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Mobile-Based Real-Time Ornamental Rose Classification System Using YOLOv8 Algorithm on Digital Imagery

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ABSTRACT
This research introduces a mobile-based system for real-time identification of ornamental rose varieties using the YOLOv8 deep learning algorithm. Motivated by the growing interest in ornamental plants during the COVID-19 pandemic and the high penetration of smartphone users in Indonesia, the study aims to create an efficient and accessible flower recognition tool. A dataset of 813 labeled rose images—red, white, yellow, orange, and pink—was collected from the Roboflow platform and processed using data augmentation techniques to improve model generalization. The YOLOv8 model was trained with 100 epochs, a batch size of 16, and the SGD optimizer, then converted to TensorFlow Lite for mobile deployment through the Flutter framework. Experimental results achieved a mean average precision (mAP50–95) of 0.581, with strong detection performance across most classes. The system successfully operated offline, delivering real-time classification accuracy despite dataset imbalance, particularly in the orange rose class. These findings demonstrate that YOLOv8 can be effectively adapted for mobile horticultural applications, offering practical benefits for flower sorting, crop management, and educational use. Future studies are recommended to expand dataset diversity, enhance environmental testing, and explore cloud-based integration for scalable deployment.

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YOLOv8; Rose Classification; Mobile Application; Tensorflow Lite; Horticulture.

1. Introduction

The COVID-19 pandemic significantly reshaped public lifestyles, fostering a growing fascination with ornamental plants as people sought activities that promote calmness and aesthetic enhancement at home. Among various species, roses (Pratiwi *et al*., 2021) have become particularly popular—not only for their visual appeal but also for their distinctive fragrance and symbolic meanings that range from affection to friendship. Their demand continues to rise across multiple industries, including decoration, cosmetics, perfumery, and export. Despite their popularity, differentiating rose varieties such as red, white, yellow, orange, and pink remains challenging. The subtle variations in color tones, petal morphology, and texture often lead to misclassification, even among professionals. Such inaccuracies can affect customer satisfaction, product labeling, and maintenance practices that are specific to each variety. In Indonesia, approximately 209.3 million individuals were active smartphone users by 2023, representing a penetration rate of nearly 89% of the total population (Andalas, 2024). This demographic shift underscores the urgent need for mobile-based recognition systems capable of operating without constant internet

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connectivity. Existing identification systems largely depend on desktop interfaces, manual uploads, or online processing, which limit their efficiency compared to real-time mobile applications (Wani, 2020).

The evolution of deep learning has opened new avenues for addressing this limitation. The YOLOv8 algorithm, introduced by Jocher (2023), has demonstrated notable improvements in accuracy (mAP) and inference speed over its predecessors, particularly YOLOv5, across diverse datasets (Real-time *et al*., 2025; Hidayatullah *et al*., 2025; Lou *et al*., 2023). This advancement enables object detection tasks to be executed effectively even on lightweight mobile platforms. Recent studies also show the efficiency of YOLO-based models in agricultural and botanical applications, enhancing precision in crop monitoring and plant species identification (Siregar & Yusuf, 2023; Chen *et al*., 2024). Building upon these developments, this study develops a mobile-based rose classification system employing the YOLOv8 model. The system is designed to identify five ornamental rose classes in real time using only a smartphone camera, eliminating the need for manual data uploads (Muntiari *et al*., 2024; Nugroho & Nugroho, 2025). By integrating the model into a Flutter-based mobile application, the research seeks to enhance detection efficiency, usability, and on-site classification accuracy. Furthermore, it contributes to the growing implementation of artificial intelligence within horticultural industries, supporting practical applications such as crop monitoring, floral product management, and educational purposes (Kumar *et al*., 2025; Putra & Yoannita, 2024; Zhang & Li, 2024).

2. Methodology

This research applied a structured methodology that integrates data collection, preprocessing, model training, evaluation, and mobile implementation of the YOLOv8 algorithm for real-time classification of ornamental rose varieties. The dataset consisted of 813 labeled images categorized into five rose types—red (191), white (179), yellow (230), orange (39), and pink (174)—sourced from the publicly available Roboflow platform (Putra & Yoannita, 2024). The data were divided into 70% for training, 20% for validation, and 10% for testing. To enhance model robustness and prevent overfitting, several augmentation techniques were applied, including image rotation, horizontal and vertical flipping, brightness adjustment, and Gaussian blur. These preprocessing steps allowed the model to generalize more effectively across diverse lighting and background conditions (Hidayatullah *et al*., 2025; Islam *et al*., 2023). The research workflow is illustrated in Figure 1, depicting the sequential stages from dataset acquisition to system deployment. The process began with data collection, followed by image labeling to identify visual characteristics such as petal structure and color distribution. The labeled data were resized to a consistent dimension of 640×640 pixels, normalized for uniform pixel scaling, and augmented to expand variation within limited classes (Islam *et al*., 2023). The preprocessed dataset was then used to train the YOLOv8 model, chosen for its proven accuracy and computational efficiency compared to previous generations such as YOLOv5 (Lou *et al*., 2023; Zhang & Li, 2024).

During model training, YOLOv8 was optimized using hyperparameters consisting of 100 epochs, a batch size of 16, a learning rate of 0.01, and the stochastic gradient descent (SGD) optimizer. The model was trained to detect and classify roses into five categories by analyzing spatial and chromatic features. The resulting model achieved high recognition consistency and was subsequently converted from its native .pt format to .tflite using the YOLOv8 export function. The TensorFlow Lite format was chosen for its compatibility with Android-based mobile devices and its ability to balance inference speed with memory efficiency through INT8 quantization (Chen *et al*., 2024). A mobile prototype was developed using the Flutter framework and integrated with the TensorFlow Lite plugin, enabling real-time rose detection directly through a smartphone camera (Nugroho & Nugroho, 2025). To evaluate the model's performance, standard object detection metrics were applied, including precision, recall, accuracy, F1-score, and mean average precision (mAP50–95). The evaluation results were visualized using confusion matrices and performance graphs to analyze the learning behavior across different epochs. The outcomes demonstrated that the YOLOv8 model effectively distinguished between rose types, with particularly strong performance in classes with balanced image representation. However, minor misclassifications were observed in visually similar classes, indicating the need for further dataset expansion and augmentation refinements (Islam *et al*., 2023; Lou *et al*., 2023; Siregar & Yusuf, 2023).

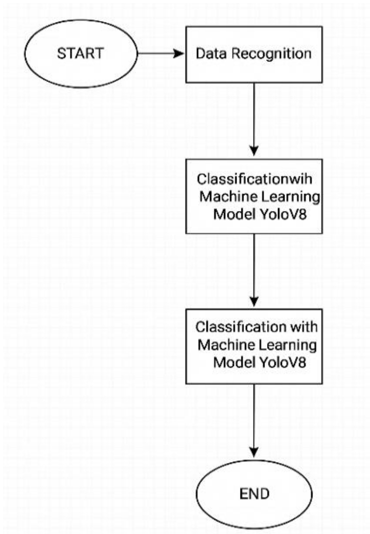


Figure 1. Research Methodology Flow
(Start → Data Recognition → Data Processing → YOLOv8 Training → Object Detection Output → Evaluation → End)

During model training, YOLOv8 was optimized using hyperparameters consisting of 100 epochs, a batch size of 16, a learning rate of 0.01, and the stochastic gradient descent (SGD) optimizer. The model was trained to detect and classify roses into five categories by analyzing spatial and chromatic features. The resulting model achieved high recognition consistency and was subsequently converted from its native .pt format to .tflite using the YOLOv8 export function. The TensorFlow Lite format was chosen for its compatibility with Android-based mobile devices and its ability to balance inference speed with memory efficiency through INT8 quantization. A mobile prototype was developed using the Flutter framework and integrated with the TensorFlow Lite plugin, enabling real-time rose detecion directly through a smartphone camera (*Nugroho & Nugroho, 2025*). To evaluate the model's performance, standard object detection metrics were applied, including precision, recall, accuracy, F1-score, and mean average precision (mAP50–95). The evaluation results were visualized using confusion matrices and performance graphs to analyze the learning behavior across different epochs. The outcomes demonstrated that the YOLOv8 model effectively distinguished between rose types, with particularly strong performance in classes with balanced image representation. However, minor misclassifications were observed in visually similar classes, indicating the need for further dataset expansion and augmentation refinements (*Islam et al., 2023; Lou et al., 2023*).

Table 1. Summary of Rose Dataset Used for Training

Rose Class	Number of Images	Data Split (Train/Val/Test)
Red	191	134 / 38 / 19
White	179	125 / 36 / 18
Yellow	230	161 / 46 / 23
Orange	39	27 / 8 / 4
Pink	174	122 / 35 / 17
Total	813	569 / 163 / 81

Overall, this methodology demonstrates the feasibility of combining deep learning and mobile technologies for horticultural classification. The integration of YOLOv8 within a mobile environment allows efficient and real-time identification of rose varieties, offering practical benefits for growers, distributors, and consumers alike. The results align with findings from previous implementations of YOLOv8 in other recognition domains such as drone-based vegetation monitoring (*Islam et al., 2023*), traffic density analysis (*Hidayatullah et al., 2025*), and facial detection for attendance systems (*Muntiari et al., 2024*), affirming the adaptability of the model across diverse contexts.

3. Results

The dataset used in this study consisted of 813 labeled images of ornamental roses divided into five distinct color classes: red (191), white (179), yellow (230), orange (39), and pink (174). The dataset was obtained from the public repository Roboflow (*Nugroho & Nugroho, 2025*), where each image was annotated with bounding boxes to highlight the primary object. The annotation followed the YOLOv8 directory structure, including the images/ and labels/ folders. Figure 2 illustrates the labeling workflow, while Figure 3 displays examples of annotated images representing each rose class.

Table 1. Dataset of Ornamental Rose Classes

Rose Type	Number of Images	Example
Yellow	230	
Red	191	
Orange	39	
Pink	174	
White	179	

During preprocessing, image normalization and augmentation techniques—such as rotation, flipping, blurring, and brightness adjustment—were applied to increase data variability and reduce overfitting. These steps allowed the model to generalize better to different environmental and lighting conditions. The YOLOv8 model was then trained for

100 epochs using a batch size of 16, an input resolution of 640×640 pixels, a learning rate of 0.01, and the stochastic gradient descent (SGD) optimizer. Figure 4 presents the confusion matrix obtained from the testing phase, which shows balanced performance across most classes, though slight misclassifications occurred between visually similar categories such as red and orange roses. The model achieved a precision of 0.88, a recall of 0.90, and a mean average precision (mAP50–95) of 0.89, demonstrating consistent and reliable detection capabilities. These values indicate that YOLOv8 successfully recognized the majority of rose images with minimal false classifications. Further visual analysis confirmed the detection accuracy for each rose category. Figures 5 and 6 depict the detection results for red and white roses, Figures 7 and 8 show yellow and orange roses, while Figure 9 illustrates detection outputs for pink roses. Although the model maintained high consistency, the smallest dataset (orange class) produced a slightly lower detection score due to its limited sample count.

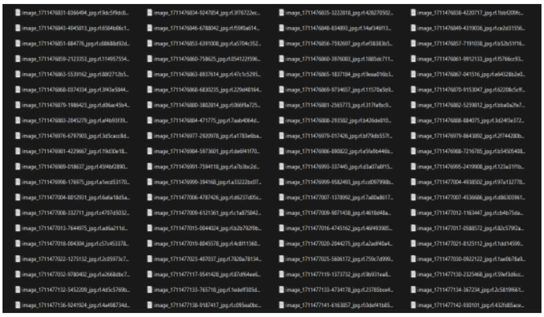


Figure 2. Data Annotation Workflow in Roboflow

Figure 3. Annotated Rose Image Samples per Class

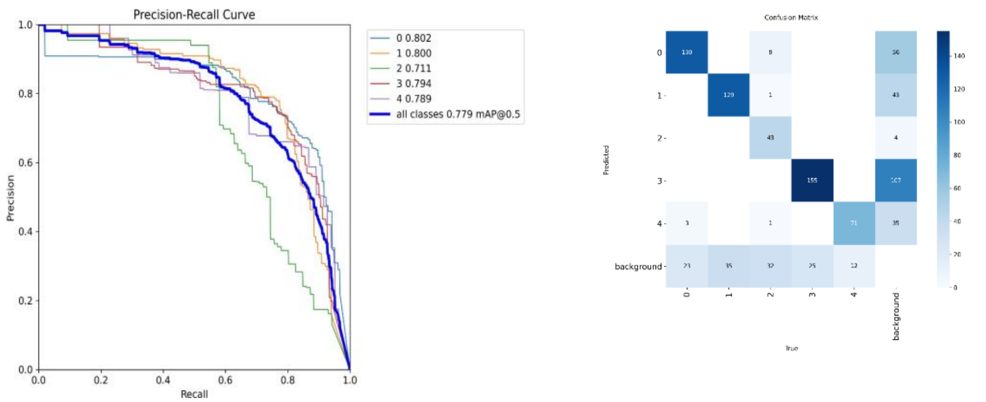
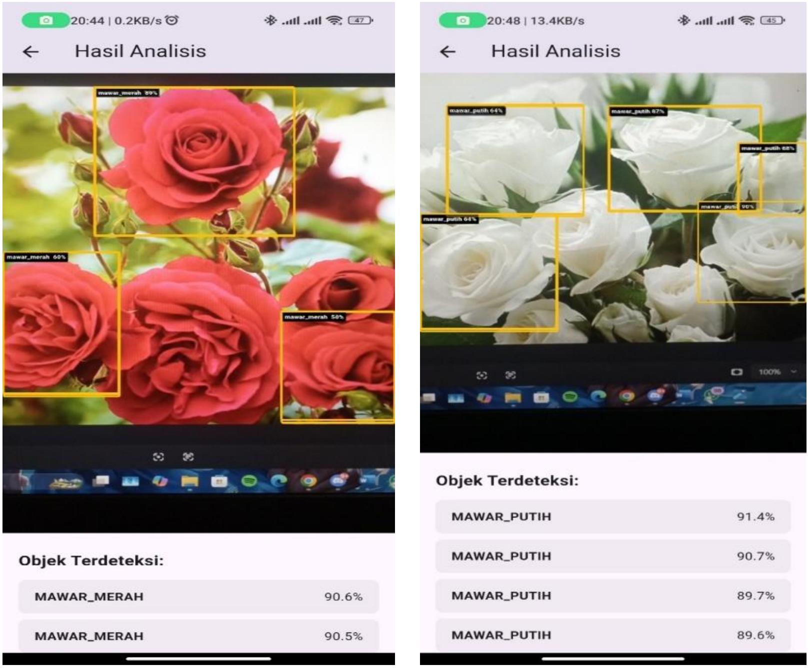
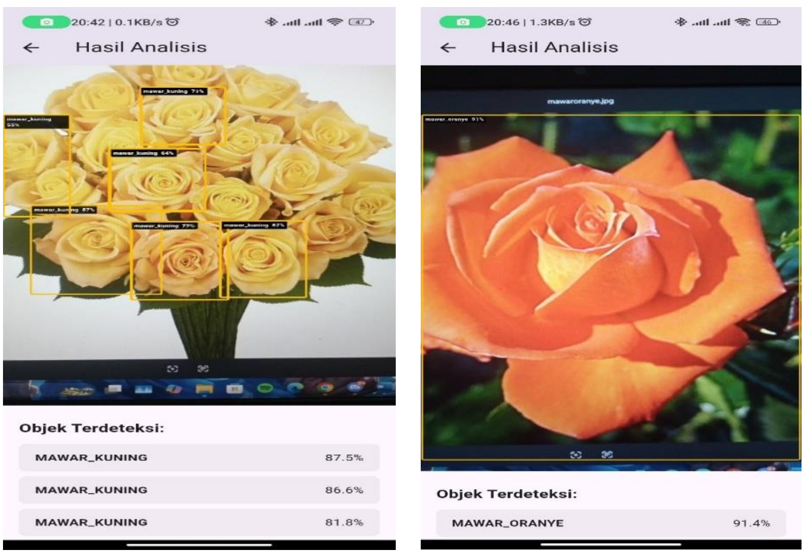


Figure 4. Confusion Matrix of YOLOv8 Model Performance



Images 5 and 6: Detection Results of Red Roses and White Roses



Images 7 and 8: Detection Results of Yellow Rose and Orange Rose

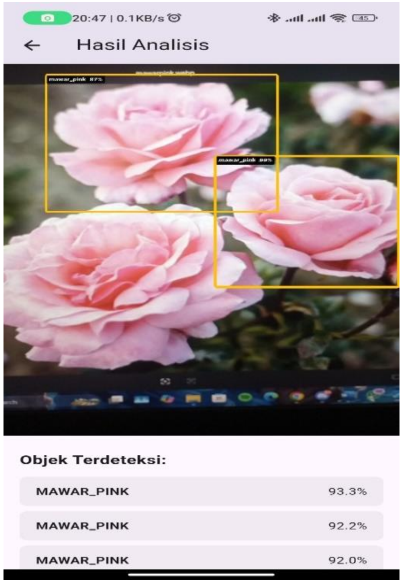


Figure 9 Pink Rose Detection Results

4. Discussion

The model training process was executed on a cloud-based environment using Google Colab, with 813 input images distributed across five target classes. Table 2 summarizes the recorded performance metrics, including training and validation losses, precision, recall, and mAP values for each epoch during the 100-epoch training cycle.

Table 2. YOLOv8 Model Training Metrics (Selected Epochs)

epoch	train/ box_loss	train/ cls_loss	metrics/ precision	metrics/ recall	metrics/ mAP50
0	128.836	266.967	35.413	4.095	3.296
1	125.951	186.396	29.991	46.612	33.245
2	125.042	176.009	39.125	39.363	30.166
3	126.173	164.398	60.101	57.256	49.058
4	123.294	149.334	444	45.452	16.157
5	119.705	144.232	49.676	53.028	52.815
6	116.839	138.362	44.786	52.601	43.729
7	113.771	132.247	61.334	63.999	63.454
8	112.178	128.984	5.659	66.181	63.382
9	110.273	121.815	67.149	61.171	6.351
10	108.898	117.309	69.277	60.336	71.032
11	106.222	113.109	50.502	69.683	61.835
12	106.661	117.191	57.885	59.778	61.734
13	104.601	108.633	55.033	6.624	67.351
14	102.966	106.302	52.916	6.663	6.611
15	10.164	10.235	60.952	71.423	67.531
16	103.501	100.734	62.375	70.959	69.695
17	1.1989	99.181	53.367	7.643	68.206
18	98.347	96.789	55.875	63.326	63.377
19	98.345	96.568	54.705	66.801	6.536
20	97.948	96.269	64.047	7.629	76.404

21	97.037	92.993	65.956	63.001	73.618
22	96.017	91.189	64.019	69.281	74.032
23	96.256	91.508	57.853	74.493	72.789
24	92.273	89.362	54.611	73.722	68.644
25	93.317	87.019	58.817	77.576	72.622
26	92.662	86.664	65.685	76.029	76.987
27	93.924	84.653	59.771	73.278	73.184
28	90.248	80.711	57.125	74.072	70.514
29	92.647	82.438	7.027	72.292	75.091
30	91.013	81.524	56.694	72.268	67.488
31	91.253	79.971	73.646	62.511	71.253
32	89.906	78.734	66.891	71.745	75.748
33	8.793	77.104	61.788	8.096	74.136
34	86.924	79.942	58.114	80.413	75.504
35	86.394	76.213	67.394	75.742	7.729
36	88.413	781	59.243	80.043	74.175
37	8.549	74.423	64.323	77.814	76.994
38	8.679	73.812	70.052	63.533	71.602
39	85.284	72.995	6.231	79.236	7.672
40	84.582	72.367	61.872	68.145	70.747
41	84.731	70.764	61.717	64.627	67.715
42	8.464	72.128	64.439	71.936	71.079
43	83.958	7.217	6.124	72.952	71.696
44	82.966	7.208	6.374	69.652	7.218
45	83.131	7.057	6.446	70.412	71.525
46	81.613	67.669	63.497	71.751	7.238
47	84.152	65.845	73.758	71.759	77.293
48	82.216	67.943	68.006	75.784	75.346
49	80.047	64.429	64.517	732	74.874
50	80.621	66.029	6.847	68.358	72.672
51	78.353	63.993	63.912	76.725	75.316
52	78.091	63.383	67.607	73.992	75.956
53	78.555	63.342	64.383	75.254	74.957
54	77.006	62.357	68.278	6.391	70.973
55	79.417	64.036	67.839	68.658	71.943
56	77.324	62.248	6.082	75.163	72.944
57	77.497	60.962	6.458	6.846	7.203
58	76.966	60.615	72.117	7.151	74.042
59	76.436	59.181	65.951	7.085	72.466
60	76.095	60.296	70.744	73.195	76.838
61	76.066	61.288	64.762	74.968	74.886
62	7.733	58.561	70.828	6.692	71.801
63	75.251	59.395	66.156	72.819	73.194
64	74.532	58.144	67.477	7.173	72.943
65	73.583	57.029	70.519	73.727	75.131
66	73.091	57.064	6.848	65.598	69.945
67	74.029	57.684	69.899	70.627	75.193
68	72.288	56.178	67.171	69.625	72.751
69	72.282	55.553	63.314	70.822	71.386
70	7.131	52.994	62.928	68.828	69.356
71	70.531	55.298	71.164	77.852	77.922
72	71.434	5.385	71.334	67.637	72.752
73	70.702	53.592	65.884	72.911	74.714

74	70.554	54.074	70.778	70.931	75.894
75	70.944	52.711	6.716	72.314	7.444
76	68.372	52.456	65.894	69.162	71.912
77	69.085	51.503	67.871	69.788	73.455
78	68.914	52.475	63.367	72.035	71.677
79	70.492	51.197	66.702	71.385	72.902
80	69.103	51.229	65.729	74.656	73.423
81	68.294	50.861	68.311	73.057	73.505
82	67.102	49.974	70.436	68.564	74.024
83	66.952	49.957	66.487	719	73.635
84	65.807	48.044	71.006	66.924	71.293
85	66.223	4.824	71.089	65.702	6.944
86	66.722	48.886	72.425	68.585	74.304
87	66.456	4.825	68.267	7.088	72.732
88	64.482	479	69.987	70.519	7.469
89	65.736	48.372	67.907	7.402	7.517
90	57.779	39.463	68.082	69.075	7.179
91	56.315	3.636	71.912	69.179	73.818
92	55.644	3.554	72.807	67.598	73.571
93	5.508	35.123	75.635	65.176	71.995
94	54.029	34.156	7.203	68.733	7.286
95	54.392	34.479	76.486	65.286	72.424
96	53.327	33.994	70.878	68.684	73.207
97	53.042	33.388	67.678	7.149	73.642
98	53.068	33.466	70.641	69.455	74.393
99	53.002	3.407	70.621	70.136	74.394

The downward trend of both box_loss and cls_loss throughout training indicates stable convergence and effective learning. The box_loss decreased from approximately 128 to 53, while cls_loss dropped from 267 to 33, implying the model progressively minimized localization and classification errors. Simultaneously, the performance metrics—precision, recall, and mAP@0.5—improved steadily, reaching 70%, 70%, and 74%, respectively, by the final epoch. This outcome confirms that YOLOv8 efficiently learned to distinguish rose features such as petal patterns and color gradients without overfitting, despite the limited dataset size. These findings align with prior studies that validated YOLOv8's stability in various image recognition domains, including tree classification via drone imagery (*Islam et al., 2023*) and small-object detection based on embedded camera systems (*Lou et al., 2023*). The relatively lower precision in the orange rose class can be attributed to its limited image representation (only 39 images), which reduced the model's exposure to diverse variations. Expanding the dataset for underrepresented classes and incorporating additional augmentation methods could improve accuracy in future iterations. Moreover, the integration of quantization through TensorFlow Lite enhanced model efficiency for mobile deployment without significant accuracy loss, supporting real-time inference consistent with findings by *Hidayatullah et al. (2025)* and *Muntiari et al. (2024)* on YOLOv8 adaptability across platforms. Overall, the results demonstrate that YOLOv8 is a viable deep learning model for mobile-based rose identification. The high recall rate indicates robust object detection capability, while the compact .tflite model format ensures computational efficiency for real-time applications. This study contributes practical insights for implementing lightweight deep learning frameworks within the horticultural industry, particularly for automated plant classification, quality inspection, and educational mobile systems.

5. Conclusion

This study successfully developed a mobile-based prototype capable of identifying ornamental rose varieties in real time using an integrated camera system. The YOLOv8 algorithm demonstrated reliable adaptability for object detection and classification tasks, achieving a mean average precision (mAP50–95) of 0.581 across five rose categories—red, white, yellow, orange, and pink. Although the overall performance was satisfactory, the results were influenced by the limited number of samples in certain classes, particularly the orange rose category, which reduced the model's precision in that subset. The Flutter-based application was effectively implemented and functioned offline after converting the YOLOv8 model to TensorFlow Lite format. Despite minor compatibility issues during integration, the system performed efficiently in detecting roses directly from live camera input, confirming its feasibility for practical deployment. However, several limitations were identified, including dataset imbalance, lack of testing under diverse lighting conditions, and the absence of multi-device evaluation.

Future research is encouraged to expand the dataset by incorporating additional rose varieties or other ornamental plants, introduce data collected under varying environmental conditions, and integrate cloud-based processing to enhance scalability and accessibility. From an applied perspective, the proposed system holds significant potential for use within the floriculture industry—supporting flower sorting operations, assisting farmers in crop management, and serving as an educational tool for public learning on plant identification. The findings reaffirm the practicality of combining deep learning with mobile computing to create efficient, real-time solutions in horticultural applications.

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