Classification system of banana types and ripeness levels based on convolutional neural network

Lucia Jambola, Arsyad Ramadhan Darlis, Windi Malaha, Dwi Aryanta
Department of Electrical Engineering, Institut Teknologi Nasional Bandung, Bandung, Indonesia

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ABSTRACT

Recently, the availability of bananas in supermarkets has been relatively abundant. However, most buyers experience problems categorizing the type and level of ripeness of bananas, so the level of purchases of this fruit decreases. This study implements a real-time system that can automatically classify bananas in the dual classification based on type and level of ripeness. so that buyers can choose them based on their needs. In this study, the proposed system could classify bananas using a convolutional neural network (CNN), where the system was implemented in real-time using the hardware of the Jetson Nano as a processing unit and a camera system as a sensor. The methodology adopted in this research involves implementing CNN architectures, i.e., ResNet-18 and ResNet-50, under various conditions. The training phase comprises 60 epochs, while testing considers illumination parameters from LED lights with power of 6 watts, 12 watts, and 22 watts under distances ranging from 10 to 100 cm. The results show that the system could classify the type and level of ripeness of bananas in real-time with an accuracy of 93% which is achieved using the 22-watt power for all types and ripeness levels.

Corresponding Author:

Arsyad Ramadhan Darlis
Department of Electrical Engineering, Institut Teknologi Nasional Bandung, Bandung, Indonesia
Phh. Mustofa No.23 Street, Bandung City, West Java-40124, Indonesia
Email: arsyad@itenas.ac.id

1. INTRODUCTION

Fruits constitute a significant horticultural commodity, playing an important role in Indonesia. These fruits play an important role in body metabolism because of their abundant vitamin and mineral content. This aspect serves as a benchmark for citizens in cultivating and propagating diverse fruit-yielding plant species [1]. Among these, bananas represent a varietal fruit within the agricultural sphere that bestows various health benefits due to their rich nutritional composition [2].

One of the common issues that this research considers is that many banana stocks are sold in minimarkets and supermarkets. Yet, consumers remain unable to distinguish the degree of ripeness of the bananas on their own, potentially decreasing their purchasing interest. In this research, a real-time system-based convolutional neural network (CNN) methodology is utilized to classify dual classification of banana, i.e., type and its level of ripeness. This approach entails directing banana specimens toward a camera to attain a heightened level of accuracy to determine and classify the banana type and ripeness level [3]. This approach may allow the computer to recognize the image similar to the human level in categorizing banana type and ripeness levels [4].

The current technological advancements have facilitated human capability in determining banana ripeness based on color through the utilization of CNN, as explored in the investigation by Zhang *et al.* [5] and

Sri *et al.* [6]. Another study by Saranya *et al.* [7] was conducted. However, the studies could not determine the types of bananas and did not support real-time implementation.

In fruit type classification, previous studies have used image-based objects, similar to the research conducted by Ashraf *et al.* [8]. Subsequently, this is supported by Pathak and Makwana [9] about fruits classification using a CNN. A further contribution of this research is the classification of banana types using a CNN, which was conducted by Shuprajhaa *et al.* [10]. However, none of these studies can determine the banana ripeness in real time.

All of this research only considers one type and ripeness of banana, and most of them were not implemented in real time. Research conducted by Baldovino *et al.* [11], which focuses on real-time recognition and classification of banana objects via webcam using fast algorithms such as CNN and YOLO, states that this model is able to detect and categorize objects with an accuracy of around 90% across all classes on a static image test dataset. For real-time model detection, samples were placed on a blue background, considering that the yellow and green colors in banana samples are complementary pairs according to the RGB color wheel. Banana samples were tested both in groups and individually. However, this model only achieved 80% accuracy during real-time testing of individual samples.

Object classification in images is one of the primary challenges within computer vision. Its primary objective is to empower computers to emulate human capabilities in interpreting visual information. One successful approach has been through the application of artificial neural networks (ANNs) inspired by human neural networks, which have further evolved into the concept of deep learning (DL) [12], [13]. In the study conducted by Said *et al.* [14], utilizing the support vector machine (SVM) method for classifying banana types results in promising outcomes [14], [15]. However, most of the researches were not implemented in real time and has low accuracy.

DL represents a branch of machine learning (ML) grounded in ANNs [16]. The foundation of DL is primarily rooted in ANNs within the domain of ML [17]. Various types of neural networks exist within the realm of DL, encompassing ANNs, CNNs, and recurrent neural networks (RNNs) [18]. A subset of DL methodologies, the CNN, derives from the principles of the multilayer perceptron (MLP); however, CNN is specially engineered to process two-dimensional data formats such as audio and images [19]. CNN is harnessed for supervised learning-based classification of labeled data [20]. One commonly employed neural network architecture for image data is the CNN. Presently, the most widely adopted approach in DL involves CNNs. At a certain depth, CNN falls within the classification of deep neural networks, frequently applied in image data processing [21], [22].

This study implemented a real-time system that can automatically classify bananas in the dual classification based on type and level of ripeness. so that buyers can choose them based on their needs. In this study, the proposed system could classify bananas using a CNN, where the system was implemented using the hardware of the Jetson Nano as a processing unit and a camera system as a sensor. The methodology adopted in this research involves implementing CNN architectures under various conditions. The ResNet architecture comprises several variations with varying layer depths, such as ResNet-18, ResNet-34, ResNet-50, ResNet-101, and ResNet-152. In this study, the Python programming language was employed to implement CNNs with ResNet-18 for type banana classification and ResNet-50 architectures for ripeness banana classification. Despite the enhancements the ResNet model brings to the input, it also demonstrates superior stability in handling gradient variations during the training process [23]. For instance, ResNet consists of 16 convolutional layers, two downsampling layers, and multiple fully connected (FC) layers [24].

2. METHOD

Figure 1 explains the overall workflow of a banana ripeness classification system, utilizing several devices, i.e., a laptop, a camera, and a Jetson Nano. The first step is collecting a dataset with three banana ripeness captured through a camera, serving as input for the Jetson Nano 2 GB. This process was executed at distinct time intervals. This utilized a 5 V DC power supply to cater to the Jetson Nano 2 GB's energy requirements, with an additional internet connection facilitated via local area network (LAN) cable. Subsequently, a USB cable established a link between the Jetson Nano 2 GB and a laptop, where the computer assumed the role of managing the Jetson Nano 2 GB operations. Once all components were interconnected, the camera activation ensued. Having been integrated with the Jetson Nano 2 GB, the camera assumed the responsibility of real-time classification of banana type and ripeness level.

The Jetson Nano 2 GB initiated the dataset collection process, followed by a training phase to refine the system. Consequently, a model was derived. This model then underwent testing to ascertain the accuracy values for banana type and ripeness level classifications. The obtained results were subsequently showcased on a monitor. Figure 2 shows the banana classification system.

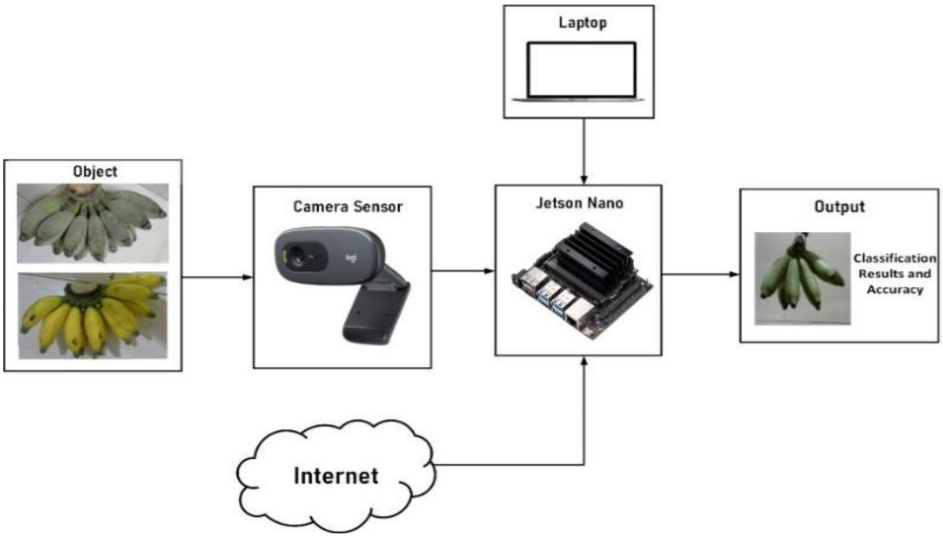


Figure 1. System block diagram

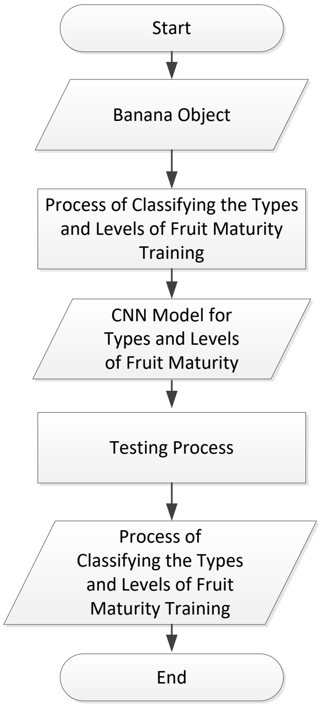


Figure 2. System flowchart

The program starts with capturing banana samples through a connected camera, which is subsequently employed for training in the classification of banana types and ripeness levels. Before classification, the acquired object outcomes are organized into datasets to facilitate the training process. Upon completion of training, a model is derived, serving as the foundation for subsequent classification of banana type and ripeness. This is followed by the testing phase, during which the camera is directed toward the banana specimens, yielding accuracy values indicative of banana type and ripeness level. This research is conducted utilizing Google Colab Pro, which can help with code building, training, and testing the data, or generating the visualization result of the training process. The Python programming language is used to achieve system development.

The initial stage involves acquiring data for banana type recognition to verify the system's ability to classify banana types accurately. This will determine the next maturity level classification process. The dataset in this study is categorized into two groups: data for training and data for testing. The data outcomes encompass the presentation of banana types and accuracy metrics. The specific banana types employed in this study are enumerated in Table 1. In this study, ResNet-18 was used to classify banana types due to its relatively low complexity, while ResNet-50 was used to classify ripeness levels due to the need to achieve high accuracy across several ripeness classes. In real-time implementation, the ResNet architecture model is considered lightweight enough to be implemented on hardware.

Table 1. Banana dataset

Total dataset	1,000	
Banana type	1.	Kepok
	2.	Muli
Banana ripeness level	1.	Unripe
	2.	Semi-ripe
	3.	Ripe
	4.	Partially ripe
	5.	Overripen

3. RESULTS AND DISCUSSION
3.1. Dataset collection

Building a DL system also requires a huge amount of data, which is used for training and testing. Training data is a bunch of data collection consisting of labels and classes, which machines use to improve identifying characteristics of an image, intending to establish a pattern or data model. On the other side, testing data represents a dataset similarly equipped with labels or classes, serving to assess the extent to which the developed pattern or model can accurately classify the evaluation data [25]. Figure 3 shows a dataset example that consists of 2 banana types, i.e., kepok in Figure 3(a) and muli in Figure 3(b). Then, Figure 4 shows the dataset for the kepok banana is shown in Figure 4(a) with several varying degrees of ripeness levels, and likewise for muli banana as shown in Figure 4(b) with several predetermined ripeness stages within this study.

(a) (b)

Figure 3. Type-based banana dataset: (a) kepok and (b) muli

(a)

(b)

Figure 4. Ripeness level-based banana dataset: (a) kepok and (b) muli

Each ripeness level comprises 100 images, contributing to a dataset of 500 images for kepok and 500 for muli. Consequently, the combined dataset amassed for both types of bananas and each ripeness stage totals 1,000 images. The amassed dataset will be categorized into five distinct stages of ripeness. These stages encompass unripe, characterized by the banana retaining a green hue; partially ripe, displaying a transition from green to a yellowish tint; ripe, portraying a uniformly yellow coloration; partially overripe, marked by brown spots on the banana's surface; and fully overripe, where the banana has turned predominantly brown.

3.2. Training process

Training data comprises the dataset utilized to instruct the constructed model. The model's outcomes are trained to align with the anticipated values. They were, conversely, testing data functions to evaluate the model that had undergone the training phase. Table 2 shows the model architecture for the training process.

Figure 5 delineates the testing scenario involving ResNet-18 for banana-type classification and ResNet-50 for ripeness-level classification within the model architecture above. This scenario was designed to compare the accuracy levels and loss outcomes based on a dataset size of 1,000 instances. The optimal system performance was achieved using a parameter configuration of 60 epochs. An epoch denotes a state in which the entire dataset, serving as input for the training model, completes a full traversal through the neural network within a single cycle [26]. Table 3 explains the training result, revealing the highest achieved accuracy value for banana-type classification at 0.9998, with a corresponding loss value of 0.0008. A lower loss value generally indicates a more optimal accuracy value for the obtained model [27], a factor crucial for further validation through the testing process.

Table 2. The model architecture

Number of datasets	1,000 images
Model	ResNet-18 and ResNet-50
Epoch	60
Optimizer	Adam
Batch	8
Learning rate	0.001

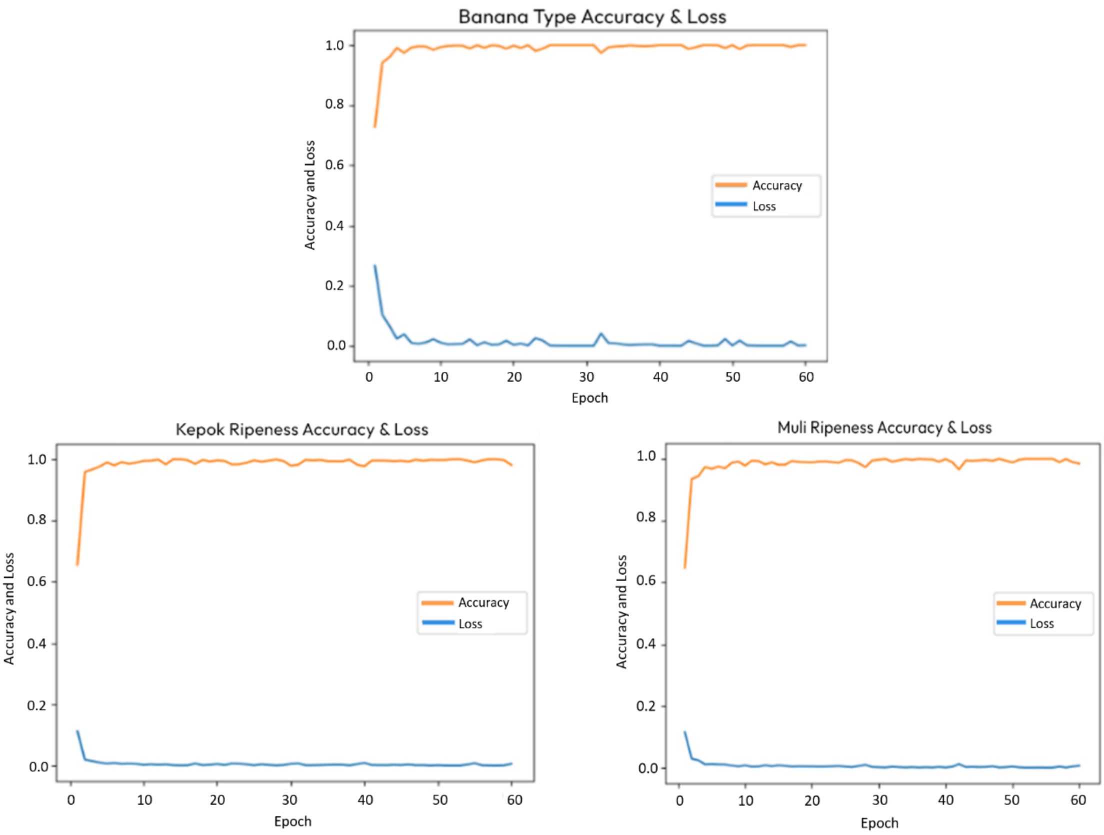


Figure 5. Training graphic result

Table 3. Accuracy and loss achieved from training process

Dataset	Accuracy	Loss
Banana type	0.9998	0.0008
Kepok ripeness level	0.9969	0.0009
Muli ripeness level	0.9969	0.0039

3.3. Testing process

The testing phase of this study employed the PyTorch model within the CNN methodology. This involved assessing the accuracy of the classification outcomes for both banana type and ripeness level. To execute the testing process, the initial step involved activating the camera to facilitate real-time operation. The camera was then directed towards the banana object for analysis. For testing purposes, devices such as a laptop, a camera, and a Jetson Nano are used. The details of each device are elaborated in Table 4.

Figure 6 illustrates the banana type classification process involving identifying and capturing banana objects. Subsequently, accuracy and predictions are displayed on the monitor screen. During the testing phase, the author conducted real-time tests for both banana type and ripeness level classification at a fixed distance of 30 cm. These tests were executed under varying LED lighting conditions, with wattages of 6 watts (520 lm), 12 watts (1,200 lm), and 22 watts (2,400 lm), within an enclosed indoor space measuring 3×2.5 meters.

Table 4. Testing device specifications

Device	Specification
Laptop	Processor: Intel Core i5-8250U, Intel UHD Graphics 620
	RAM: 8 GB
	Operation System: Windows 10
NVIDIA Jetson Nano 2 GB	Processor: Quad-core ARM® A57
	GHz: 2 GB 64-LPDDR4, 25.6 GB/s
	SD Card Support: Micro SD (Card not included)
Logitech C270 camera	Resolution Ratio: 720p/30 fps
	Megapixel Camera: 0.9
	Focus Types: fixed focus

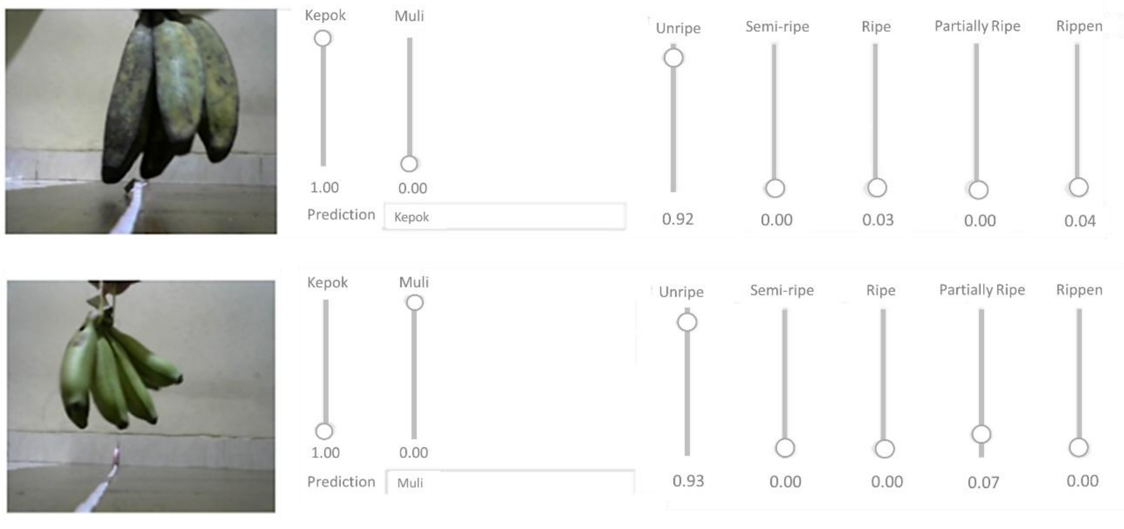
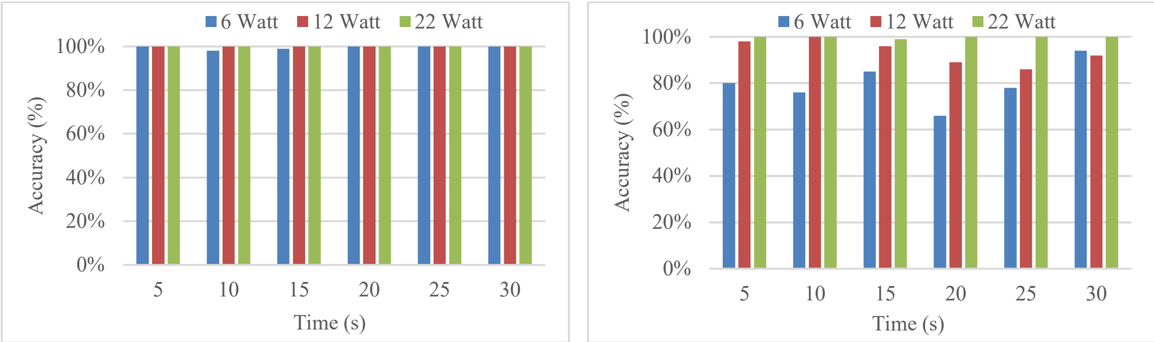


Figure 6. Real-time proposed system testing

Figure 7 shows the classification result; where kepok banana types in Figure 7(a) and muli banana type in Figure 7(b), which are categorized into three illumination levels: 6 watts, 12 watts, and 22 watts. The system demonstrates effective classification of kepok type, achieving a remarkable accuracy rate of 100% under the 22-watt category. Notably, the kepok type within the 6-watt category exhibits a slight variance of 1%-2% at 10 and 15 seconds, attributed to the lower illumination power of 6 watts. Conversely, lesser accuracy is observed in the 6-watt category at the 20-second mark for the multi-type. The 22-watt category, however, successfully achieves accurate classification, attaining a perfect accuracy score of 100%. In summation, it can be deduced that the lower accuracy values, as reflected by the overall average accuracy, align with the 6-watt illumination category.



(a) (b)

Figure 7. Banana type classification result under various lamp power: (a) kepok and (b) muli

Figure 8 illustrates the accuracy values of kepok at the unripe ripeness level under the 6-watt illumination category, displaying a 4% difference from other categories, with an average accuracy of 94%. For the partially ripe muli, the 6-watt category fails to achieve effective ripeness detection, yielding an average accuracy of 12%. Additionally, accuracy remains below 20% across distances spanning 10 cm to 100 cm due to inadequate lighting conditions. In contrast, the 12-watt and 22-watt categories yield average accuracy values of 95% and 100%, respectively. The system excels in classification, particularly under the 12-watt and 22-watt categories, achieving notable accuracy rates.

Then, Figure 9 shows the classification of semi-ripe kepok ripeness levels under the 6-watt illumination category, indicating a lack of accuracy detection, as reflected by an average accuracy of 25%. Furthermore, accuracy levels at varying distances fall below 25%. Conversely, within the 12-watt and 22-watt categories, the average accuracy values soar to 97% and 93%, respectively, signifying superior performance. This variance can be attributed to the insufficiency of illumination within the 6-watt category. Conversely, the partially ripe muli exhibits robust results, boasting an average accuracy of 98% under the 6-watt illumination category. Notably, this system excels in classifying semi-ripe muli specimens across the 6-watt, 12-watt, and 22-watt categories.

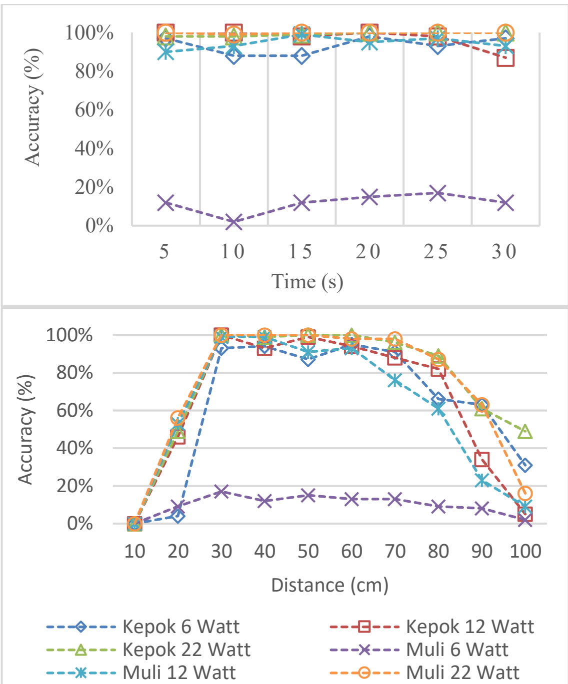


Figure 8. Unripe classification under various lamp power

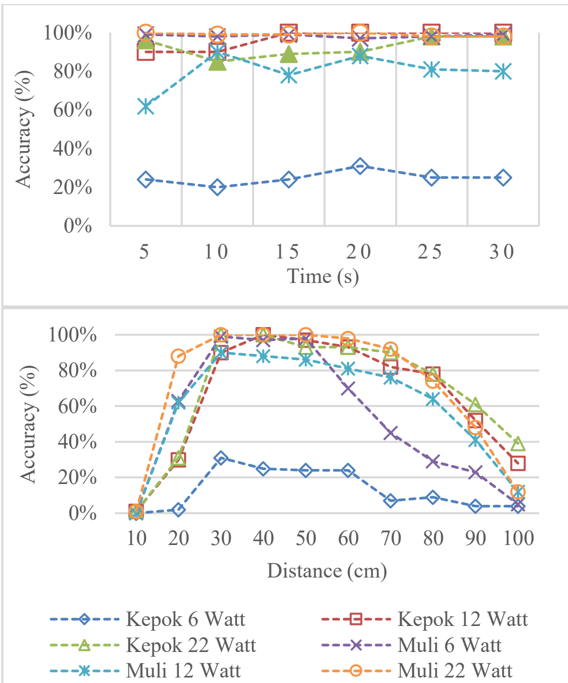


Figure 9. Semi-ripe classification result under various lamp power

As shown in Figure 10, the 22-watt category demonstrates an exceptional accuracy trend when examined at intervals of 5 to 30 seconds, resulting in a remarkably accurate of 100% for both kepok and muli. Within the 12-watt category, during the ripe ripeness level, the average accuracy values for kepok and muli stand at 91% and 84%, respectively. Conversely, under the 6-watt category, accuracy diminishes to an average of 41% for kepok and 62% for muli. This discrepancy can be attributed to the impact of lighting conditions, affecting the accuracy of the classification process. Furthermore, the classification accuracy decreases as the distance between the classified banana objects and the camera increases. Notably, this system effectively and accurately classifies ripe states for both kepok and muli under the 12-watt and 22-watt illumination categories.

Figure 11 provides insight into the graph representing the partially ripe kepok and muli accuracy levels under different illumination conditions. Within the 6-watt category, the average accuracy values for kepok and muli are 62% and 52%, respectively. In the 12-watt category, these values improve to an average of 84% for kepok and 75% for muli. The 22-watt category demonstrates a remarkable average accuracy of 99% for both types of bananas. Notably, variations in accuracy across the 6-watt, 12-watt, and 22-watt categories stem from differences in lighting conditions. Additionally, the partially ripe state of bananas exhibits subtle differences in appearance compared to fully ripe ones, characterized by brown spots. The system effectively achieves accurate classification, particularly in the 22-watt category, where it attains a notable success rate of 99% in delineating partially ripe banana states. And the last result, Figure 12, illustrates the proposed system's effective functionality, with high accuracy achieved in classifying the ripeness levels of overripe kepok and muli.

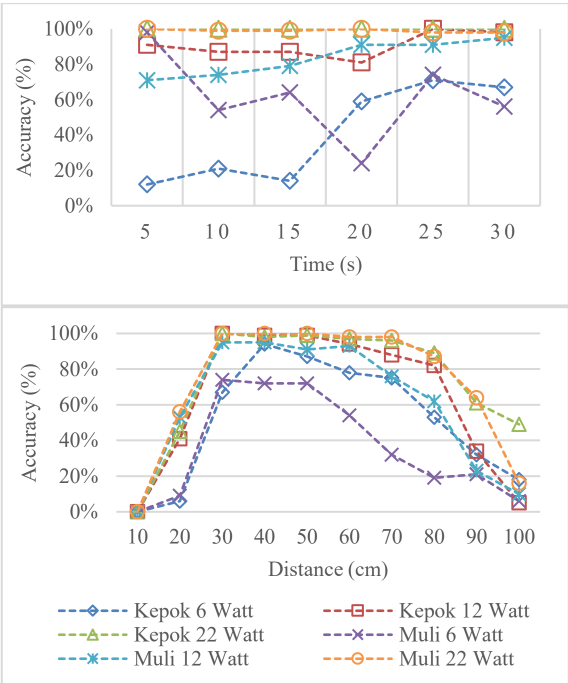


Figure 10. Ripe classification result under various lamp power

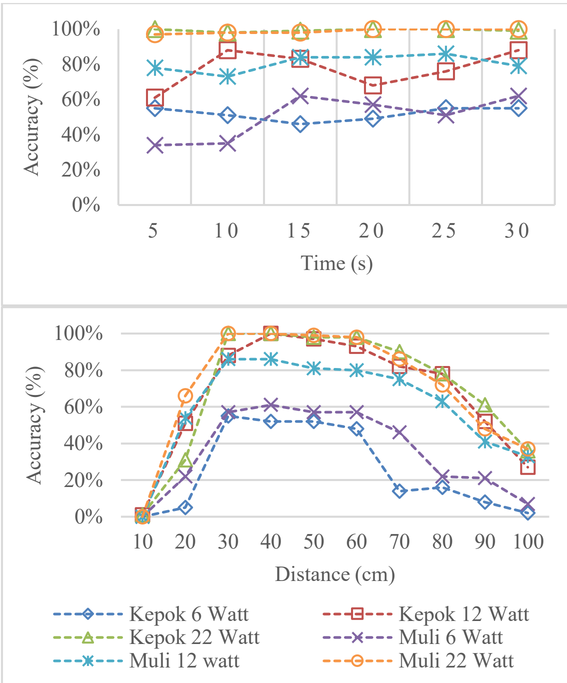


Figure 11. Partially ripe classification result under various lamp power

For kepok, under the 6-watt illumination category, an average accuracy of 99% is achieved; the 12-watt category demonstrates a perfect 100% accuracy rate, while the 22-watt category maintains an equally impressive average accuracy of 100%. Similarly, for muli, the 6-watt category attains an average accuracy of 95%, the 12-watt category reaches 100% accuracy, and the 22-watt category secures an accuracy rate of 98%. Intriguingly, the system continues to uphold its performance even when the specimens are positioned at distances between 30 cm and 60 cm. In both kepok and muli cases, the accurate classification remains consistent, boasting an average accuracy of 100% within this distance range.

These results show that illumination impacts accuracy. This is because the level of illumination increases the camera's ability to better recognize objects. This will influence the user system to consider using higher-wattage lights when displaying bananas of various varieties and ripeness levels.

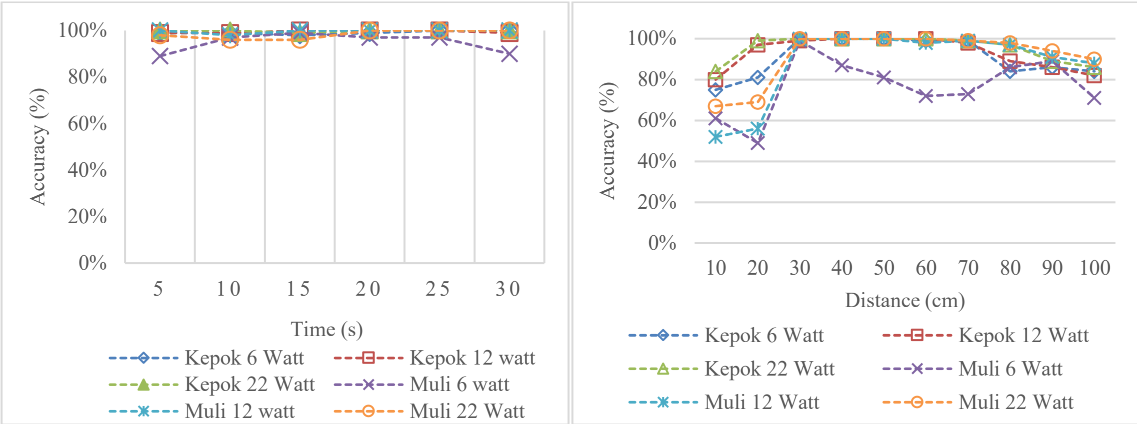


Figure 12. Overripe classification result under various lamp power

4. CONCLUSION

In this study, the proposed system could classify banana type and level of ripeness in real-time conditions using a CNN and Jetson Nano as hardware. The result of the classification process based on banana type within the categories of 6 watts, 12 watts, and 22 watts exhibit elevated accuracy values, with an average accuracy rate between 80% to 100%. The assessment of ripeness levels in the 12-watt and 22-watt categories yields average accuracy values exceeding 80%, while the 6-watt category demonstrates a lower accuracy result, falling below 60%. Notably, the luminance of the system significantly influences the system's performance. Higher illumination during testing correlates with elevated accuracy levels, as observed in the 12-watt and 22-watt settings. Furthermore, the impact of distance during testing is evident, revealing higher accuracy values within the range of 30 cm to 50 cm, averaging above 85%. Conversely, accuracy diminishes as the distance increases. Then, it showed that illumination impacts accuracy due to the level of illumination increases the camera's ability to better recognize objects. This system will be useful in helping supermarket officers and buyers in automatically classifying the type and level of ripeness of bananas. In the future, the type of banana, especially imported bananas, i.e., Cavendish, needs to be increased as a dataset, and the application of the banana classification system in real environments needs to be developed. In addition, the use of the same system can be applied to other fruits or vegetables, so that the smart market will be a very good development in the future.

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AUTHOR CONTRIBUTIONS STATEMENT

All authors have contributed significantly to the conceptualization, methodology, research and writing of the paper, and they have all read and agreed to the current version of the manuscript. Using the journal Contributor Roles Taxonomy (CRediT), the contributions are summarised as follows.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Lucia Jambola	✓	✓		✓	✓	✓			✓	✓		✓	✓	
Arsyad Ramadhan Darlis	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓		✓
Windi Malaha		✓	✓	✓			✓	✓	✓	✓	✓		✓	
Dwi Aryanta			✓		✓	✓	✓	✓		✓	✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT
Authors state no conflict of interest.

DATA AVAILABILITY
Data availability is not applicable to this paper as no new data were created or analyzed in this study.

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BIOGRAPHIES OF AUTHORS

Lucia Jambola graduated Department of Electrical Engineering, Institut Teknologi Nasional Bandung, Indonesia, in 2001. She received the master's degree in Electrical Engineering from the Institut Teknologi Bandung, Indonesia, in 2006. Her research interests are primarily in optic communications, wirelesss communication, and artificial intelligence. She can be contacted at email: lucia@itenas.ac.id.

Arsyad Ramadhan Darlis is an Associate Professor at the Department of Electrical Engineering, Institut Teknologi Nasional, Bandung, Indonesia, where he has been a faculty member since 2010. He received a bachelor's degree in Electrical Engineering from Institut Teknologi Nasional Bandung, Indonesia, in 2009, and a master's degree from Institut Teknologi Bandung, Indonesia, in 2011. He received a doctoral degree from the Department of Electrical Engineering, Universitas Indonesia, Indonesia. His research interests are primarily in wireless communication, optical communication, artificial intelligence, and signal processing. He can be contacted at email: arsyad@itenas.ac.id.

Windi Malaha received Bachelor of Engineering from the Department of Electrical Engineering, Institut Teknologi Nasional Bandung, Indonesia. Her research interests are signal processing and applied artificial intelligence. She can be contacted at email: windymalaha1@gmail.com.

Dwi Aryanta is a lecture at the Department of Electrical, Institut Teknologi Nasional, Bandung, Indonesia, where he has been a faculty member since 1999. He received a bachelor's degree in electrical engineering from Institut Teknologi Nasional Bandung, Indonesia, in 1997, and a master's degree from Institut Teknologi Bandung, Indonesia, in 2004. His research interests are primarily in signal processing and cellular communication. He can be contacted at email: dwiaryanta@itenas.ac.id.