# Machine Vision for Automated Maturity Grading of Oil Palm Fruits: A Systematic Review


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**Abstract** The maturity of oil palm fruits is a very crucial factor for oil extraction industry in Indonesia, Malaysia, Thailand, and other countries to ensure the oil quality and increase productivity. This literature review examines the various machine learning techniques, especially the deep learning techniques used to automate the maturity grading process of oil palm fresh fruit bunches. The crucial advantages of using machine learning approaches were highlighted, and the limitations and prospects of each research article were discussed. This review describes the various image pre-processing techniques utilized to prepare images for model training. CNN is identified as the dominant over all classification techniques of machine learning to classify the oil palm fruits images based on maturity level, due to its ability of learning complex features.



**Keywords:** machine Learning, deep Learning, CNN, feature extraction, Computer Vision, maturity grading.


## 1. Introduction

The maturity grading of oil palm fruits plays a pivotal role in the overall success and sustainability of the palm industry. To find out the accurate estimation of fruit maturity is a central key point for improving agricultural practices, ensuring oil quality, and maximizing the palm fruit production. In the recent era, the implementation of machine learning algorithm has become a transformative way to increase the efficiency and precision of maturity grading process. This literature review is based on to explore the existing body of knowledge on the uses of machine learning techniques in the field of maturity grading of palm fruit, focussing on to provide the comprehensive overview of the current research, methodologies used and the key findings.

Computer Vision and Image Processing techniques are the two correlated and interconnected fields of machine learning in Computer Science. The potentiality of these techniques is to derive and conclude the information from the visual data and train the machines with the ability to interpret like human visual perception. There are many applications based on Computer Vision and Image Processing across various domains, including fruit categorization, surveillance system, healthcare, object detection, and more [113].

Computer Vision techniques are utilized to develop the algorithms and models to impart the systems with the ability to make decisions from the visual data and interpret into the human demand. Many tasks, such as recognition, detection, segmentation, and visual understanding are being performed within the range of Computer Vision Technique. The decisive goal is to enhance machine capability to be able to comprehend and make interaction with the visual world [37]. Image Processing as the name suggests, it has the role of manipulate and analyse the images to boost their qualities, extract information and perform a subsequent analysis. It has basic operations such as compression, enhancement, filtering, and restoration among the others. It plays a vital and potential role in pre-process data before being applied to higher tasks in Computer Vision [41].

The grading system of oil palm fruits has its own potential role by categorising them based on the parameters such as color, bunches, and shape to enhance the efficiency and improve the productivity. The Machine Learning approach has the great impact of automating the maturity grading process. The Machine Learning approach can analyse the images captured in RGB format, and it can extract the morphological and color features. There are many Machine Learning techniques, such as CNN, KNN, fuzzy logic, and other that are employed to detect the fruits accurately and classify them accordingly [52].

## 2. Literature survey

Palm oil is an important commodity that is widely used in the food industry, biofuels, and various other industries [96]. The maturity of palm fruits influences the quality of palm oil, with different grades of oil produced from fruits at different stages of maturity [133]. Therefore, accurate detection and grading of palm fruits is crucial to ensure the quality of the oil produced.

Traditional methods of palm fruit detection and grading are time-consuming, labor-intensive, and prone to errors. In recent years, machine learning techniques, particularly deep learning, have presented hopeful outcomes in numerous computer vision tasks, containing object detection and classification [70]. However, by incorporating quantum computing techniques, researchers can further improve the performance of these methods.

Quantum deep learning (QDL) is an emerging field that combines quantum computing and deep learning to achieve better performance in machine learning tasks [39]. QDL uses quantum circuits to enhance the performance of classical deep learning models. The potential of QDL in enhancing machine learning tasks has been demonstrated in various applications, such as image classification and natural language processing.

Zheng et al. (2020) proposed a QDL-based approach, Quantum PalmNet, for palm tree detection, which outperformed classical deep learning models in terms of accuracy and speed [5]. This approach can be extended to palm fruit detection and maturity grading.

In the agriculture sector, computer vision techniques have been used to analyze various crops, including fruits and vegetables. Machine learning algorithms have been used to detect and classify different types of fruits and vegetables based on their color and shape features [103]. QDL has the potential to improve the performance of these algorithms by leveraging the power of quantum computing. Sabri et al. (2017) used deep learning techniques to classify palm fruits based on color features. The study showed promising results in identifying fruits at different maturity stages [98]. However, incorporating QDL techniques can improve the performance of the model.

### 2.1. Pre-processing

As the name suggests, the pre-processing refers to the stage of images before going to be processed. It plays a crucial role to prepare and transform the image data for machine learning tasks such as recognition, classification, prediction, analysis, detection, and segmentation by using the image acquisition, enhancement, resizing, normalization, extracting relevant features and others [117].

#### 2.1.1. Image acquisition

The first step in pre-processing is to collect the image data using the high quality of input devices. To ensure the extensive acquisition of image characteristics, you must capture the images on different angles under the predefined lighting conditions. The classical spectrum imaging technique captures images using cameras based on the RGB wavelength. These images can be utilized to provide color information for assistance in maturity grading [31]. Unlike the visible spectrum imaging technique where only three or four bands (e.g., RGB and sometimes nearer to Infrared) are used to capture the image data, the HSI (Hyperspectral Imaging) technique works on minor continuous spectral bands to capture images to improve the image feasibility. The HSI has the great impact on maturity grading of palm fruits based on the spectral characteristics [26]. While the NIR (Near-Infrared) Imaging technique captures electromagnetic radiation within the range of wavelength 700-2500 nanometers. This feature offers the insights to ponder into the pulp of fruit and produces feature extraction such as biochemical composition and moisture amount. This technique is useful to assess the fruit quality [114].

#### 2.1.2. Image enhancement

Image enhancement is an important pre-processing step for the computer vision task, employed to enhance the image quality and extract the relevance information from the acquired images. This step may consist of adjusting sharpness, maintaining brightness, and increasing the contrast to reduce the noise and enhance the feature selection of fruit images. In the current era, machine learning techniques significantly have advancement and improvement to the image enhancement methods [12].

The classical image enhancement approaches consist of the techniques like contrast stretching [125], histogram equalization [129], and spatial filtering [1]. These techniques are simple, easy to use and computationally efficient, but commonly they don't produce satisfactory outputs, especially in the noise and lightening conditions. To deal with such type of conditions, deep learning techniques are utilized, especially CNNs (Convolutional Neural Network) have gained the popularity for image enhancement due to their capability of learning from complex features directly or indirectly from image data. There are many methodologies proposed in this field, such as SISR [126] (Single Image Super Resolution) has the potential goal to enhance the quality of low-resolution images. The other approaches such as SRGAN [72] (Super-Resolution Generative Adversarial Network), and ESRGAN [121] (Enhanced Super-Resolution Generative Adversarial Networks) and SRCNN [29] (Super-Resolution Convolutional Neural Network) have produced the satisfactory results in preparing the high-resolution images from the lower resolution input images. Enhancing and converting the images captured in the low-light situation is a tedious job due to the poor visibility and external noises. The Retinex-based model [74], Fusion-based approach, and CNN-based technique [23] offer solutions to handle this type of situations.

To fulfil the criteria of image enhancement is impossible without dealing with the unwanted noise. The deep learning-based Noise reduction methods, such as RIDNet [8] (Real Image Denoising Network), CBDNet [42] (Convolutional Blind Denoising Network), and DnCNN [130] (Denoising Convolutional Neural Network), have the superior priority over classical denoising techniques. To deal with the blurred images is also a critical task in accomplishing the image enhancement process. Removing the blurriness of the images becomes essential while working on medical imaging or surveillance applications. The most used CNN-based deblurring models like DeblurGAN [66] (Deblurring Generative Adversarial Network) and SRN-DeblurNet [81] (Spatial Recurrent Network for Image Deblurring) have presented the satisfactory result to restore the sharpness to the blurred images.

GANs (Generative Adversarial Networks) have emerged as the effective frameworks to satisfy the image enhancement tasks. They follow the process of adversarial training to generate the visual and realistic required images. The task of image enhancement is accomplished by several models, including Pix2Pix [53], SRGAN [72], and CycleGAN [132], which utilize Generative Adversarial Networks. These models enable image-to-image translation, higher resolution generation, and enhancement of unpaired images, respectively.

### 2.1.3. Image resizing

Image resizing is a crucial task in image pre-processing and computer vision. Image resampling or image scaling is another name for it. In the machine learning context, researchers have implemented many techniques to resize the images while maintaining and preserving the actual visual effects of images. Bicubic interpolation [94] is a commonly used methodology to resize the images. It produces the computationally efficient and smooth results. The recent advancement in deep learning technology has led the CNN model to do the image resizing tasks as well. Kim et al. (2016) proposed a model called ESPCN (Efficient Sub-Pixel Convolutional Neural Network) which modifies and scales the images from lower resolution to higher resolution. It effectively has the job for single image super resolution [62]. Content-Aware image resizing technique is also a powerful approach that preserves the visual content and minimizes the distortion in the region of interest.

Avidan and Shamir (2007) introduced Seam carving algorithm, a standard content-aware image resizing technique that inserts or eliminates the seams of the lower resolution pixel to resize the images [10]. Although it plays an important role in the image resizing while preserving the actual visual content, it may produce unwanted results when dealing images of high complexity. The other technique to resize the images is Learned Image Resizing, that adopts the machine learning algorithms to resize the images and produce the required result based on their content. Danon et al. (2021) proposed a learned image resizing approach to resize the images using a deep neural network being trained on the large dataset of paired images [27]. This method achieves the better response compared to a classical image resizing technique, especially in complex data with challenging images. The implementation of the multi-scale approaches to resize the images and segmented them based on the resolutions, then finally merged them to generate the required resized output image. He et al. (2016) proposed deep network architecture for the multi-scale high-resolution images. This approach progressively scales the images on various measures to get the best result [46].

Table 1 presents a comprehensive overview of color parameters and features used in various studies, including color spaces, color values, statistical color features, color histograms, and texture analysis, with references to relevant literature.

### 2.1.4. Color normalization

Color Normalization is a critical image pre-processing step to ensure the color persistent across various imaging stages to perform accurate analysis and interpretation of visual image data in the computer vision applications. It ensures the reliability and robustness in numerous machine learning applications. Numerous techniques have been proposed to normalize the color distribution and minimize the changing effects caused by lightening, sensors, or other input devices. The Table 2 lists various techniques for image processing and color normalization, including Histogram Equalization for enhancing contrast, Deep

Tab. 1. Comparison of color features for oil palm fruits analysis.

| Ref. | Color parameters & features | Color Space |
|---|---|---|
| [54] | Photogrammetric, L*a*b color space | RGB |
| [5] | Color Values, Statistical Color Features, Color Histogram | RGB |
| [112] | Uniformity, inverse difference, homogeneity, & Outer Color | RGB |
| [78] | Visual Inspection, black/dark purple color, | RGB |
| [45] | Surface Color, Dark purple, orange red | RGB |
| [2] | Color histogram & Statistical color, UV, RGB, & NIR | RGB |
| [9] | Color composition, Red & orange skin color, blackish brown, black skin | RGB, HSV |
| [80] | TCS3200, RGB | RGB, HSV |
| [4] | Statistical color features & color histograms | RGB, HSV, L*a*b |
| [3] | Statistical color features & color histograms | RGB, HSV, L*a*b |
| [58] | Random brightness ranges from -40% to +60%, RGB | RGB, L*a*b |
| [59] | Gray-scale threshold, RGB | HSI, L*a*b |
| [110] | Histogram Analysis, RGB & L*a*b | CIE L*a*b |
| [40] | Hue value, Hue measurement | RGB, HSI, HSV |
| [49] | HOG & FREAK, RGB color channels | RGB, HSI |
| [124] | Hue, Saturation & Value conversion from RGB to HSV | HSV |
| [92] | FRedS4, IRedS4, etc., Blue, Green, Amber, Red, Deep Red | Far-Red band |
| [116] | Mesocarp color, Orange for ripe, yellowish/yellow for unripe | Wavelength |
| [13] | Spectral bands & reflectance values, Carotenoids and Chlorophylls | Spectral Bands |
| [77] | Surface Color, Dark Purple, Red Orange | Yellowish Red |

Learning-based Methods like CNN for color normalization, Batch Renormalization to standardize image activations, Gray-Level Co-Occurrence Matrix (GLCM) for texture analysis, Retinex Algorithm for improving color consistency, Instance Normalization for per-pixel color adjustments, Color Transfer for matching color distributions between images, and Color Constancy Algorithms for maintaining consistent colors despite lighting variations.

### 2.1.5. Image segmentation

The primary goal of this fundamental task is to partition an image into meaningful pixel or segments. These segments correspond to the region of interests in an image. Image Segmentation approach is used in various machine learning tasks such as image classification, object detection and semantic segmentation. The Tab 3 outlines various segmentation techniques, including Thresholding-Based Methods, like Otsu's method for optimal threshold selection, Edge-Based Segmentation techniques, such as Canny Edge

Tab. 2. Various techniques used in color normalization for image processing.

| Techniques | Description |
|---|---|
| Histogram Equalization | This technique is used to enhance the contrast of an image by adjusting the intensity distribution of pixels [89]. |
| Deep Learning based Methods | In the deep learning-based approach, CNN methodology is used to normalize the color directly from the image data [131]. |
| Batch Renormalization | Batch Renormalization is an extended version of Batch Normalization technique, fundamentally used in deep learning to normalize the activations of mini batches in the neural network. It transforms the color distribution of images into a standard form, also reduces the generated color variations because of lightening situations, cameras, sensors, and other devices that affect the image appearances [50]. |
| Gray Level Co-Occurrence Matrix (GLCM) | GLCM is a technique, particularly used in texture analysis. It also employed as the feature selection method to quantify the texture of an image, which enhances the robustness and performance of a machine learning model on trained images [36]. |
| Retinex Algorithm | It is a very powerful tool used in the process of image pre-processing to accomplish the task of color normalization. It manages to reestablish the gaps due to the lightening variations, sensors, or other imaging input devices, eventually the image color looks more realistic and natural. Basically, it improves the consistency of color, enables robust feature selection, and enhances the interoperability and visual quality of the images [68]. |
| Instance Normalization | Instance Normalization is a technique, specially used to normalize the colors and features across the various instances. It performs the normalization task separately on each pixel values of each individual image. It also computes the mean value and standard deviation of each color (Red, Green, and Blue) of an image [119]. |
| Color Transfer | Color transfer is a machine learning approach used in color normalization as it provides the consistency and accuracy to image analysis and the computer vision tasks. This approach tries to match the color distribution from source image to targeted image. It transfers the color features from the target to source image while preserving the dimensional information [95]. |
| Color Constancy Algorithms | This algorithm has a crucial role in a condition in which lightening may vary on images due to any reason. The goal is to keep the image color consistent irrespective of any lightening situation. This is helpful in the object detection process where variations in lightening may affect the object appearance [35]. |

Detection and Sobel Operator, Region-Based Segmentation for partitioning images based on attributes, Deep Learning-Based Methods utilizing CNN architectures like U-Net, and Clustering-Based Methods, like K-means and Fuzzy C-means for grouping similar pixels.

These are many image segmentation techniques; each has its own advantages and disadvantages. The better selection of image segmentation techniques depends on various factors like image nature, computational resources, objects complexity, etc. Table 4 shows that various segmentation techniques, including K-means Clustering, Gray-scale thresholding, and Histogram-based Analysis, have been applied in maturity detection, ripeness detection, and weight prediction of agricultural products between 2009 and 2023.

Tab. 3. Techniques used in image segmentation for image processing.

| Techniques | Description |
|---|---|
| Thresholding Based Methods | This method uses the gray-level histogram analysis to determine the optimal threshold value for an image segmentation. The method works on to increase the inter-class variance of pixel intensities in an image. Otsu (1979) implemented a threshold selection method, that is very effective in object detection, image analysis in the medical field, document processing and other applications [85]. |
| Edge Based Segmentation | This technique identifies the boundaries/edges of an object within an image. These edges refer to the transitions in color, texture and intensity that is useful for object detection, feature selection and image pre-processing. Here is an overview of edge-based segmentation in image pre-processing:<br>1. Canny Edge Detection: The Canny edge detection method is common to identify the edges in an image. This method follows the different steps like gradient computation to detect the edge strength, hysteresis thresholding to recognise and interconnect the edges, non-maxima suppression to decrease the edge thickness, Gaussian smoothing for the noise reduction and others. It minimizes the false detection and maximizes the true edge detection and can robust the noises [18].<br>2. Sobel Operator: It is a convolutional based gradient method to detect the simple edges of an image. It involves with separate kernels to detect horizontal and vertical edges of an image by calculating the approximate gradient magnitude [108].<br>3. Laplacian of Gaussian (LoG): LoG is the combination of Laplacian edge detection and Gaussian smoothing to enhance edge clarity and to reduce the noise as well [76].<br>4. Gradient-Based Methods: This method extracts gradient magnitude and the direction of pixels in an image for edge detection. Techniques like Scharr operator [17], Prewitt operator [21], Robert Cross operator [82] are mostly used in gradient-based method for edge detection [91]. |
| Region Based Segmentation | This segmentation technique is used to partition an image based on its color intensity, pixel resolution, texture, or other attributes. It is also employed to combine pixels that have same features into an identical region. It provides the meaningful and more obvious result in the presence of unwanted background and noise, compared to other methods like pixel-wise segmentation technique. The watershed algorithm is also used for image segmentation based on image gradient [120]. |
| Deep Learning Based Methods | CNNs have achieved the incredible success in the field of image segmentation of machine learning tasks. It works with different architectures like SegNet [60], FCN (Fully Convolutional Network) [57] and U-Net [6] and uses coder decoder structures to produce safeguard for spatial information [97]. |
| Clustering Based Methods | Clustering based methodology partitions an image into different segments/regions based on the pixels' similarity and try to combine them that have common features like similar color, intensity, resolution, spatial proximity, texture, and others.<br>1. K-mean clustering methods partition image pixels into the number of K clusters based on their similar features. It also involves in color based (RGB) segmentation or LAB (Lightness, Green-Red, Blue yellow) spaces [44].<br>2. Fuzzy C-means clustering method is an extended version of K-mean clustering method, in which every pixel is assigned to a degree in each cluster to accomplish the task of image segmentation [15]. |

Tab. 4. Descriptions of segmentation techniques used for palm fruits analysis.

| Year | Segmentation Techniques | Applications | Reference |
|---|---|---|---|
| 2009 | K-means Clustering Algorithm | Maturity Detection | [54] |
| 2009 | Gray-scale thresholding | Maturity & Weight Prediction | [59] |
| 2015 | Histogram-based Analysis | Maturity Detection | [102] |
| 2019 | K-means Clustering Algorithm | Maturity Detection | [40] |
| 2023 | K-means Clustering Algorithm | Ripeness Detection | [58] |

Tab. 5. Various methodologies of feature extraction in image pre-processing

| Methods | Description |
|---|---|
| Histogram based | This method is a graphical representation to analyse the distribution of pixel intensities in an image. By analysing the histogram, many features like skewness, entropy and uniformity can be extracted to deliver the detailed information about an image [11]. Popular histogram methods are:<br>1. Histogram Equalization: It improves the contrast of an image by applying the redistribution task on pixel intensities in an image [85].<br>2. Local Binary Patterns (LBP): Extracting the features of an image by performing the comparison on each pixel with its nearest pixels [84]<br>3. This method introduced by Dalal and Triggs in 2005 to represent the edge characteristics, local gradient texture and shape information of an image. In this method, an image is divided into small regions that are called cells, then the histogram orientation for each cell is computed [25]. |
| Transform based | Mathematical transformation is applied in this method to extract the image features from the specified domain. It transforms the basic image attributes into other domain where features extraction can be performed easily. In this method, Principal Component Analysis (PCA) technique is used to reduce dimension and Discrete Wavelet Transform (DWT) to acquire the information about an image with multi-resolution [61]. Common Transformed-based methods are:<br>1. Wavelet Transformation: It transforms the images into different frequency patterns and captures each minor details of an image [75].<br>2. Discrete Fourier Transform (DFT): This transformation method is used to compress and filter the image. It transforms the images into different frequency domains [55]. |
| Deep Learning Based Methods | The Deep Learning-based method involves the Convolutional Neural Network (CNNs) for features selection in the image pre-processing to automate the learning of hierarchical demonstration from raw image data [24]. |
| Texture Analysis | This technique is used to collect the information about the correlation between image pixels based on its texture. It describes and categorize the repetitive patterns found in an image. The methods like Gabor Filter and Local Binary Patterns (LBP) are common to provide the information about patterns and texture properties within an image [48]. Gabor Filters named after a physicist Dennis Gabor, generally used for texture analysis. They are the linear filters employed on multiple orientations and scales [73]. The other method used in Texture Analysis is Gray-Level Co-occurrence Matrix (GLCM) to capture the statistical features of image textures by performing analysis on pixel correlations [51]. |
| Statistical Features | These methods used to capture the statistical features of an image, such as kurtosis, skewness, mean and standard deviation for each color pixel or the entire image. These methods are very efficient to provide information about the distribution of an image intensity [28]. |

### 2.1.6. Feature extraction

Feature extraction in image pre-processing involves determining and identify the color features from the segmented image. Color features have the attributes of shape, texture patterns and histogram which distinguish one image from others. The goal of this task is to acquire the most relevant features from an image to satisfy the criteria of machine learning models. The Tab 5 summarizes various image feature extraction methods, including histogram-based, transform-based, deep learning-based, texture analysis, and statistical features, providing a comprehensive overview of techniques used to analyze and understand image content.

Tab. 6. Techniques used in feature scaling for image processing.

| Techniques | Description |
|---|---|
| Min-Max Scaling | This is a most common technique to scale the pixel values into a fixed range, usually between 0 and 1. This is a widely used technique due to its effectiveness and simplicity [107]. |
| Z-Score Normalization | It is also known as the Standardization, to transform the pixel values into the mean value of 0 and the standard deviation with 1. This technique is best suitable and most effective in the case where the pixel values vary significantly across the images [22]. |
| Robust Scaling | This technique is used to scale the image according to the model needs. The Median absolute technique (MAD) method is generally used in this technique to reduce the effect of outliers. It is a more robust method compared to other classical mean and standard deviation-based normalization techniques [19]. |
| Histogram Equalization | This technique is commonly used to redistribute the intensities of the pixel to boost the image's contrast. It modifies and improves the visual view of images and make it beneficial for the task in segmentation and object detection [38]. |
| PCA-Based Methods | It stands for Principal Component Analysis (PCA), used for feature extraction and to decrease the dimensionality of image data. It converts the original pixel space into a lower dimensional space while maintaining the relevant information about an image. It minimizes the computational complexity and improves the performance of the model [105]. |
| Adaptive Histogram Equalization (AHE) | It is a standard version of Histogram Equalization technique that employed on only small regions of an image to adapt the variations of local contrast. This technique is highly recommended when lightening conditions are not uniform [89]. |
| Contrast Limited Adaptive Histogram Equalization(CLAHE) | It is an extension of AHE, widely used in processing of medical imaging and satellite images. It limits the contrast amplification and minimizes the over noise in an image [88]. |

### 2.1.7. Feature scaling

The term Feature Scaling in image pre-processing of machine learning refers to the standardization and normalization of image pixels before utilizing in machine learning model. Image is represented in the form of array with pixel values, where each pixel in the array corresponds to a numerical value that represents the color or intensity of an image. Pixel values depend on many factors such as image capturing devices, sensors, or the lightening conditions. Therefore, Feature Scaling technique is applied to bring them with common pixel values to form a similar scale and improve the performance. The table 6 provides a comprehensive overview of various image preprocessing techniques, including normalization methods (Min-Max Scaling, Z-Score Normalization, Robust Scaling), histogram equalization techniques (Histogram Equalization, Adaptive Histogram Equalization, Contrast Limited Adaptive Histogram Equalization), and feature extraction methods (PCA-Based Methods), highlighting their applications and benefits in image analysis tasks.

Tab. 7. Techniques used in feature scaling for image processing

| Data Types | Description |
|---|---|
| Image | Image data augmentation technique is fundamentally used to increase the size and diversity of original image datasets by applying various transformation methods. Some common functionalities for image data augmentation are: Flipping, Cropping, Addition of Gaussian noise, Adjustment of contrast, Elastic transformation, Rotation, Scaling, Translation, Adjustment of brightness, Color jittering and so on. These techniques can be applied independently or in the combined to generate the augmented image datasets. The selection criteria for image augmentation techniques depends on various factors such as dataset features, task consideration and the level of augmentation required [106]. |
| Textual | Textual data augmentation technique is employed to improve the performance and robustness of NLP, especially with limited training datasets. This technique generates the new synthetic data points by applying numerous transformations to the existing text data. Some functionalities in textual data augmentation technique are Addition, deletion, and word swapping, paraphrasing and replacement of synonyms. These are generally used in NLP tasks such as sentiment analysis, textual classification and to make the model capable to generate a wide range of training datasets [122]. |
| Audio | Audio data augmentation technique is basically used in background sound classification, speaker identification and automatic speech recognition (ASR). This technique is involved in generating the new audio samples from the existing one to increase the size of datasets. The tasks involve in this technique are Time stretching, addition of background noise, Speed setup, shifting of pitch and the time warping [87]. |
| Tabular | Tabular data augmentation technique is used to address the challenges faced with imbalanced datasets and to increase the size of tabular datasets from the existing one. The tabular data are organised in rows and columns, typically found in databases or spreadsheets. The tasks involve in tabular data augmentation techniques are: Synthetic Minority Over-Sampling Technique (SMOTE), Noise injection and Random sampling etc [34]. |
| Video | Video augmentation technique is aimed to generate the new samples while preserving the significant content of the original videos. The involved in these techniques are: Temporal cropping, Frame sampling and Frame changing, etc. These tasks may be applied individually or in a combined mode to enhance the diversity of training datasets [20]. |

### 2.1.8. Data augmentation

Data augmentation technique aimed to improve the robustness and model generalization by increasing the training size of datasets. It typically generates the new datasets from the existing ones. The Tab 7 provides a comprehensive overview of data augmentation techniques for various data types, including image, textual, audio, tabular, and video data, highlighting the methods used to increase dataset size and diversity while preserving data integrity and enhancing model performance.

## 2.2. Classification methods

Classification is very essential task in the context of machine learning, used to categorize the data into predefined labels or classes based on their features. It is a supervised learning technique in which model is trained with the labelled data and each data point is assigned with a class label. The main goal of the classification task is to perform a mapping from input features to class labels, then can be utilized later to predict the class label of unseen, new data. There are many classification algorithms, each has its own application, pros, and cons, etc. The common classification algorithms will be presented in the following sections.

#### 2.2.1. Traditional Classification Methods

The classification methods used to categorize the data based on features have been used for several decades. They are the main foundations for modern classification algorithms in the current era. However, due to the advancement in the field of deep learning and neural networks, the modern classification methods have become a popular choice for larger and complex datasets. The common traditional classification methods are:

1. **Decision Trees:** As the name suggests, it is a hierarchical or tree like structure in which leaf node represents the class label, branches to decision rule and internal node represents the features. It is the most famous supervised machine learning algorithm known for its simplicity, easiness for implementation and interpretability. It is used for classification and regression to handle both numerical and categorical data [63].
2. **k-Nearest Neighbors (*k*-NN or KNN):** KNN is a very simple and effective algorithm for the image classification task. In this method, the class label of the new dataset is basically determined by the class label of its nearest neighbors. Because of the non-parametric method, it classifies instances based on the majority class labels of its nearest neighbors. It is widely used for both classification and regression tasks [64].
3. **Support Vector Machines (SVM):** SVM is a very powerful, effective, and popular supervised machine learning algorithm for image classification, especially with small to medium size datasets where interpretability for the model is required. It constructs an optimal hyperplane or a set of hyperplanes to separate the different classes while minimizing the classification errors and maximizing the margin between classes. It is designed to work very well as a linear and nonlinear classification in high-dimensional space [47].
4. **Logistic Regression:** Logistic Regression is widely used linear model for binary classification in machine learning, also applied for image classification. It uses the logistic function to estimate the probability that given instances belong to a specific class label or not [69].

#### 2.2.2. Deep Learning-Based Classification Methods

Deep learning-based image classification is significantly a revolutionized advancement in the field of computer vision, capable of achieving a high level of accuracy and scalability across numerous applications. This classification method takes the advantages of deep neural networks, particularly CNNs, to automatically learn hierarchical representations from raw image datasets.

**Convolutional Neural Networks (CNN):** CNN is a deep learning model, especially designed for analysing and processing the grid data, such as images. It has revolutionized the deep learning-based image classification method. It consists of different types of layers, and each layer plays an important role in the predefined network to automatically learn the hierarchical representation from the raw image data. There are mainly three types of layers found in CNN, such as convolutional layers, pooling layers, and fully connected layers [86].

**Recurrent Neural Networks (RNN):** It is a type of artificial neural network, primarily designed for time-series and sequential data to be processed. It comes under the category of supervised machine learning techniques based on neuron with at least one feedback loop. It is capable of handling a sequence of random length, unlike the feedforward neural network, which can only process the fixed size of input vectors. Backpropagation though time (BPTT) or its variant, truncated backpropagation through time is used to train RNN for the classification tasks. It has been applied to various classification tasks, such as speech recognition, NLP, sentiment analysis, and others. However, it has the limitation of a gradient problem that makes it unable to train on long range dependencies. To solve this problem, researchers have proposed many advanced RNN architectures, such as GRUs and LSTM. Overall, it is a very powerful tool for performing classification tasks [101].

**Generative Adversarial Networks (GANs):** GANs primarily focus on image generation tasks because of being a generative model, but may also be used for image classification tasks. A single GAN is designed with two neural networks: generator and discriminator. The generator is responsible for producing fake images while discriminator makes attempts to differentiate between the fake and real images. By using the continuous learning and training process, the generative enhances its capability to create seemingly actual images. They may be utilized to perform the image classification by using data augmentation technique, features selection and other semi-supervised learning model [128].

### 2.2.3. Ensemble learning methods

Ensemble learning methods are emerging powerful machine learning techniques, especially to perform the image classification tasks. The methods are employed to make improvements in model performance by achieving the goal of combining multiple base learners to get a stronger robust predictor. These methods are extensively effective, proven to be robustness and explore the generalization ability in image classification.

However, training of ensemble methods requires some attentions during the process of main learner selection and diversity to improve the efficiency. Here's an overview of the ensemble learning methods used for image classification in machine learning.

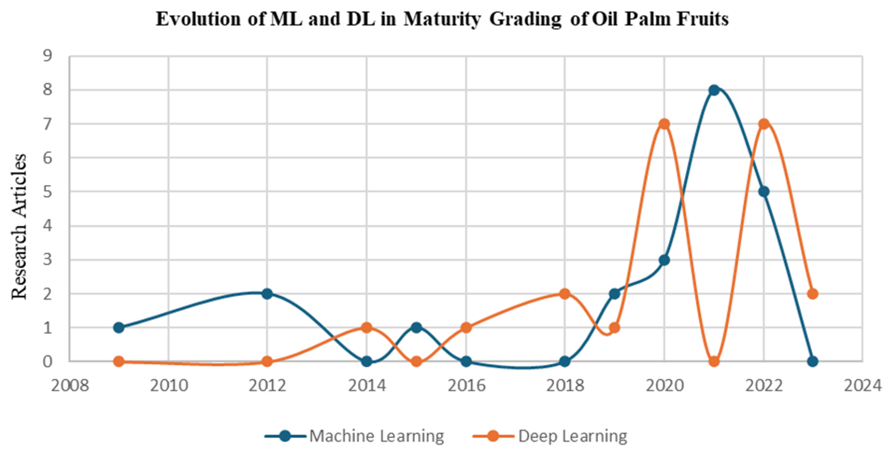


Fig. 1. Research publications (2009-2023) for Maturity Grading of Oil Palm Fruits.

**Random Forest:** Random forest is an ensemble method that can achieve the required performance with limited computational instances, or in a case where interpretability is needed. It is not normally used for the image classification tasks, but it can be served as a baseline model in the ensemble method, as it constructs the multiple decision tree during model training and predicts the class labels. It is capable of enhancing accuracy and reduce the overfitting [16].

**Gradient Boosting Machines (GBM):** GBM is not the first choice for image classification, but still can be considerable as an alternative where robustness, interpretability and effectiveness is required. It is a powerful classification method associated with tabular and structured datasets. It can be used for image classification with some applicable features and pre-processing techniques. The fundamental work of GBM is to build a series of weak learners, usually in the form of decision tree to form a stronger learner [14].

Fig. 1 illustrates the evolution of the number of research articles on machine learning and deep learning in the context of oil palm fruit maturity grading over the period from 2008 to 2023, showing a significant increase in the use of deep learning techniques in recent years.

Table 8 provides a comprehensive overview of research on oil palm fruit maturity grading using various machine learning and deep learning classifiers, including PCA, MLP, QDA, ANN, CNN, SVM, ELM, FCM Clustering, Simple Logistic, Lazy KStar, LDA, MDA, YOLO, and YOLOv4, with varying accuracies and dataset sizes.

Tab. 8. Comparative analysis of classification techniques used for maturity grading of oil palm fruits with their accuracy. Tr: training set, Ts: testing set, Val: validation set.

| Year | Classifiers | Classification Classes | Data-set Size | Dataset Partition | Accuracy | Ref. |
|---|---|---|---|---|---|---|
| 2009 | PCA | Unripe, Under-Ripe, Ripe, Over-Ripe | 48 | Tr: 32, Ts: 16 | 99.2% | [59] |
| 2012 | MLP | Unripe, Under-Ripe, Ripe, Over-Ripe | n/a | n/a | 93% (reduced features), 91.67% (full feat.) | [33] |
| | QDA | Unripe, Ripe, Over-Ripe | 120 | Tr: 90, Ts: 30 | 85% | [99] |
| 2014 | ANN | Under-Ripe, Ripe, Over-Ripe | 469 | Tr: 439, Ts: 30 | 95% | [13] |
| 2015 | Ripeness Index derived from GA | Under-Ripe, Ripe | 76 | Tr: 40, Ts: 36 | 67.10% | [102] |
| 2016 | ANN | Under-Ripe, Ripe | 60 | Tr: 40, Ts: 20 | 70% | [104] |
| 2018 | CNN | Unripe, Under-Ripe, Ripe, Over-Ripe | 120 | Tr: 96, Ts: 24 | 100% | [98] |
| | ANN | Under-Ripe, Ripe, Over-Ripe | 180 | Tr: 120, Ts: 60 | 93% | [4] |
| 2019 | SVM | Unripe, Under-Ripe, Ripe, Over-Ripe | 400 | Tr: 360, Ts: 40 | 57% by color features, 70% by Bag of Visual Words | [40] |
| | ELM | Very Good, Good, Quite Good and Poor | 297 | n/a | MAPE:20-50% | [115] |
| | CNN | Young Trees<br>Mature Trees | 284<br>244 | Tr: 199, Ts: 85<br>Tr: 159, Ts: 85 | 95.11% (Young)<br>92.96% (Mature) | [79] |
| 2020 | CNN | Unripe, Under-Ripe, Ripe | 200 | n/a | 85% | [124] |
| | ANN | Under-Ripe, Ripe, Over-Ripe | 450 | Tr: 180, Ts: 270 | 94% | [5] |
| | FCM Clustering | Unripe, Ripe, Over-Ripe | n/a | n/a | Tr: 73.07%, Ts: 71.04% | [112] |
| | Simple Logistic | Unripe, Ripe, Over-Ripe | 30 | n/a | 83.8% by OPRiD, 86.8% by NLI | [92] |
| | Lazy KStar | Unripe, Under-Ripe, Ripe, Over-Ripe | 106 | Tr: 95, Ts: 11 | 63% | [116] |
| | CNN | Unripe and Ripe | n/a | n/a | 96% (training) | [100] |
| | CNN | Unripe, Ripening, Less-Ripe, Almost-Ripe, Ripe, Perfect-Ripe, Over-Ripe | 400 | Tr: 253, Ts: 77, Val: 80 | 69% (DenseNet Sigmoid), 69% (ResAtt DenseNet), 64% (DenseNet+SE Layer), 60% (AlexNet) | [111] |
| | CNN | Unripe (Full), Unripe, Almost-Ripe, Ripe, Ripe (Full), Over-Ripe, Over-Ripe (Full) | 400 | Tr: 240, Ts: 160 | 71.34% | [43] |
| | R-CNN | FFB Detection & Counting | 100 | Tr: 80, Val: 20 | 80% | [90] |
| | CNN | Ripe, Unripe | 628 | n/a | 95.6% | [32] |

to be continued in the next page

Tab. 8. Comparative analysis of classification techniques. . . (continued)

| Year | Classifiers | Classification Classes | Data-set Size | Dataset Partition | Accuracy | Ref. |
|---|---|---|---|---|---|---|
| 2021 | Fine KNN | Under-Ripe, Ripe, Over-Ripe | 46 | n/a | 100% | [93] |
| | Weighted KNN | | | | 91.3% | |
| | SVM fine Gaussian kernel | | | | 80.4% | |
| | SVM medium Gaussian | | | | 97.8% | |
| | SVM medium Gaussian kernel | | | | 91.3% | |
| | SVM Quadratic kernel | | | | 95.7% | |
| | SVM Cubic kernel | | | | 97.8% | |
| | Quadratic discriminant | | | | 97.8% | |
| 2022 | CNN | Crude, Ripe, Rotten | 400 | Tr: 320, Ts: 80 | Tr: 98%, Ts: 76% | [9] |
| | ANN | Under-Ripe, Ripe, Over-Ripe | 270 | 90 (ambiguity) | 93% (Using BGLAM, ROI2, & ROI3), 93% (statistical color features) | [2] |
| | KNN | | | | 93% | |
| | SVM | | | | 92% | |
| | LDA | Under-Ripe, Ripe, Over-Ripe | 297 | n/a | Tr: 86%, Ts: 85.4% | [134] |
| | MDA | | | | Tr: 86.7%, Ts: 81.8% | |
| | ANN | | | | Tr: 99.1%, Ts: 92.5% | |
| | KNN | | | | Tr: 82%, Ts: 74.2% | |
| | ANN | Under-Ripe, Ripe, Over-Ripe | 52 | Tr: 33, Ts: 14 | 97.90% | [118] |
| | DNN | Bare soil, built-up area, forest, water, immature and mature oil palm | 13218 | Tr: 10574, Ts: 2644 | 99.35% (Overall Accuracy), 98.49% (Kappa Accuracy) | [56] |
| | CNN | Unripe, Ripe | 490 | Tr: 430, Ts: 60 | 87.9% | [67] |
| | YOLO | Oil palm tree or Not | 3100 | n/a | 85.6% [83] | |
| 2023 | YOLOv4-Tiny 3L (Model_16) | Unripe, Under-ripe, Ripe, Over-Ripe, Abnormal, Empty | 57 | Tr: 47, Ts: 10 | mAP of 90.56% (SingleClass category) | [58] |
| | CNN | Unripe, Under-ripe, Ripe, Over-Ripe, Abnormal, Empty | 4160 | Tr: 2908, Ts: 417, Val: 835 | 88.01% (YOLOv4-320), 88.27% (YOLOv4-416), 88.94% (YOLOv4-512) | [109] |

## 3. Deep learning models

Deep learning models have emerged as the revolutionary in various fields such as the healthcare, NLP, and Computer Vision, due to their ability to learn automatically from hierarchical data. These models are inspired by the human brain in functionality and structures, consisting of multiple layers of interconnected AI neurons that make classification and prediction process a success. CNN is very useful and well suited for the tasks involving spatial data and images. AlexNet [65] and LeNet-5 [71] are the pioneer architecture of CNN that demonstrated their effectiveness in image classification tasks. Alfatni et al. (2018) proposed a real-time maturity grading system for oil palm FFBs using SVM, ANN and KNN classifiers [4]. Table 9 presents a comprehensive overview of deep learning models used in oil palm fruit maturity grading, including AlexNet, LeNet, DenseNet, ResNet, Inception, CNN, RCANet, VGG-16, MLP, ANN, YOLO, and YOLOv4, with their corresponding accuracies and references.

Tab. 9. Summary of deep learning models applied in palm fruit detection.

| Year | Deep Learning Model | Accuracy | Reference |
|---|---|---|---|
| 2018 | AlexNet | 100% | [49] |
| 2019 | LeNet | 95.11% (Young),<br>92.96% (Mature) | [79] |
| 2020 | AlexNet | 85% | [124] |
| | DenseNet Sigmoid | 69% | [111] |
| | ResAtt DenseNet | 69% | |
| | DenseNet + SE Layer | 64% | |
| | AlexNet | 60% | |
| | ResNet152 | 71.34% | [43] |
| | ResNet-50 | 86% | [90] |
| | ResNet-101 | 82% | |
| | Inception V2 | 85% | |
| | Inception ResNet V2 | 82% | |
| | CNN | 95.6% | [32] |
| | RCANet | 96.88% | [30] |
| 2021 | ResNet-50 | 91.24% | [127] |
| | VGG-16 | 98.13% | |
| 2022 | CNN | Tr: 98%, Ts: 76% | [9] |
| | Multilayer Perceptron (MLP) | 92.5% | [134] |
| | ANN | 97.90% | [118] |
| | DNN | 99.35% | [56] |
| | YOLOv4 | 70.19% | [67] |
| | YOLO | 85.6% | [83] |
| | YOLOv3 | 97.28% | [123] |
| | YOLOv4 | 97.74% | |
| | YOLOv5m | 94.94% | |
| | DNN | 91% | [7] |

to be continued in the next page

Tab. 9. Summary of deep learning models... (continued)

| Year | Deep Learning Model | Accuracy | Reference |
|---|---|---|---|
| 2023 | YOLOv4-CSPDarknet53 | mAP 97.64% | [58] |
| | YOLOv4-Tiny | mAP 83.57% | |
| | YOLOv4-Tiny 3L | mAP 90.56% | |
| | YOLOv4-320 | 88.01% | [109] |

## 4. Conclusion

This review paper explores and examines the various classical methods and DL methods used for the maturity grading of oil palm FFBs. Each journal paper has been analyzed with its merits and demerits. It contains the exploration of deep knowledge regarding image analysis techniques, deep learning algorithms and spectral imaging techniques. This review highlights the advancements of existing approaches, including enhanced efficiency, improved accuracy, and reliable consistency. It also observes the efficacy of various color features used for image analysis. Additionally, the challenges or limitations associated with each paper were also mentioned after implementing these techniques, such as limited dataset size, the impact of environmental and regional variations. The review also focuses on the future prospectives for further research and development in the field of maturity grading of oil palm FFBs. This systematic review presents a valuable remark for researchers to optimize the maturity assessment of oil palm fruits.

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