = \lambda_{\text{coord}} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_{ij}^{obj} \ \left[(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + (w_i - \hat{w}_i)^2 + \left(h_i - \hat{h}_i\right)^2\right] \\ + \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_{ij}^{obj} \left(\hat{C}_i - C_i\right)^2 + \lambda_{\text{noobj}} \sum_{i=0}^{s^2} \sum_{j=0}^{B} 1_{ij}^{noobj} \left(\hat{C}_i - C_i\right)^2 \\ + \sum_{i=0}^{s^2} 1_{i}^{obj} \sum_{c \in \text{ classss}} (p_i(c) - \hat{p}_i(c))^2 \end{aligned} \qquad (4)$$

Where λ_{coord} and λ_{noobj} are constants that determine the weight of the coordinate loss and the no-object confidence loss. The CNN model is then trained and validated using the cropped images to classify the ripeness of the pineapples. This step involves training the CNN model and validating its accuracy in classifying the ripeness stages. CNNs are used for image classification tasks and consist of several layers, including convolutional layers, pooling layers, and fully connected layers [20].

ISSN: 2576-8484
Vol. 9, No. 2: 1528-1543, 2025
DOI: 10.55214/25768484.v9i2.4802

In the convolutional layer, the convolution operation involves applying a filter to an input to produce activation map:

$$Activation\ Map\ (i,j) = (X * W)(i,j) = \sum_m \sum_n X(i+m, j+n)\ \cdot W(m,n) \quad (5)$$

Where X is the input matrix, W is the filter matrix, and (i,j) are the coordinates of the activation map. Then, the activation function (ReLU), the Rectified Linear Unit (ReLU) is commonly used to introduce non-linearity:

$$ReLU(x) = max\ (0, x) \quad (6)$$

In the pooling layer reduce the spatial dimensions of the input, commonly using max pooling:

$$Max\ \ Pool\ (i,j) = \max_{m,n}(X(i+m, j+n)) \quad (7)$$

Where (i, j) are the coordinates in the pooling window. In the fully connected layers connect every neuron in one layer to every neuron in another layer, typically represented as:

$$Output = W\ \cdot x + b \quad (8)$$

Where W is the weight matrix, x is the input vector, and b is the bias vector. In the loss function (Cross-Entropy Loss), it is used for classification tasks [21] the cross-entropy loss is commonly used:

$$L = -\sum_i y_i \log(\hat{y}_i) \quad (9)$$

Where y_i is the true label, and $y\hat{}_i$is the predicted probability for class i. The overall performance of the integrated YOLOv8 and CNN pipeline is then evaluated using metrics such as accuracy, precision, recall, and F1-score. A detailed report of the classification results is generated. Finally, the process concludes, having successfully processed and classified the pineapple images.

3. Result and Discussion

In this research, the YOLOv8 algorithm was successfully implemented to automatically detect and classify the ripeness levels of pineapples. The process involved training a model using a meticulously annotated dataset of pineapple images, categorized into four distinct ripeness stages: Unripe, Half-Ripe, Ripe, and Overripe. The annotations were crucial in enabling the model to learn and recognize the visual cues associated with each ripeness level. The implementation and evaluation of the model were carried out through a series of comprehensive tests. Initially, the dataset was trained using the PyCharm development environment, where the trained model was subsequently tested on various media types. This included static photos, recorded videos, and live feeds from a webcam. These tests aimed to assess the model's performance in different scenarios and ensure its robustness in practical applications.

In addition to the PyCharm tests, the model was also evaluated using the Roboflow platform. On Roboflow, the model underwent further testing with additional photo and video data. This dual-platform approach allowed for a thorough examination of the model's capabilities and provided insights into its accuracy and reliability across different data sources and testing environments. The extensive testing confirmed the effectiveness of the YOLOv8 algorithm in detecting and classifying pineapple ripeness levels accurately. The successful implementation demonstrated the potential for automating the assessment of fruit ripeness, which could be beneficial for farmers and the agriculture industry by providing a reliable and efficient tool for determining the optimal harvest time and ensuring fruit quality.

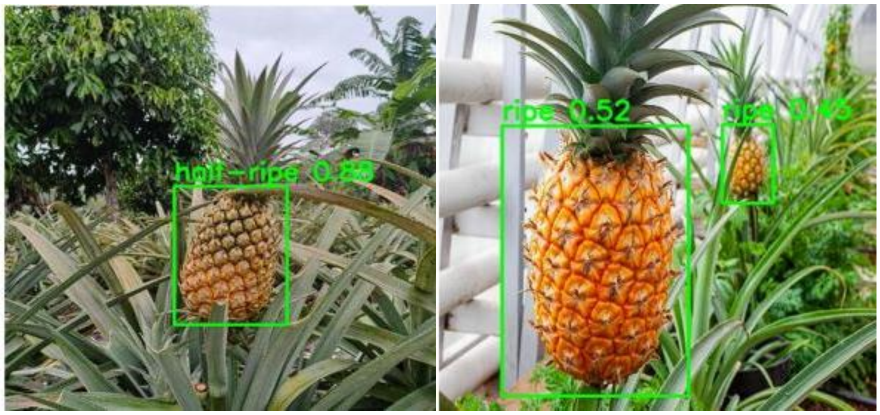

Figure 2.
Implementation with Pycharm Ultralytics YOLOv8.

In Figure 2, the comparison of pineapple ripeness classification based on digital images with various backgrounds and light intensities revealed intriguing results. The evaluation conducted through PyCharm involved rigorous testing with a range of confidence thresholds. This process identified four distinct ripeness labels. Each image that was successfully detected, despite noise, varying light conditions affecting color intensity, or diverse backgrounds, enabled the system to display the classification of pineapple ripeness along with its confidence score. Additionally, by leveraging the real-time webcam capabilities within PyCharm, the system achieved a commendable confidence score. This allowed for accurate classification of the pineapple as unripe, half-ripe, ripe, and overripe, showcasing the system's robustness in dynamic real-world scenarios. These findings underscored the effectiveness of the YOLOv8 algorithm in precise fruit ripeness assessment, highlighting its practical applicability in agricultural and consumer contexts.

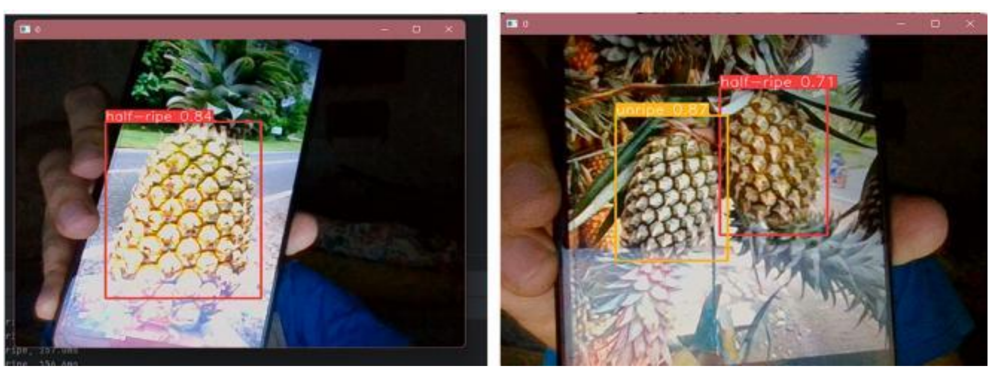

Figure 3.
Implementation with Pycharm Ultralytics YOLOv8 and Roboflow in realtime.

In Figure 3 shows an example of real-time detection of pineapple ripeness using PyCharm and Roboflow. In this sample, despite the significant influence of background and lighting conditions, the classification still yields results with certain confidence values.

ISSN: 2576-8484
Vol. 9, No. 2: 1528-1543, 2025
DOI: 10.55214/25768484.v9i2.4802

Figure 4.
Implementation with Pycharm Ultralytics YOLOv8 and Roboflow in video.

In Figure 4, which comprised two images—one from video data and the other from a photograph—the process of digital image identification was employed using the Roboflow application to classify the ripeness levels of pineapples. The classification yielded various confidence values, ultimately assigning a single ripeness label. Moreover, an image of a pineapple with a confidence score was identified as being categorized. Additionally, the study involved selecting samples data points from the training dataset as detailed in Table 1.

DOI: 10.55214/25768484.v9i2.4802

Table 1.
Training result.

Epoch	Train/box_ loss	Train/ cls_loss	Train/dfl_ loss	Metrics/precision(B)	Metrics/ recall(B)	Metrics/ mAP50(B)	Metrics/mAP50-95(B)	Val/ Box_Loss	Val/ Cls_Loss	Val/ Dfl_Loss	Lr/pg 0	Lr/pg 1	Lr/pg 2
1	3.010	4.660	4.221	0.0003	0.072	0.0002	8e-05	2.512	4.735	4.116	0.00040984	0.00040984	0.00040984
2	2.975	4.294	3.971	0.0008	0.211	0.022	0.007	2.410	4.521	3.921	0.00081014	0.00081014	0.00081014
3	2.935	3.843	3.650	0.434	0.327	0.201	0.082	2.579	8.549	3.432	0.0011939	0.0011939	0.0011939
10	2.076	2.685	2.689	0.370	0.478	0.416	0.230	1.735	2.435	2.521	0.0010273	0.0010273	0.0010273
11	2.083	2.679	2.675	0.429	0.480	0.417	0.189	1.724	2.506	2.519	0.0010025	0.0010025	0.0010025
12	2.043	2.586	2.619	0.364	0.573	0.474	0.257	1.795	2.612	2.625	0.00097775	0.00097775	0.00097775
20	1.762	2.106	2.308	0.469	0.592	0.583	0.342	1.489	2.034	2.245	0.0007797	0.0007797	0.0007797
21	1.788	2.122	2.314	0.559	0.667	0.633	0.359	1.531	1.746	2.259	0.000755	0.000755	0.000755
22	1.714	1.991	2.267	0.543	0.654	0.618	0.366	1.517	1.783	2.249	0.00073025	0.00073025	0.00073025
30	1.602	1.854	2.127	0.607	0.758	0.676	0.411	1.388	1.586	2.110	0.00053225	0.00053225	0.00053225
31	1.633	1.826	2.141	0.578	0.795	0.687	0.408	1.463	1.465	2.165	0.0005075	0.0005075	0.0005075
32	1.584	1.736	2.097	0.561	0.653	0.639	0.395	1.439	1.624	2.137	0.00048275	0.00048275	0.00048275
40	1.507	1.641	2.044	0.655	0.863	0.729	0.438	1.432	1.375	2.127	0.00028475	0.00028475	0.00028475
41	1.415	1.543	2.089	0.580	0.809	0.680	0.436	1.403	1.382	2.077	0.00026	0.00026	0.00026
42	1.365	1.472	2.021	0.624	0.846	0.719	0.458	1.349	1.385	2.018	0.00023525	0.00023525	0.00023525
50	1.279	1.301	1.936	0.644	0.873	0.754	0.478	1.345	1.263	2.021	3.725e-05	3.725e-05	3.725e-05

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At the final epoch, the results in Table 1 indicate that the YOLOv8 model performs well in detecting and classifying objects within images. The Train/Box_Loss (1.279) and Train/Cls_Loss (1.301) values demonstrate the model's ability to recognize object positions and classes with moderate error levels. Additionally, the precision score of 0.644 indicates that approximately 64.4% of the model's positive predictions are correct, while the high recall of 0.873 reflects strong sensitivity, meaning the model successfully detects most objects in the images. The mAP@0.5 value of 0.754 confirms a good overall accuracy at a moderate overlap threshold, whereas the mAP@0.5:0.95 value of 0.478 shows satisfactory performance under stricter overlap conditions. In the validation data, the loss metrics (Val/Box_Loss, Val/Cls_Loss, and Val/Dfl_Loss) are consistent with the training results, indicating that the model does not suffer from overfitting and is thus expected to perform well on new data. With a small and stable learning rate of 3.725e-05, the model learns at a controlled pace, helping maintain a balance between accuracy and generalization. Overall, the YOLOv8 model shows significant potential for object detection applications, with strong recall and map values, although there remains room for improving precision to enhance classification accuracy. The visualizations provide further insights into the system's performance. Additionally, throughout the training and testing process across each epoch, the system shows progress and performance improvements, which are illustrated in Figure 5.

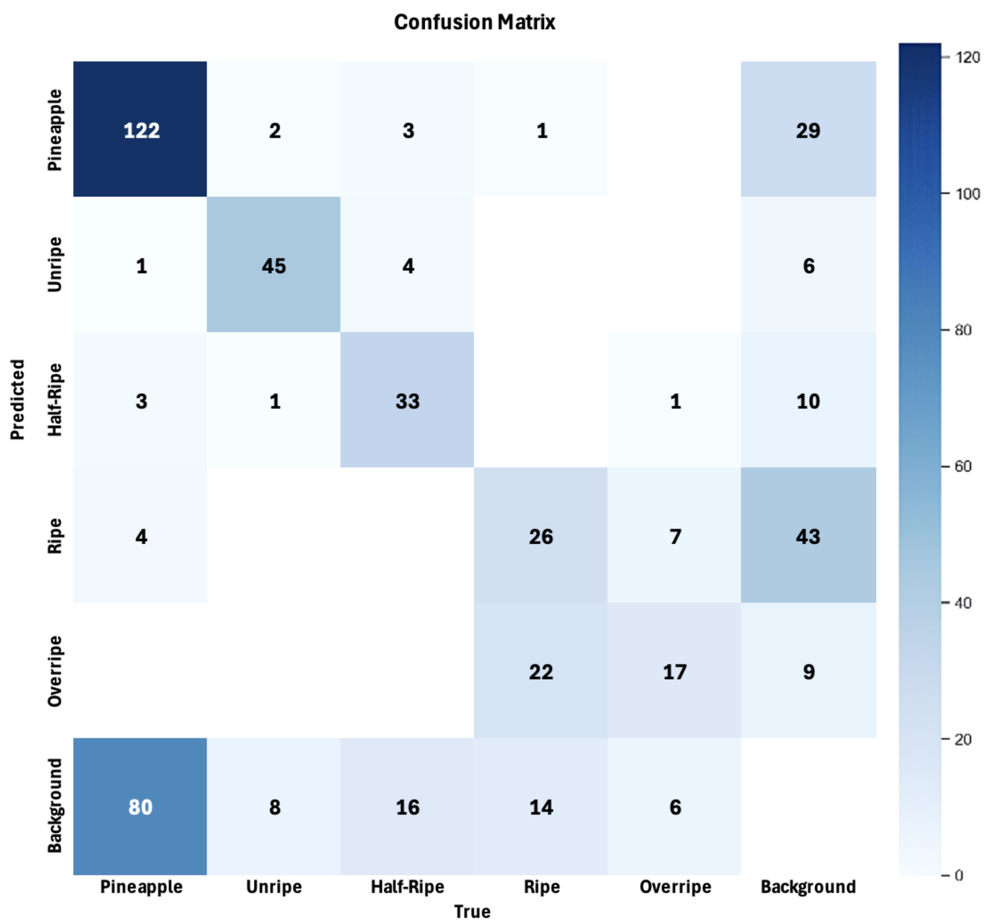

Figure 5.
Confusion matrix normalized.

The confusion matrix depicted in Figure 5 serves as a crucial evaluation tool, offering a detailed comparison between the actual classifications of pineapple ripeness levels and the predictions generated by the YOLOv8 model. This matrix provides a comprehensive breakdown of how well the model performs across different ripeness categories—Unripe, Half-ripe, Ripe, and Over-ripe. Each cell in the matrix represents the count of observations where the model correctly or incorrectly classified pineapples into these categories. By analyzing this matrix, researchers can assess the model's accuracy, precision, recall, and overall effectiveness in accurately identifying the ripeness stage of pineapples based on the visual cues captured in the dataset.

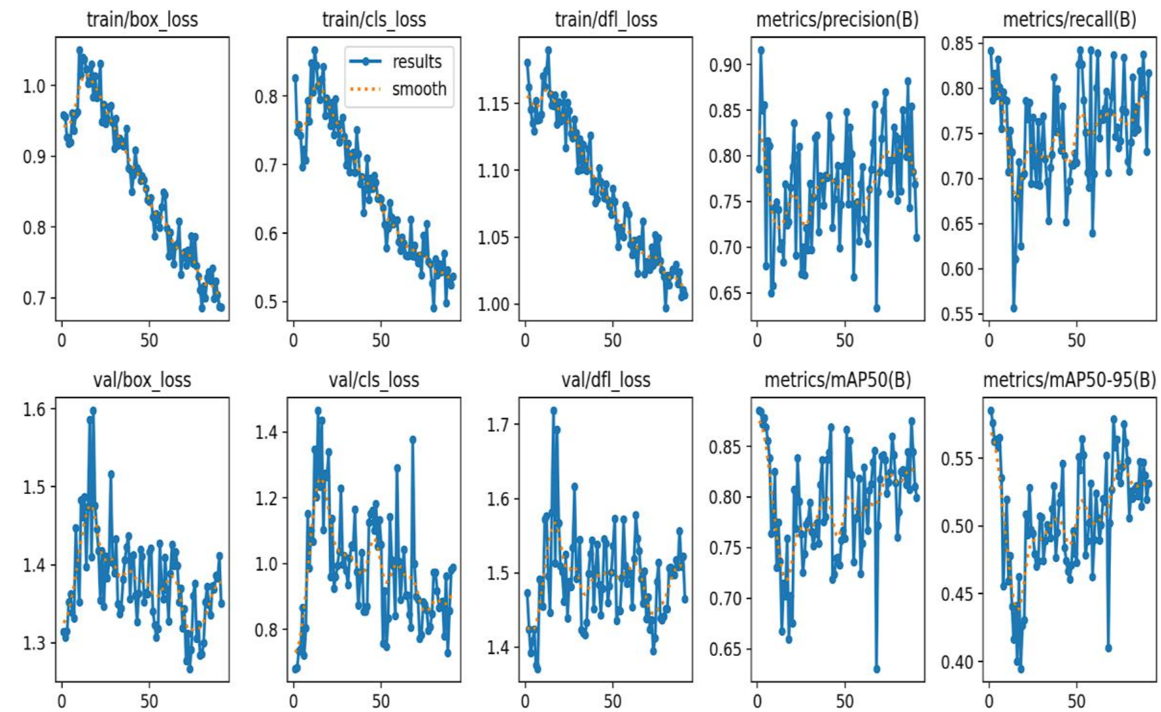

Figure 6.
Diagram mAP result.

The map diagram presented in Figure 6 offers a comprehensive visualization of the model's performance across varying IoU thresholds, showcasing the intricate balance between recall and precision in object detection tasks. In the provided image, the x-axis in each plot represents the number of epochs or training steps, indicating the training progression over time. The y-axis varies by plot: for loss metrics (train/box_loss, train/cls_loss, train/dfl_loss, val/box_loss, val/cls_loss, and val/dfl_loss), it shows the loss values, which measure the model's error; for performance metrics (metrics/precision(B) and metrics/recall(B)), it represents the precision and recall scores, assessing accuracy and detection coverage; and for metrics/mAP@0.5 and metrics/mAP@0.5:0.95, the y-axis indicates mean Average Precision (mAP) at different IoU thresholds, reflecting prediction accuracy across varying levels of overlap requirements. IoU, or Intersection over Union, serves as a critical metric that quantifies the spatial overlap between predicted bounding boxes and ground truth annotations. By incrementally adjusting the IoU threshold from 0 to 1, researchers can analyze how the model's precision and recall metrics evolve. Typically, as the IoU threshold increases, the model becomes more stringent in its detection criteria, leading to higher precision but potentially lower recall, as fewer predictions meet the stricter overlap criterion. Conversely, lowering the IoU threshold can increase recall by capturing more instances but might sacrifice precision due to increased false positives.

ISSN: 2576-8484
Vol. 9, No. 2: 1528-1543, 2025
DOI: 10.55214/25768484.v9i2.4802

This curve provides valuable insights into the model's robustness and effectiveness in detecting pineapple ripeness levels across different IoU thresholds. It enables researchers to make informed decisions about model configuration and optimization, aiming to strike a balance that aligns with specific application requirements, whether prioritizing precision, recall, or a trade-off between both metrics. The visual representation in Figure 6 aids in understanding how changes in IoU thresholds impact the overall performance and reliability of the YOLOv8 model in fruit ripeness assessment tasks.

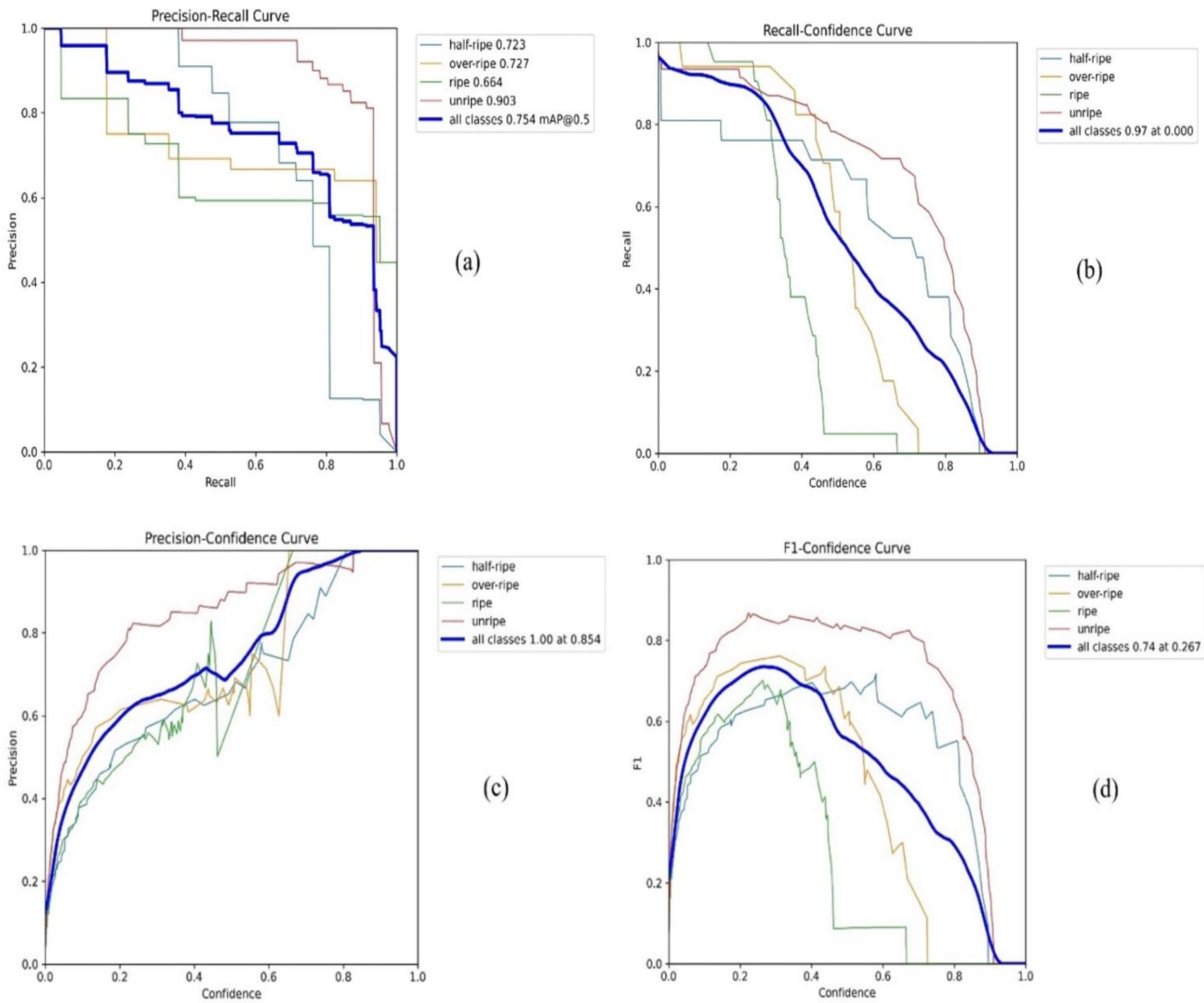

Figure 7.
Testing parameter correlation curve.

Figure 7 illustrated the relationships among key testing parameters in the YOLOv8-based pineapple ripeness detection model, offering insights into model performance across different thresholds. In the Precision-Recall Curve (a), the x-axis represents recall, and the y-axis represents precision, showing the balance between correctly identified positives and true positives detected. The Recall-Confidence Curve (b) plots recall on the y-axis against varying confidence levels on the x-axis, indicating model sensitivity across different confidence thresholds. Similarly, the Precision-Confidence Curve (c) has precision on the y-axis and confidence on the x-axis, reflecting accuracy in positive detections at different confidence levels. Lastly, the F1-Confidence Curve (d) shows the F1 score on the y-axis against confidence on the x-axis, providing a balanced view of precision and recall across

Edelweiss Applied Science and Technology
ISSN: 2576-8484
Vol. 9, No. 2: 1528-1543, 2025
DOI: 10.55214/25768484.v9i2.4802

confidence levels, underscoring the importance of optimizing confidence thresholds to enhance overall model performance.

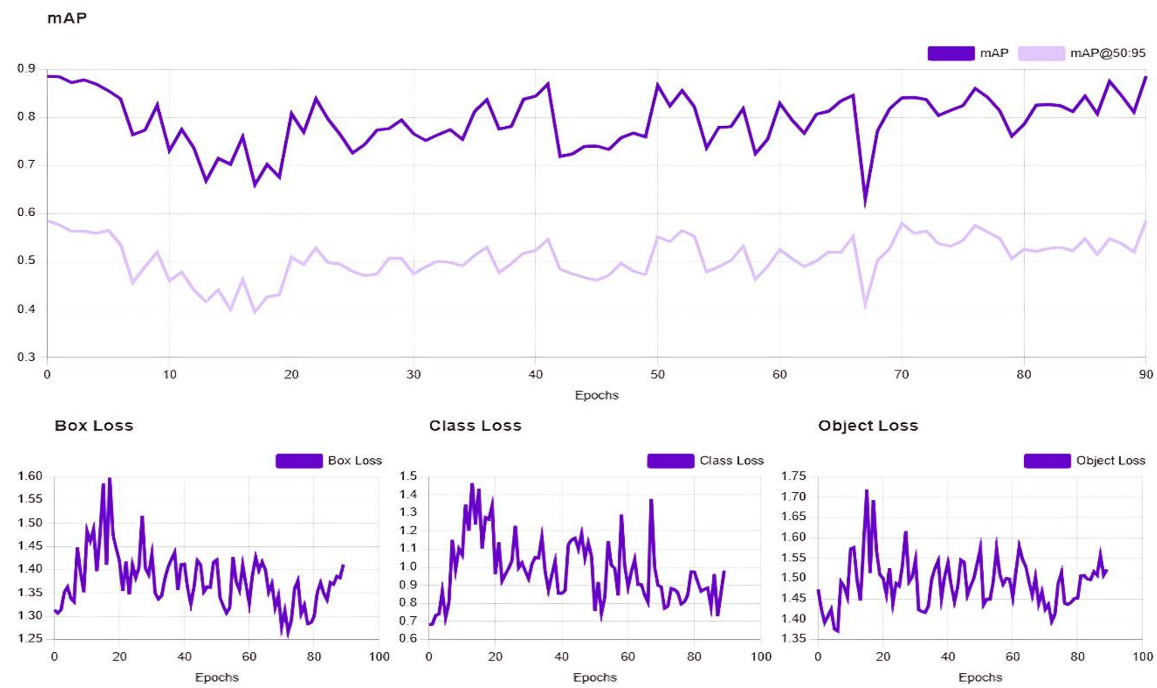

Figure 8.
Diagram mAP result in roboflow.

Figure 8 showed the performance measurement results of the algorithm with an map of 88.5%, precision of 78.4%, and recall of 84.2%. The application of the YOLOv8 algorithm for detecting and classifying pineapple ripeness showed promising results, as evidenced by the performance metrics achieved. These results demonstrated the model's ability to effectively distinguish between various stages of pineapple ripeness, consistent with the findings of previous studies discussed in the introduction. As reviewed in the literature, various studies highlighted the advantages of CNNs and object detection algorithms like YOLO in improving the accuracy and efficiency of fruit ripeness assessment. The application of CNNs in image-based tasks proved to be highly effective, particularly in fruit classification, where the accuracy achieved was very high. Similarly, this study reaffirmed the ability of CNNs to process pineapple images and classify their ripeness stages with high precision. YOLOv8, with its real-time object detection capabilities, was employed in various studies to enhance the speed and accuracy of fruit ripeness detection. This study also showed that YOLOv8 could quickly and accurately identify pineapple ripeness stages, which aligned with previous findings regarding the advantages of YOLOv8 in object detection tasks across various environmental conditions.

The study's findings align with and expand upon previous research. YOLOv8's real-time object detection has been widely recognized for accuracy and speed across various agricultural applications, as reviewed in Li and Chen [11] and Wang and Zhang [12]. The model's performance on pineapple ripeness classification confirms its utility for agricultural automation, with results that echo those of similar studies using CNN and YOLO for fruit ripeness classification under controlled conditions. This research, however, uniquely demonstrates that YOLOv8 performs consistently across variable environmental conditions, addressing a significant gap noted in prior studies which operated in controlled settings.

However, the results of this study also revealed challenges, particularly related to the variation in the dataset. This aligned with criticisms in previous studies that many investigations were conducted in controlled environments that did not fully reflect the complexity and variability of real-world agricultural conditions. This challenge underscored the importance of using high-quality data and high-performance imaging devices to enhance the reliability of real-time applications. Additionally, this study emphasized the importance of parameter optimization in achieving robust detection and classification capabilities. As suggested in previous literature, using data augmentation techniques and transfer learning could help overcome dataset limitations and improve the model's adaptability to diverse environmental conditions. In this context, this study contributed to our understanding of the application of YOLOv8 for fruit ripeness assessment, particularly for pineapples, and identified areas that required further improvement. By combining the findings from this study and existing literature, it could be concluded that while YOLOv8 showed significant potential for practical agricultural applications, improvements in data quality and better model optimization techniques were still needed to achieve optimal results in various environmental conditions. This study aimed to develop and evaluate a pineapple ripeness classification system using CNN with YOLOv8, focusing on enhancing harvest operation efficiency, improving quality control measures, and reducing losses associated with improper timing. The outcomes of this research could optimize pineapple production practices, reduce economic losses, and increase the competitiveness of farmers in local and global markets. By advancing automated ripeness assessment techniques, this study contributed to sustainable agricultural practices and food security, ensuring a consistent supply of high-quality produce.

4. Conclusion

This research successfully demonstrated the effectiveness of the YOLOv8 algorithm in automating pineapple ripeness detection and classification, achieving a high level of accuracy across multiple ripeness stages (Unripe, Half-Ripe, Ripe, and Overripe). Through extensive testing in varied environments and media (static images, videos, and real-time webcam feeds), the model attained commendable performance metrics, including an map of 88.5%, precision of 78.4%, and recall of 84.2%. These results validate the potential of YOLOv8 for practical applications in agriculture, specifically in enhancing the efficiency of harvest operations and improving quality control in fruit production.

However, to further advance this field, future research should address the challenges posed by environmental variability—such as changes in lighting and background conditions—that can affect model accuracy in real-world settings. It is suggested that future studies consider expanding the dataset with diverse environmental conditions and employing techniques like data augmentation and transfer learning to improve model adaptability. Additionally, investigating the use of higher quality imaging devices or integrating additional sensory data could further enhance detection reliability. By building on these findings, subsequent research can contribute to developing more robust and scalable solutions for automated ripeness assessment, ultimately supporting sustainable agricultural practices and strengthening food supply chains.

Funding:

Gratitude is expressed by the authors for the funding provided by the university during the preparation, data processing, and publication of this research.

Transparency:

The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Competing Interests:

The authors declare that they have no competing interests.

Authors' Contributions:
All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

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