BanaNAS: An Automated Ripeness Classification Robotic Arm of Lakatan (*Musa acuminata Colla*) using YOLO-NAS Model

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Abstract— The BanaNAS project presents an innovative approach to automated ripeness classification of Lakatan bananas using the YOLO-NAS model. Lakatan bananas play a significant role in the Philippines' agricultural economy, offering unique nutritional benefits such as potassium, vitamin B6, and vitamin C. Traditional manual sorting methods are time-consuming and prone to errors, emphasizing the need for an efficient automated system. The robotic arm, integrated with an Arduino controller, utilizes image-based deep learning models to classify bananas into categories like unripe, ripe, overripe, and rotten. Performance analysis demonstrates the system's accuracy and reliability, with significant improvements observed with increased training epochs. By streamlining the sorting process and maintaining high-quality standards, BanaNAS contributes to enhancing efficiency and standardizing quality assessments in the banana industry.

Keywords— Lakatan bananas, Automated ripeness classification, YOLO-NAS model, Robotic arm, Deep learning, Efficiency, Quality standards, Agricultural industry, Nutritional benefits

I. Introduction

The Philippines is a major player in the global banana industry, with the Lakatan variety (Musa acuminata Colla) standing out due to its sweet flavor and widespread popularity [1]. The Lakatan banana, along with other varieties such as Cavendish and Saba, contributes significantly to the country's agricultural economy. Each variety offers unique nutritional benefits: Lakatan is particularly rich in potassium, vitamin B6, and vitamin C; Cavendish is known for its high fiber content and vitamin A; and Saba provides a good source of complex carbohydrates and iron [2].

Bananas, including the Lakatan variety, are not only a delicious fruit but also a powerhouse of essential nutrients. Lakatan bananas are packed with potassium, which is vital for maintaining healthy blood pressure levels and supporting heart health. The precise classification of ripeness is important because it directly affects the nutritional value and taste, ensuring that consumers receive the best possible product.

In the thriving banana industry, the need for an efficient and accurate sorting system is critical to ensure consistent quality and meet market demands. Traditional manual sorting methods are time-consuming and prone to human error, leading to inconsistencies in the ripeness levels of bananas reaching consumers. This highlights the necessity for an automated ripeness classification system that can streamline the sorting process and maintain high standards of quality [4].

Proper sorting is essential to minimize contamination risks, which can occur during handling and transportation. Contaminated bananas can lead to health concerns and financial losses for producers [5]. By implementing automated sorting systems that utilize YOLO-NAS Model, it is possible to accurately classify the ripeness of Lakatan bananas, reducing the likelihood of contamination and ensuring that only the highest quality fruit reaches consumers.

Automated ripeness classification systems offer numerous benefits, including increased efficiency, reduced labor costs, and enhanced quality control. These systems use advanced technologies to analyze the physical characteristics of bananas, such as color, size, and texture, to determine their ripeness level [6]. This not only ensures a consistent product for consumers but also helps producers maintain their reputation for quality and reliability.

The integration of the YOLO-NAS Model and deep learning algorithms in the ripeness classification of Lakatan bananas presents a promising solution to the challenges faced by the banana industry. By improving the accuracy and efficiency of sorting processes, these technologies can enhance the overall quality of bananas, benefiting both producers and consumers alike [7].

II. Review of Related Works

Banana Ripeness Stages and Limitations

Bananas are one of the most widely consumed fruits in the world, known for their versatility, nutritional benefits, and varying stages of ripeness. Each stage of ripeness offers unique benefits and potential uses, affecting their impact on health and suitability for different applications [8].

Bananas at each ripeness stage offer specific health benefits but also come with certain limitations [9]. Underripe bananas, although nutritious, are less versatile due to their hard and starchy texture. Barely ripe bananas are challenging to mash and incorporate into recipes requiring smooth consistency. Very ripe and overripe bananas, while suitable for baking and cooking, have a higher sugar content that may not be ideal for everyone, especially those with diabetes [10]. Understanding these limitations can help individuals make more informed choices about banana consumption based on their dietary needs and culinary preferences.

Deep Learning for Sorting and Grading Agricultural Products

Image-based deep learning models significantly enhance efficiency and standardize quality assessments in sorting and grading agricultural products. These technologies classify fruits and vegetables into quality categories, enabling producers to market their produce at different price points based on consumer needs [11]. This categorization is particularly useful when cooling capacity is limited, allowing the storage of high-value products. In high-income countries, automated sorting and grading have largely replaced manual quality estimation, increasing efficiency, reducing labor costs, and eliminating human bias [12].

Deep learning models, particularly those based on image analysis, use tools like color spectrometers to assess fruit properties such as ripeness with high precision. Spectrometers provide accurate measurements of fruit color, a key quality indicator [13].

III. Methodology

A. Project Design

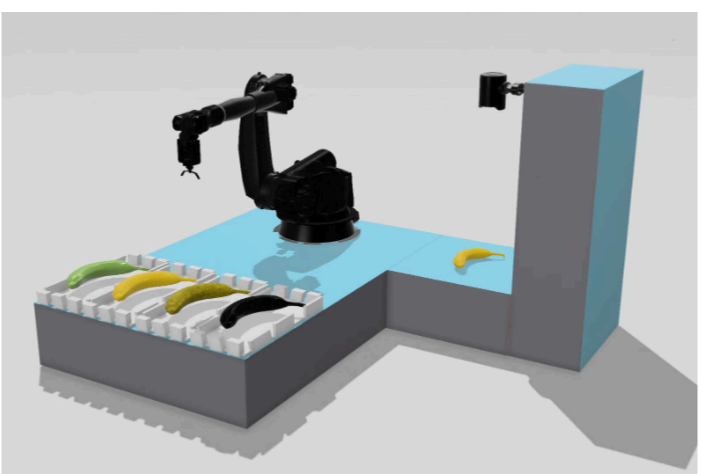

Fig. 1. The Envisioned Automated Banana Ripeness Sorter Design.

The project's design encapsulates the vision for constructing and implementing the sorter, emphasizing robustness and reliability while maintaining cost-effectiveness. The sorter is engineered to be both durable and efficient, ensuring long-term reliability. The design is optimized to be economical, making it accessible and practical for widespread use.

Fig. 2. Shapr rendition of robot arm structure.

The Shapr model of the arm's structure illustrates the links and joints of the robotic arm. The arm is designed with pitch and yaw movements at the linkages and roll at the base. These axes of motion allow the arm to move in all necessary directions, enabling it to classify bananas based on their ripeness using YOLO-NAS Model.

Fig. 3. Shapr rendition of the data acquisition device, camera.

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The Shapr version of the Data Acquisition Device is designed based on a small camera model. This camera is placed on a camera stand positioned in front of the robotic arm. Despite initial concerns about structural and technological challenges, the implementation of the small camera was successful and functioned without any issues, effectively contributing to the ripeness classification system.

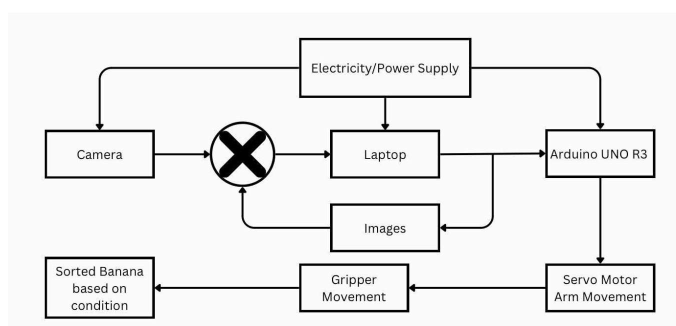

Fig. 4. Control System

This figure illustrates the control system of the Lakatan banana sorter. The camera, powered by electricity, captures images of the bananas and transmits them to a laptop for processing. UsingYOLO-NAS Model, the laptop analyzes these images to classify bananas into categories such as unripe, ripe, overripe, and rotten, facilitated by a feedback summing junction. Upon classification, the laptop, serving as the core of the AI system, sends instructions to an Arduino controller. The Arduino controller then directs the robotic arm to adjust the gripper accordingly. Following this process, the bananas are segregated based on their ripeness class.

B. Materials

The construction of BanaNAS includes both electronic and non-electronic devices. The electronic components include M996 Metal Servo Motor, Arduino Uno, Arduino Sensor Shield, robotic arm, gripper, computer, Norgicool 1080p camera, were all essential components in making sure that the robotic arm is able to see the data.

QUANTITY	MATERIALS	PRICE
6	Tower Pro Digital Robot Servo Motor - MG996R	1500
1	Arduino Uno R3 ATmega328p	450
1	Sensor Shield V5.0	95
1	5V 10A Switching Power Supply	400
1	Robotic Arm and Gripper Frame	1200
1	40pcs. Female to Male Solid Core #22 Wires	60
1	Standard AWG #16 AC Power Cord	50

Table 1. Bill of Materials.

C. Datasets

The research utilized a comprehensive set of four datasets: Unripe, Ripe, Overripe, and Rotten, each containing a variety of images depicting bananas at different stages of ripeness. These datasets were essential for the study's objective of accurately categorizing banana images based on their ripeness levels. By leveraging these datasets, the study aimed to enhance automated ripeness classification methods for Lakatan bananas (Musa acuminata Colla).

Fig. 5. Sample Images of Unripe Category

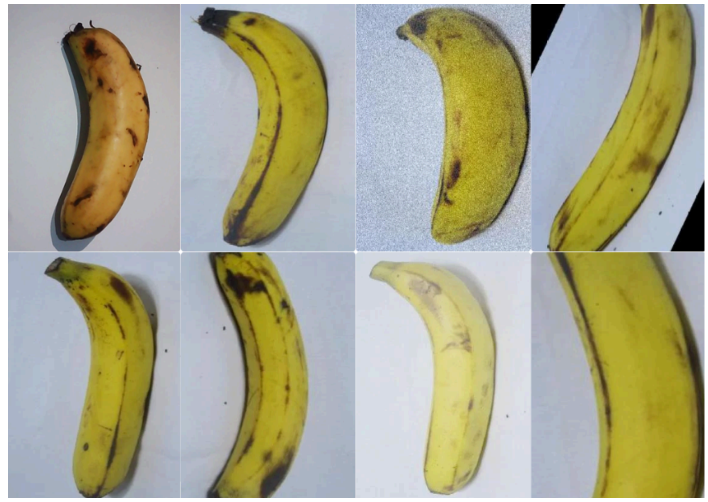

Fig.6. Sample Images of Ripe Category

Fig. 7. Sample Images of Overripe Category

Fig. 8. Sample Images of Rotten Category

	Unripe	**Ripe**	**Overripe**	**Rotten**
Peel color/appearance	Solid light green with some light	Mostly yellow with very faint	Solid yellow with very faint or no	Mostly dark yellow with very large

	greenish-yellow	green along edges and at tips and stem	green coloring near tips and has sporadic small brown spotting	portions of dark brown or black. Stem is black and shriveled
Peel Texture	Very firm to the touch; peel strongly adheres to flesh and is difficult to remove	Firm, but not soft; peel adheres only slightly to the flesh	Soft and pliable, but holds shape when removed from flesh; peel does not adhere to flesh and is easily removed	Extreme thin, soft and pliable; will tear away easily from flesh; deterioration of flesh (increased softness) can be felt through the peel
Aroma	No significant aroma, faint "plant" smell up close	Faint banana aroma	Noticeably strong banana aroma in close proximity to bananas	Strong and pervasive banana aroma noticeable from a distance
Taste	Very firm texture when biting and difficult to bite a piece off; very bitter upon tasting and leaves a very bitter aftertaste	Soft texture; could be considered "al dente"; slightly sweet taste with some bitterness	Soft texture and easy to bite through; taste sweet with no bitterness	Not tasted

Table 2. Criteria for assessed ripeness of bananas.

The ripeness and size of the bananas were evaluated as detailed in Fig._ , adhering to the criteria set by the International Journal on Food, Agriculture, and Natural Resources [1], which defines stage 2 as "unripe," stages 4-5 as "ripe," stages 6-7 as "overripe," and stage 7+ as "rotten." Measurements, as well as visual and sensory evaluations, were conducted as follows: sensory evaluation involved at least three individuals independently assessing each fruit. Aroma was evaluated by smelling the unpeeled bananas in each sample, while taste was assessed through the destructive sampling of bananas that represented the ripeness levels of the sample.

D. Software

The software components for the automated ripeness classification of Lakatan bananas are Python and the Roboflow platform. The system performs real-time detection using the YOLO-NAS model, interfaced through the Roboflow API, and communicates classification results to an Arduino-controlled system to perform corresponding actions, ensuring efficient and accurate ripeness classification.

The YOLO-NAS (You Only Look Once - Neural Architecture Search) is an advanced object detection model that authorizes neural architecture search to optimize its performance across various tasks, including real-time applications. It builds on the foundational YOLO series of models, known for their speed and accuracy in object detection tasks, by incorporating NAS techniques to fine-tune the architecture for optimal performance. The model is capable of high precision and speed, making it well-suited for real-time applications such as the automated ripeness classification of bananas.

IV. Results and Discussion

The final design of the robotic arm introduces six degrees of freedom (DOF), which includes the gripper, elbow, shoulder, and waist. The robotic gripper operates with a 90-degree grip for holding and a 45-degree angle for opening, sorting bananas based on their ripeness. The elbow and shoulder coordinate to ensure the gripper is correctly positioned and elevated, both capable of rotating up to 180 degrees to facilitate easy target collection. The waist controls the lateral movement of the entire robotic arm, enabling it to turn left and right, which is crucial for placing the gripped and collected bananas into their specific containers.

When deciding between the YOLO V8 and YOLO Nas models, several factors such as performance, speed, and specific use cases should be considered. Both models offer impressive performance with accurate object detection capabilities. Nonetheless, the YOLO Nas model often provides slightly superior predictions in various scenarios [14].

Regarding speed, the YOLO V8 model outperforms the YOLO Nas model. The YOLO V8 model achieves a faster average inference speed of around 15 frames per second, whereas the YOLO Nas model may require further optimization to match these speeds [15]. The choice between YOLO V8 and YOLO Nas models largely depend on the particular use case and dataset. The YOLO V8 model is more user-friendly and requires less code, making it suitable for specific applications. Conversely, the YOLO Nas model generally offers more accurate predictions [16].

A. Confusion Matrix and Performance Metrics Parameters

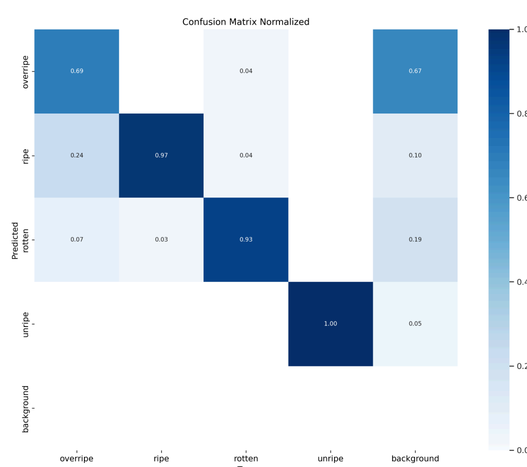

Fig. 9. Confusion Matrix using YOLOv8 (10 epoch)

This table shows the normalized confusion matrix for the YOLOv8 model trained for 10 epochs. The model performs well in identifying unripe (true positive rate of 1.00) and ripe (true positive rate of 0.97) bananas. However, the model struggles more with overripe (true positive rate of 0.69) and rotten (true positive rate of 0.93) bananas.

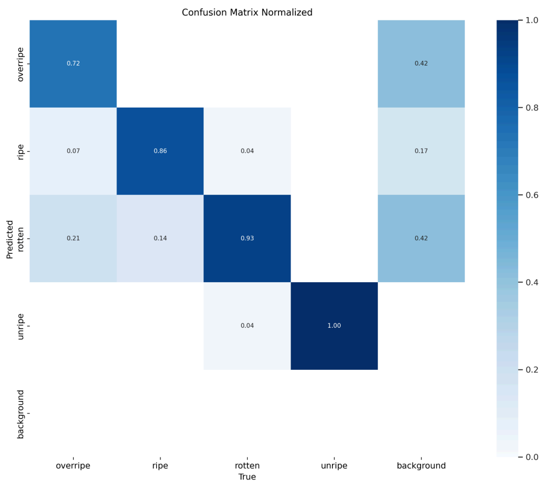

Fig. 10. Confusion Matrix using YOLOv8 (15 epoch)

This table shows the normalized confusion matrix for the YOLOv8 model trained for 15 epochs. The model's performance improves, with true positive rates of 1.00 for unripe, 0.86 for ripe, 0.72 for overripe, and 0.93 for rotten bananas.

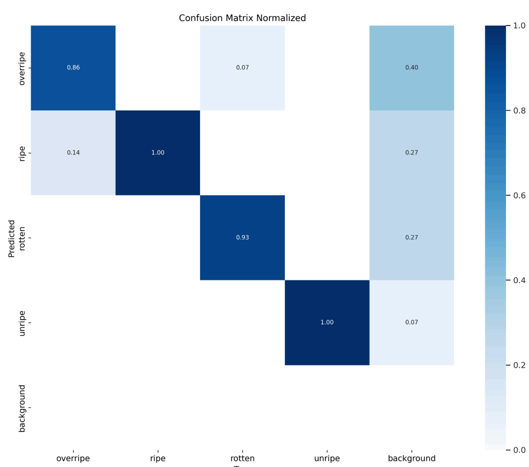

Fig. 11. Confusion Matrix using YOLOv8 (25 epoch)

This table shows the normalized confusion matrix for the YOLOv8 model trained for 25 epochs. The model's performance further improves, with true positive rates of 1.00 for unripe, 1.00 for ripe, 0.86 for overripe, and 0.93 for rotten bananas.

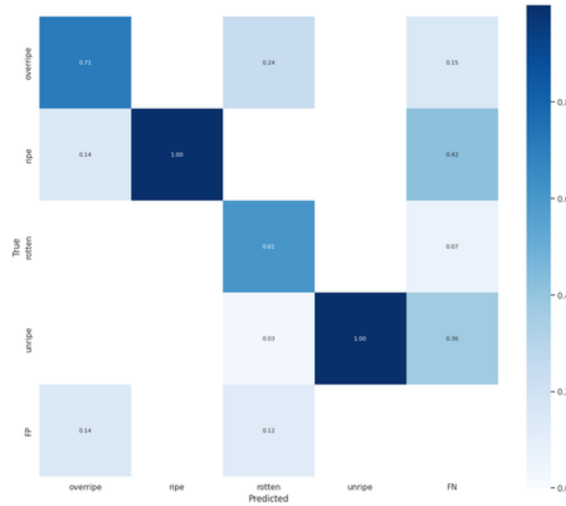

Fig. 12. Confusion Matrix using YOLO-NAS (10 epoch)

This table shows the normalized confusion matrix for the YOLO-NAS model trained for 10 epochs. The model performs well, with true positive rates of 1.00 for unripe, 1.00 for ripe, 0.71 for overripe, and 0.61 for rotten bananas.

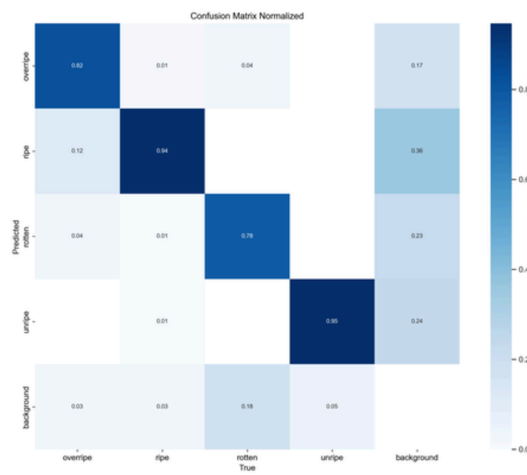

Fig. 13. Confusion Matrix using YOLO-NAS (15 epoch)

This table shows the normalized confusion matrix for the YOLO-NAS model trained for 15 epochs. The model's performance improves, with true positive rates of 0.95 for unripe, 0.94 for ripe, 0.82 for overripe, and 0.78 for rotten bananas.

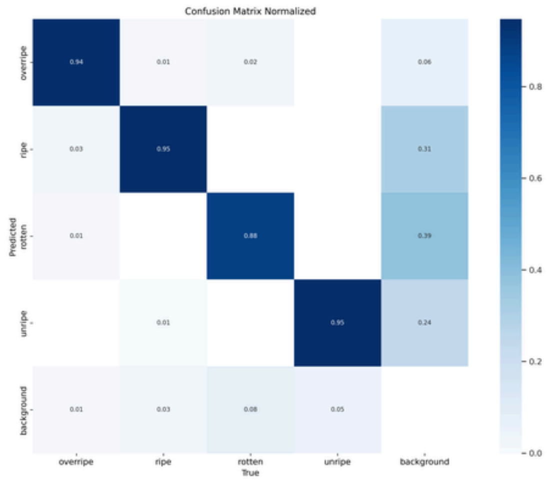

Fig. 14. Confusion Matrix using YOLO-NAS (25 epoch)

This table shows the normalized confusion matrix for the YOLO-NAS model trained for 25 epochs. The model's performance further improves, with true positive rates of 0.95 for unripe, 0.95 for ripe, 0.94 for overripe, and 0.88 for rotten bananas.

Model	No. of Epochs	Confusion Matrix Normalized			
		Unripe	Ripe	Overripe	Rotten
YOLO v8	10	1.00	0.97	0.69	0.93
	15	1.00	0.86	0.72	0.93
	25	1.00	1.00	0.86	0.93
YOLO-NAS	10	1.00	1.00	0.71	0.61
	15	0.95	0.94	0.82	0.78
	25	0.95	0.95	0.94	0.88

Table 3. Normalized Confusion Matrix based on Model and Epochs

Table 3 compares the Normalized Confusion Matrix based on the model (YOLOv8 and YOLO-NAS) and the number of epochs (10, 15, and 25). The values in the table represent the true positive rates for each category of bananas (unripe, ripe, overripe, and rotten) as classified by the models. A higher true positive rate indicates better accuracy in classifying bananas into their respective ripeness categories. For example, in the YOLO-NAS model with 25 epochs, the true positive rates for unripe, ripe, overripe, and rotten bananas are 0.95, 0.95, 0.94, and 0.88, respectively.

Model	No. of Epochs	Parameters			
		Precision@0.50	Recall @0.50	mAP @0.50	F1 @0.50
YOLO v8	10	0.887	0.80	0.97	0.91
	15	0.849	0.86	0.972	0.90
	25	0.784	0.80	0.988	0.95
YOLO-NAS	10	0.392	1.0	0.8363	0.753
	15	0.351	1.0	0.8769	0.678
	25	0.472	1.0	0.9324	0.905

Table 4. Parameters based on Model and Epochs

Table 4 presents parameters such as Precision@0.50, Recall@0.50, mAP@0.50, and F1@0.50 based on the model (YOLOv8 and YOLO-NAS) and the number of epochs (10, 15, and 25). These parameters are essential metrics for evaluating the performance of the models in terms of precision, recall, mean average precision, and F1 score at a specific threshold of 0.50. For instance, in the YOLO-NAS model with 25 epochs, the Precision@0.50 is 0.472, Recall@0.50 is 1.0, mAP@0.50 is 0.9324, and F1@0.50 is 0.905. These values provide insights into the model's accuracy, completeness, and overall performance in classifying banana ripeness categories.

V. Conclusion

In developing a sophisticated AI object detection robotic gripper sorter, we integrated YOLOv8 and YOLO NAS models to achieve exceptional accuracy and efficiency in sorting bananas based on their ripeness. The final design features a robotic arm with six degrees of freedom, including a gripper, elbow, shoulder, and waist, enabling precise and efficient positioning and movement. The gripper operates with a 90-degree grip for holding and a 45-degree angle for opening, effectively sorting bananas. The elbow and shoulder, capable of rotating up to 180 degrees, coordinate to ensure correct positioning, while the waist controls lateral movement, crucial for placing the bananas into specific containers. This intricate design allows the system to handle various sizes and shapes with precision and care, fulfilling our objective of developing a robust sorting mechanism seamlessly integrated with the Arduino-controlled robotic gripper.

Performance analysis demonstrated significant improvements with increased training epochs. The YOLOv8 model trained for 25 epochs achieved high true positive rates for all banana categories—unripe, ripe, overripe, and rotten—significantly improving from the 10-epoch model. The Precision-Confidence Curve for the 25-epoch model indicated a precision of 1.00 at a confidence level of 0.926, underscoring the model's reliability. The YOLO NAS model further demonstrated effective learning and refinement, with mAP values stabilizing across epochs, offering a comprehensive assessment of localization accuracy. These results underscore the system's real-time object detection and sorting capability, with a sorting rate of at least one object every 5 seconds. The combination of advanced AI models and a sophisticated robotic arm design marks a significant advancement in automated sorting technology, with potential scalability and adaptability for various objects and sorting requirements.

VI. Recommendations

For the BanaNAS system, which is designed for the automated ripeness classification of Lakatan bananas (Musa acuminata Colla) using the YOLO-NAS model, several recommendations can enhance its efficiency and accuracy. Firstly, considering the superior predictive capabilities of the YOLO-NAS model, further optimization should be pursued to improve its inference speed. This can ensure that the system operates in real time, which is critical for industrial applications.

Additionally, it is recommended to widen the distance separation of each classification category during the sorting process. Increasing the space between unripe, ripe, overripe, and rotten categories can minimize the risk of misclassification and physical damage to the bananas. This adjustment can enhance the overall accuracy and reliability of the sorting mechanism, ensuring that the BanaNAS system consistently delivers high-quality results.

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