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A Comprehensive Methodology for Image Recognition Utilizing Machine Learning and Computer Vision: Automation of the Harvesting Process

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***Abstract**: This study aims to investigate the machine learning techniques implemented in image recognition technology for the identification and classification of oil palm fruit ripeness. The accurate determination of fruit ripeness is crucial for optimising harvest timing and enhancing oil yield. The palm oil industry is one of the major plantations in Malaysia. The harvesting process of oil palm fruit was conducted using traditional methods, relying on manual inspection, which can be subjective and inconsistent. Plus, it required several workers. A model of image recognition was developed using machine learning algorithms and computer vision to automate the harvesting process and address labour shortages. Implementing this technology in the field could lead to more consistent harvests and higher-quality oil production. Several machine learning models were developed, trained, and tested for their ability to classify the ripeness stages of the fruit. The findings suggest the trending techniques in implementing image recognition, which can provide a reliable and efficient tool for assessing oil palm fruit ripeness.*

Keywords: Palm Oil Fruit Ripeness Classification, Image Recognition, Machine Learning, Deep Learning

I. INTRODUCTION

As one of the primary sources for edible oil, chemical, and energy products, the palm oil industry is no exception to being a rapidly growing sector, due to the high yield and cost-effectiveness of palm oil compared to other vegetable oils. The palm oil industry is a global powerhouse, playing a critical role in the agricultural sector and the world economy. Derived from the fruit of the oil palm tree (*Elaeis guineensis*), palm oil is a versatile vegetable oil commonly found in a wide range of products, including food, cosmetics, and biofuels. Malaysia, as the world's second-largest producer and exporter of palm oil after Indonesia, highlights the significant economic impact of this industry on the country [1].

The palm oil industry in Malaysia faces numerous challenges, including sustainability, labour practices, and social issues. Challenges such as unsustainable practices, forced labour, and the need for sustainable development to meet international market demands are prevalent [2]. In August 2023, plantations reported a total worker shortage of 41,733, reflecting a 24% decrease since December 2022. This reduction is attributed to the government's decision to lift the freeze, permitting plantation companies to hire foreign workers [3].

To maintain the sustainability of this industry, Fourth Industrial Revolution (IR 4.0) technologies, such as big data analysis and artificial intelligence (AI), may be adopted in the oil palm fruit harvesting process to increase efficiency and overcome the labour shortage issue. IR 4.0 was first introduced at the Hanover Fair by Germany as a concept that integrates technology-driven manufacturing processes with information and communication technologies, aiming to enhance the country's competitive edge in the manufacturing sector [4]. In the 2024 Budget, the Malaysian government has proposed expanding automation tax incentives to include the plantation commodities sector. This initiative aims to boost productivity and lessen reliance on foreign labour by promoting mechanization and automation [3].

II. LITERATURE REVIEW

A. Artificial Intelligence

Artificial intelligence (AI) refers to a machine or computer system's ability to simulate and execute tasks typically requiring human intelligence, including logical reasoning, learning, and problem-solving [5]. Machine algorithms are extensively utilized in areas such as natural language processing, speech recognition, facial recognition, computer vision, and many other prediction systems [6]. Based on [7] reviewing the article, machine learning can be broadly divided into three categories which are supervised learning, unsupervised learning, and reinforcement learning.

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Meanwhile, based on the technical analysis article [6], there are additional categories which are semi-supervised learning and deep learning.

- Supervised Learning: This involves training a model with labelled data, enabling it to make predictions or classify new data. This approach applies to both classification and regression tasks.
- Unsupervised Learning: This involves analysing and interpreting data without labelled examples to uncover patterns and structures within the data. This approach facilitates the solution of problems such as clustering and dimensionality reduction.
- Reinforcement Learning: This involves learning from feedback received from the environment, allowing machines to develop optimal strategies for behaviour autonomously.
- Semi-supervised Learning: This involves training a model with a mix of labelled and unlabeled data. It utilises labelled data for initial guidance and leverages unlabeled data to enhance the model's performance.
- Deep Learning: This approach addresses complex, large-scale, and intangible problems. It involves feature extraction and pattern recognition using multi-layer neural networks. It also assists efficiency in data processing and analysis.

Referring to the categories above, image recognition is assumed to fall between unsupervised learning and deep learning. This section reviews the application of machine learning algorithms in image recognition models using various techniques and tools.

B. Image Recognition

Image recognition and machine learning are closely intertwined, with machine learning playing a pivotal role in advancing image recognition technology. Machine learning techniques are extensively utilized in image recognition tasks such as feature extraction, classification, segmentation, and object recognition [8]. Image recognition and image classification are closely related tasks in the field of computer vision. While image classification involves categorizing images into predefined classes, image recognition goes beyond identifying and interpreting the contents within images, encompassing tasks like object recognition and image analysis [9]. Image recognition is the process of identifying and detecting objects or features within digital images or videos. This can include recognising objects such as cars and cats, recognising faces, detecting scenes like a beach or cityscape, and understanding activities like running or jumping. Machine algorithms can learn from and process large volumes of data through deep learning and other technologies, significantly improving the accuracy of image recognition [10].

C. Oil Palm Fruit Ripeness

The ripeness of palm oil fruit is currently assessed through manual visual inspection by estate workers, which can lead to inconsistent and inaccurate grading of the fruit [11]. The harvesting process of palm fruit involves several steps to ensure the quality of the product is good. The Smallholder Oil Palm Handbook, published online by SN International Development Organisation and Wageningen University in 2016, stated that there are nine steps required in harvesting palm fruit, and four of these steps are significant in identifying the quality of fresh fruit bunch (FFB).

The four significant steps are: (1) identifying ripe bunches by visual inspection. Ripe bunches are identified by the presence of loose fruits on the ground or stuck behind frond butts on the trunk, (2) harvesting the bunch by cutting the frond according to the palm age, (3) cutting the bunch stalk and (4) collecting the harvested bunches using wheelbarrow or bicycle with buckets. Human labour is necessary for harvesting and sorting fresh fruit bunches (FFBs), and more workers need to be trained to accommodate the demands of larger plantations or growing industries [12] because it is conducted manually. However, after the pandemic, Malaysia faced a labour shortage crisis due to the slow entry of migrant workers.

Implementing image recognition to classify the ripeness of FFBs is one way to increase the efficiency of the oil palm fruit harvesting process and overcome the labour shortage issue.

III. IMAGE RECOGNITION TECHNIQUES

A. Data Pre-processing

Before implementing image recognition techniques, the data collected as datasets must undergo data pre-processing. Pre-processing of images is an essential step that significantly impacts the effectiveness of the classifier algorithm [12]. During image pre-processing, the training images were labelled according to their maturity level, and some photos were resized to reduce their computational size.

Image acquisition refers to the process of collecting raw data, the first step in the workflow of image recognition. Images of FFBs were captured using a smartphone camera under sunlight during the study [13]. Capturing images is not restricted to smartphone cameras; it can be sourced from digital cameras, scanners, or other imaging devices.

Image segmentation is the process of partitioning an image into multiple segments to simplify it and make it easier to analyse. The objective of applying segmentation to an image is to identify the variants and boundaries within it. There are several methods for image segmentation, including thresholding, clustering algorithms, and pixel grouping, among others. Image cropped using Python and going through the image segmentation process. The k-means clustering algorithm is used to segment the image [13]. Image preprocessed using the segmentation method with a threshold (remove background), resizing, and cropping [14]. Background removal is necessary to avoid the model misclassifying the image.

Image augmentation is a technique used to increase the diversity of an image dataset by applying various transformations to the original images. Image augmentation techniques will be implemented to induce variations to the dataset, such as horizontal and vertical flip, rotation, crop, zoom, and shear [15]. Fig. 1 illustrates the workflow for data pre-processing in image recognition.

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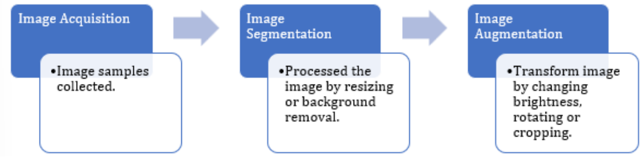
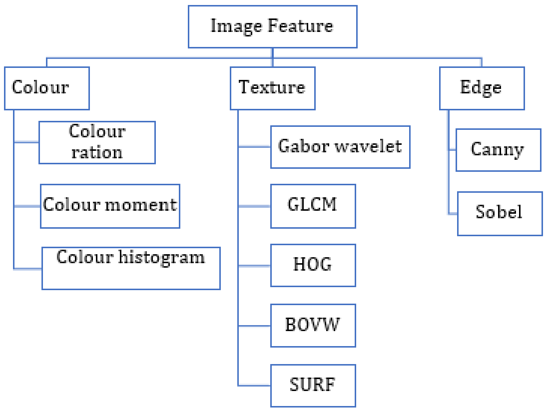


[Fig.1: Workflow of Data Pre-Processing] (source: [12, 13])

B. Feature Extraction

This step is crucial in image processing and computer vision as it extracts meaningful information from the image [12]. As shown in Fig. 2, numerous features can be extracted from an image, including colour, texture, edges, size, and more. Hue measurement is a good discriminator to determine the ripeness stage based on colour analysis for oil palm fruits compared to the RGB (Red, Green, Blue) technique or CIExy values [13]. Colour, texture, and shape features are commonly used to describe and determine the maturity level of FFB [12].

RGB is the standard technique for colour extraction, which consists of 3 colour channels: red, green, and blue [16]. Meanwhile, feature extraction using L*a*b must perform colour conversion based on L or luminance values, ranging from 0, which corresponds to dark or black, to L = 100, which corresponds to light or white. The a* component describes the colours red and green, and the b* component describes the colours blue and yellow [17].



[Fig.2: Feature Extraction Techniques] (source: [15])

C. Fruit Ripeness Classification

The Malaysian Palm Oil Board (MPOB) categorises palm fruit ripeness into four groups: unripe, underripe, ripe, and overripe (MPOB, 2003). Artificial neural networks (ANNs) and convolutional neural networks (CNNs) are two types of deep learning methods used in many applications for fruit classification. SG (Savitzky-Golay) filter is one of the preprocessing techniques, which is applied to hyperspectral images to reduce the spectral noises significantly [18].

Previous researchers conclude that the CNN algorithm is more effective in classifying images than the ANN algorithm [19]. ResNet50 is the most popular pre-trained model used for image classification, while YOLOv3 is for object detection [11] Genetic Algorithm (GA) is applied to the baseline model to get the optimal learning rate hyperparameter [20]. Based on the [21] study, several variations of the YOLOv4 model are evaluated to compare their performance in the task of FFB detection: YOLOv4-CSP and YOLOv4-tiny.

The images were labelled using "ClassifAI", an open-source data annotation platform. ResNet50, also known as Residual Neural Network, is a pre-trained DL model from the ImageNet database that can classify images into 1000 object categories [11]. Both ResNet50 and YOLOv3 utilised hyperparameters with varying numbers of epochs, image sizes, and batch sizes.

YOLO (You Only Look Once) is a single-stage object detection model that performs detection in a single pass, starting with YOLOv1 with 24 Convolution layers, improvements in YOLOv2 and YOLOv3 that uses Darknet-19 and Darknet-53 also able to detect 9.000 objects, and lastly YOLOv4 which focuses on improving performance from previous models with some term such as BoS (Bag of Specials) and BoF (Bag of Freebies) [20]. YOLO was first introduced in 2015, then YOLOv2 in 2016, YOLOv3 in 2018, and YOLOv4 in 2020. Table I summarises the advantages and limitations of the classifier techniques used in previous research. At the same time, Table II presents the classification of FFB ripeness using various machine learning models, as conducted by previous researchers.

Table 1: List of Advantages and Limitations of Classifier Techniques

Classifier techniques	Advantage	Limitation
ResNet50	Used for image classification	The images are sorted into different folders according to their category
YOLO	Used for real-time object detection	The location of the palm oil object needs to be labelled in the image
MobileNetv2	Offers more efficient memory usage for mobile applications	Designed for implementation on mobile devices
EfficientDet	Single-shot object detector	Relies on EfficientNet
Support Vector Machine	Find the optimal hyperplane that separates data points of different classes with maximum margin.	Less effective when classes overlap and are not well-separated

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Table 2: List of Related Studies Techniques

Author, Year	Number of image samples	Image size	Classification of ripeness	Feature extraction techniques	Classifier techniques	Accuracy (%)
Shuwaibatul et al., 2019	400	-	Ripe, unripe, underripe, overripe	Colour features, a bag of visual words	Linear SVM	Colour features: 57%, bag of visual words: 70%
Minarni et al., 2024	23	1024 x 1088 x 544	Ripe, unripe, overripe	SG smoothing filter	ANN	Average: 79.48%, highest: 90%
Shoffan et al., 2023	150		Ripe, unripe, intermediate	RGB, L*a*b	KNN, K-Fold cross-validation	RGB: 97.77%, RGB + KNN: 95.4%, L*a*b: 97.77%, L*a*b + KNN: 97.4%
Edy Salim and Suharjito, 2023	4160	416 x 416 pixels	Ripe, unripe, underripe, overripe, empty, abnormal	-	GA, YOLOv4	YOLOv4-tiny GA: 99.8%, YOLOv4-tiny ES GA: 97.5%
Mohamed et al., 2022	328	-	Ripe, unripe, overripe, half-ripe	-	MobileNetV2 (CNN network) SSD, EfficientDet-lite, YOLOv5	MobileNetv2: 0.478 (mAP) EfficientDet-lite0: 0.743 (mAP) YOLOv5n: 0.781 (mAP)
Nurulaqilla et al., 2022	299	757 x 568 pixels	Ripe, underripe, overripe	Edge, shape, colour, and so on.	ResNet50, YOLOv3	-
Jin et al., 2022	500	1920 x 1080 pixels	Ripe, unripe	-	YOLOv4	YOLOv4-512: 96% YOLOv4-608: 96.22% YOLOv4-CSP-512: 95.89% YOLOv4-CSP-608: 96.43% YOLOv4-tiny-512: 55.6% YOLOv4-tiny-608: 48.89%
Ahmad Sopian et al., 2022	600	416 x 416 pixels	Fraction 1, fraction 2, fraction 3	Color	YOLOv4	97%
Abdulrazak et al., 2020	-	-	Ripe, immature	Color	CNN	96%

IV. MODEL PERFORMANCE EVALUATION

Performance evaluation is conducted to measure the model's accuracy, ensuring there is no overfitting issue. Typically, data is divided into training, testing, and validation sets. ResNet50 model performance is evaluated based on precision, recall, and F1-score value, while YOLOv3 is measured based on mean average precision (mAP). Precision is the number of optimistic class predictions; recall is the number of correct optimistic class predictions made of all correct positive cases in the dataset, and the F1-score provides a single score that addresses both precision and recall concerns in a single number [21]. K-fold cross-validation is another ML technique used to evaluate the classifier model's performance. The k-fold cross-validation aims to select training and testing datasets to have ANN models with higher accuracy [18].

V. TOOLS AND FRAMEWORK

Image recognition relies on a combination of tools and frameworks designed to identify and classify objects within images accurately. Key components include deep learning libraries, such as TensorFlow, which provide the necessary infrastructure for building and training neural networks. Frameworks like YOLO offer essential image processing functions, enabling tasks like object detection and image transformation [22]. Integration tools like Keras simplify the construction and training of neural networks, making advanced image recognition accessible even to those with limited deep learning expertise. Table III shows a list of the tools and frameworks used in previous studies to implement image recognition.

Table 3: List of Tools and Frameworks for Image Recognition

Tool and framework	Functionality
Google Collaboratory	Google Colab, a free cloud-based Jupyter Notebook, offers applications for deep learning and machine learning.
Python	A high-level, interpreted programming language known for its simplicity and readability.
TensorFlow	An open-source ML framework provides a comprehensive and flexible ecosystem of tools, libraries, and community resources.
Keras	Open-source software library that provides a Python interface for artificial neural networks
SoftMax	The mathematical function used in ML for classification tasks within neural networks.
SQLite3	Open-source, serverless, zero-configuration, transactional SQL database engine.
DarkLabel	Annotating images by generating text files with the same name as the image data.

VI. RELATED STUDIES

In addition to palm fruit ripeness classification, several studies have been conducted on the classification of various fruit categories. Apple, orange, banana, and other fruit groups are among the first to be examined for classification. Subsequently, eight categories of fruits were considered, including pomegranate, orange, banana, and five different types of red apples [23]. A CNN model was developed using the stochastic gradient algorithm and Adam optimizer to process the fruit images and classify them.

The model's accuracy was 96.88% after 40 iterations of training on the dataset.

Another image recognition model was developed using CNN, RNN, and LSTM, while the performance was evaluated using SVM and ANFIS [24]. RNN is a recurrent neural network where elements build an organised association between node edges. It is a part of ANN. LSTM, or Long Short-Term Memory, provides extra memory cells that combine with the RNN to classify images of fruits.

VII. CONCLUSION

Image recognition model development involves various types of machine learning and deep learning algorithms. The implementation required several techniques to ensure that the captured images were interpreted correctly, validating the model's accuracy. Image acquisition, pre-processing, feature extraction, classifier design, and classification decision are the key steps in conducting image recognition. The current technology commonly used in image detection experiments is the YOLO framework.

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Ethical Approval and Consent to Participate	No, the article does not require ethical approval or consent to participate, as it presents evidence that is not subject to interpretation.
Availability of Data and Materials	Not relevant.
Authors Contributions	All authors have equal participation in this article.

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