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# Detection of dry and wet cocoa beans to improve quality using Convolutional Neural Network-based You Only Look Once Architecture

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### A B S T R A C T

Cocoa is one of Indonesia's leading export commodities crucial in supporting the national economy. However, a significant challenge in the post-harvest processing of cocoa lies in the drying stage, where uneven drying often leads to inconsistent bean quality. While previous studies have predominantly focused on classifying cocoa beans based on surface defects such as faded, non-faded, fragmented, moldy, and damaged beans, limited research has addressed classification based on moisture levels—specifically distinguishing between dry and wet beans, which is essential for ensuring optimal fermentation, proper storage, and overall product quality. This study presents a classification model based on a Convolutional Neural Network (CNN) employing the You Only Look Once (YOLO) architecture to detect and classify dry and wet cocoa beans by analyzing visual features, particularly color and shape. A dataset of 2,880 labeled images was compiled and used to train and evaluate the model. The proposed system demonstrated strong performance, achieving an accuracy of 99.8%, a precision of 99.15%, and a recall of 99.8%. These results indicate that the model can be a reliable and efficient tool for detecting moisture content in cocoa beans, thereby enhancing quality control, reducing human subjectivity in the inspection process, and supporting automation in the cocoa processing industry to ensure product consistency and added value in the export market.

### INTRODUCTION

Cocoa, a vital agricultural commodity, has significantly impacted Indonesia's economic development since the 1930s. As the third-largest exporter of cocoa beans globally in 2010, Indonesia has leveraged cocoa as a source of farmer income and an essential contributor to foreign exchange earnings. Given its economic importance, ensuring the quality of cocoa products is essential to maintain competitiveness in global markets. A critical step in cocoa processing is the drying phase, which reduces the moisture content to 6–8%. However, traditional drying methods, such as sun drying, often result in inconsistent dryness levels due to varying bean sizes and uneven exposure to drying conditions [1].

The processing of cocoa yields some fruit meat, as well as bean skins. Meat and skins are obtained when cocoa is processed into dry cocoa. Cocoa bean skin is one of the results of the cocoa processing used for livestock feed and fertilizer [2][3][4]. However, once the wet cocoa beans are dried, the next step is to examine the dried cocoa. Usually, farmers determine the maturity of dried beans by reducing their water content to 6% to 8% of the original rate [5]. Most dried cocoa beans can be easily recognized through visual observation. Dried cocoa beans will have an old brown or dull color and a slightly scratchy surface compared to still-wet beans.

But farmers didn't always prioritize drought consistency; instead, they focus primarily on the weight of already-dried beans. Because cocoa beans come in different sizes, not every bean will process and dry evenly. Because the beans in the cocoa fruit vary in size, it is therefore impossible to determine the quality of dried cocoa beans only based on weight. Because of this, not every bean that is dried will experience the same degree of drought. Especially in the tropics and subtropics where solar radiation is abundant, sun drying is the oldest, least expensive, most widely used, and publicly available approach that may be applied using the most basic to highly advanced and scientific procedures. Due to the fact that over 60% of cocoa from Africa and Asia is locally dried under the sun, farmers typically sell their chocolate with a higher moisture content. Solar energy is one of the renewable energy sources that will be most important in the future since it is low-cost, plentiful, endless, eco-friendly, and non-polluting [5].

In previous research on drying cocoa beans, two methods have been used in the cocoa drying process. The first method is conventional, where the drying process is carried out under sunlight. The second method is the Fluidized Bed Dryer (FBR). This method is used to shorten the time by using a heater to provide heat [6]. Another study is the classification of fermentation levels of cocoa beans. Fermented cocoa beans are divided into four classes, including fully fermented, partially fermented, unfermented, and non-fermented. Computer vision is

used as a fast and accurate method [7]. Other research also uses the SVM-CNN hybrid method to classify fermented cocoa beans [8]. Other research also uses faster R-CNN for multi-class detection [9][10]. Previous studies have shown that cocoa beans are only subjected to the drying process without knowing the quality of their dryness level. The quality of the detected beans is only those that have been dried and undergone the fermentation process [7].

Therefore, this study will use CNN to build a model on a system of the degree of drying of cocoa beans through color images. CNN is used for cocoa bean classification because CNN has several advantages in image classification over other deep learning [11][12]. One of them is that CNN is able to automatically extract important features from images through convolution and pooling processes without requiring manual feature extraction or complex preprocessing techniques. That means CNN can learn complex features such as edges, texture, and shape at different levels of the image, which is very important for classification. Then the information on the image will be extracted using the model and classified according to the color and shape of the cocoa beans. The study carried out a detection system [13] of the cocoa grain based on the colours and shapes of the chocolate beans, divided into two classes, first the undried cocoa, then the dried by sunlight or nature. The research also used the architecture of CNN YOLO (You Only Look Once) [14][15][16]. The aim of this study was to build models of the Cocoa Beans that were classified by their color and form. It aims to detect the level of drought of the coffee beans and compare the levels of driedness in cocoa beans on a dryer that has already or has not been perfected.

While previous studies have focused on classifying fermented cocoa beans or improving drying techniques, they have not comprehensively addressed the dryness quality. Farmers often rely on visual inspection, prioritizing bean weight over uniformity of dryness, which can compromise product quality. This research seeks to address these challenges by developing a real-time detection system for assessing dryness levels in cocoa beans using a deep learning approach. Convolutional Neural Networks

(CNN), particularly the YOLO (You Only Look Once) architecture, offer significant advantages for image classification and object detection. By automatically extracting critical features from images, CNNs eliminate the need for manual preprocessing, making them well-suited for tasks such as classifying cocoa beans based on color and shape. This study aims to design and implement a YOLO-based model to classify wet and dry cocoa beans, providing an efficient and accurate solution to improve cocoa quality assessment.

**METHODS**

The research builds an artificial intelligence algorithm for the drought rate of cocoa beans [17][18] using YOLO based on CNN which begins with a collection of studies and theories relevant to the research. The material studied is the drying of cocoa beans that is the reference of the data needed to carry out the research, in-depth learning of the technology that forms the basis of the research and the CNN (Convolutional Neural Network) algrity used to allow the model to recognize the dryness level of the cocoa beans used in this polishing.

CNN is a deep learning algorithm [19]-[23] capable of receiving image input and identifying various aspects of an image. This image identification will then be classified to distinguish one image from another based on defined categories such as furniture, animals, and so on. CNN consists of a training and testing process. The use of CNN focuses on neural networks [24][25][26] that receive input in the form of images. This layer series consists of convolutional layers, pooling layers and fully connected layers.

The study also used it which is the architecture of CNN and serves as a network for the detection of objects on images. Object detection itself determines the location on the image where a particular object is present. This architecture uses single neural networks on images that are divided into regions that will subsequently estimate bounding boxes [27][28][29]. The diagram of YOLO can be observed in Figure 2. Figure 3 shows an image of the input data, namely dry and wet cocoa beans.

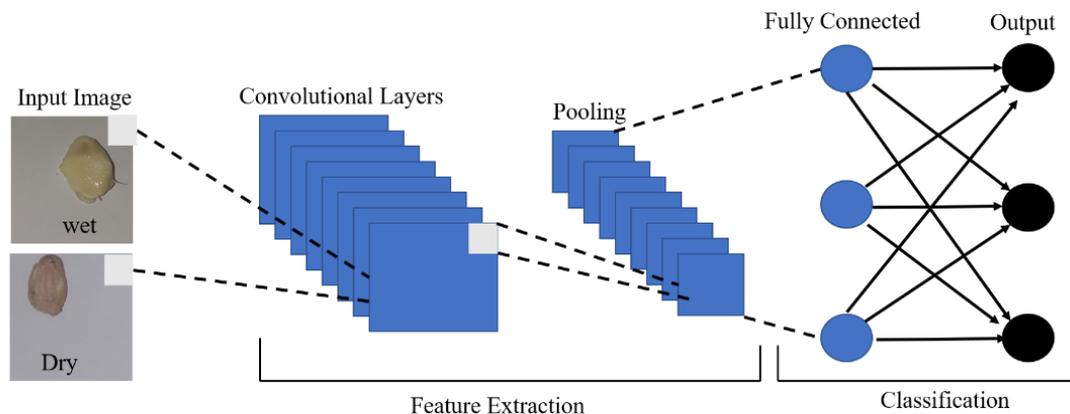


Figure 1. The process of Convolutional Neural Network

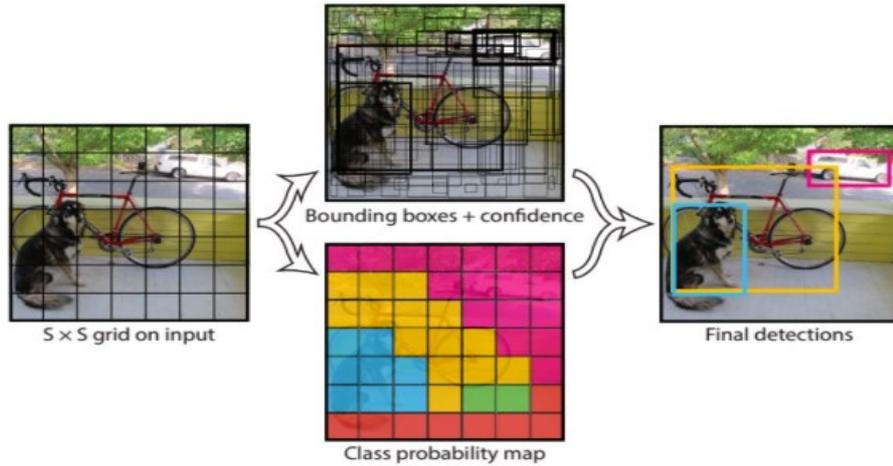


Figure 2. Model diagram of YOLO algorithm



Figure 3. Dried cocoa beans [30] and wet cocoa beans

The research employs cocoa beans as the primary material. These cocoa beans are categorized into two classes: wet cocoa beans and cocoa beans that have been naturally sun-dried. This research is conducted in stages that start with a literature study, data collection, model design using YOLO, obtaining accurate results, an analysis of the results, and evaluation based on Figure 4.

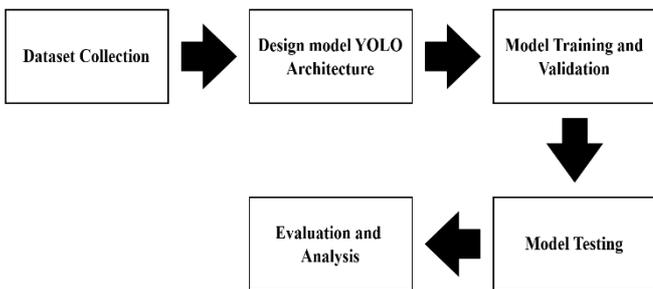


Figure 4. Research method block diagram

**Dataset**

At this stage, the process of collecting cocoa beans is being carried out which will be used in the modeling process. The cocoa beans that will be used as a data set are made up of dried and undried cocoa beans. The characteristics of dry and unsweetened cocoa are determined by the colour and shape that can be seen visually. Figure 5 shows the process of collecting datasets.

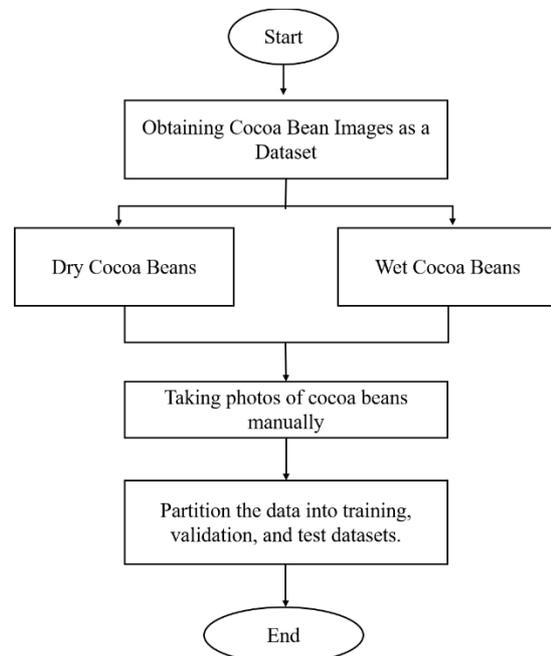


Figure 5. Dataset collection process diagram

Based on Figure 5, an image collection of cocoa beans was taken randomly, and as many as 2880 images were used for training and testing. In the process of collecting data sets from the cocoa beans image, the first thing to do is collect the cocoa beans. The cocoa

beans collected came from the cocoa that was just chopped and peeled by a cocoa farmer. The cocoa beans that have been harvested are then grouped into dried and undried cocoa. In the case of dried cocoa beans, the beans used are the ones that have already been dried by the cocoa farmer using sunlight. After obtaining the dried and undried cocoa beans, a further imaging of the cocoa beans is carried out. In the process of imaging cocoa beans, the cocoa beans were arranged on white hvs paper. After the image is taken, the next cropping process is carried out where the process of cutting from 1 image to 25 images in each dry and undried cocoa beans. There are two classes in this study, each of which consists of 1440 images in the class of undried cocoa beans and 1440 pictures in a class of sun-dried Cocoa Beans. There are 2260 images used for the training process. The image data collection process was carried out to prepare the image data used in this study, and the data collection was done manually using the camera.

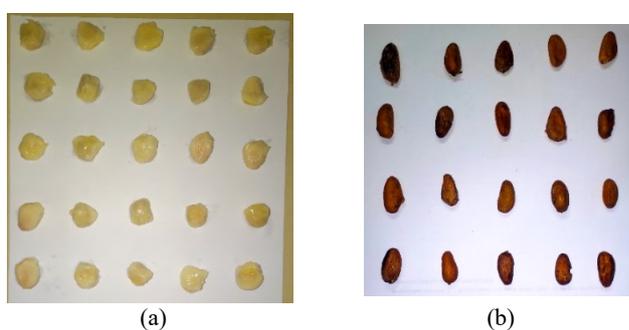


Figure 6. Scenario of wet (a) and dried (b) cocoa bean images taken with a camera

Figure 6 shows the scenario of the cocoa beans for dataset. Image data is collected by taking photos of undried cocoa beans that have already been dried with the camera. The distance between the camera and the object taken is about 40 cm from the source. This is done to cover the entire object to be photographed later.

**Model Design**

The YOLO architecture was selected for its real-time object detection capabilities. The model parameters were tuned to optimize performance, including 100 epochs, a batch size of 8, and the AdamW optimizer with a learning rate of 0.001 and a momentum of 0.937 as shown in Table 1. The loss function used was categorical cross-entropy, suitable for classification tasks. Before training, a labeling process was performed to identify objects in the dataset and distinguish between dried and wet cocoa beans.

Table 1. Parameters used in model design

Parameters	Model Design
Epoch	100
Batch Size	8
Loss Function	Categorical Cross-entropy
Optimizer	AdamW
Momentum Optimizer	0,937
Learning Rate Optimizer	0,001

**Model Training and Validation**

The dataset was split into training (2,260 images) and validation (620 images) subsets. The training process involved iterative learning to minimize loss values while maximizing accuracy.

Metrics such as precision, recall, and mAP (mean Average Precision) were evaluated to assess model performance. The model was trained to detect and classify cocoa beans based on their color and shape.

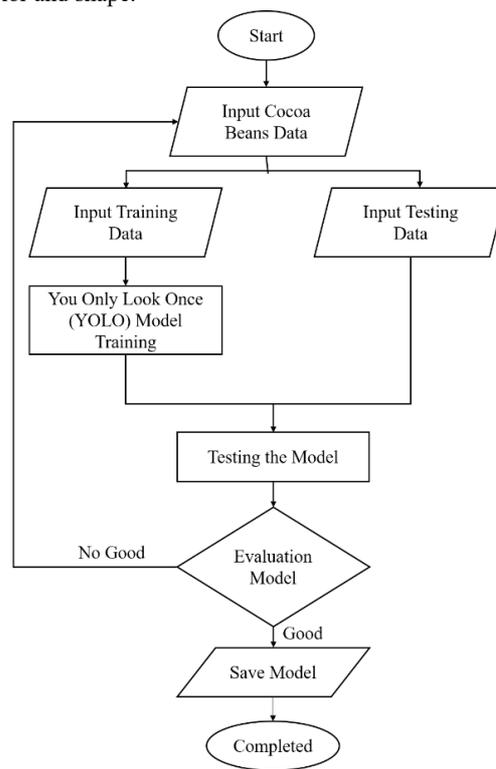


Figure 7. Flowchart of the modelling process

Figure 7 shows the process of creating a model starting from reading the dataset until the model results are good which are then saved for testing.

**Model Testing**

After training, the model was tested using separate images to evaluate its ability to distinguish between sun-dried and artificially dried cocoa beans. The testing phase aimed to determine if the model could assess whether artificially dried beans met the same quality standards as sun-dried beans.

**Evaluation and Analysis**

The model’s performance was analyzed using confusion matrices, which provided insights into true positive, false positive, and false negative rates. Key metrics such as accuracy, precision, and recall were computed for each class to validate the effectiveness of the approach. By following this structured methodology, the study aimed to develop a robust model for classifying cocoa beans and improving the quality control process in cocoa production.

**RESULTS AND DISCUSSION**

In a previous study, cocoa beans were classified based on fermentation results. Computer vision methods divided the fermented cocoa beans into 4 parts: fully fermented, partially fermented, underfermented, and unfermented. The accuracy result is an unbalanced dataset with an accuracy of 93% [7]. Another study used an artificial neural network (ANN) model to assess the fermentation index (FI) for quality control based on

color measurements in fermented cocoa beans. The result was that the ANN model can be used as a low-cost and in situ procedure to predict FI in fermented cocoa beans [30]. In another study, cocoa beans were classified into 2: fermented and unfermented. This study used computer vision methods and machine learning models. From 1143 images, an accuracy of 94% was obtained using the artificial neural network (ANN) model [31]. using the cut-test method for visual inspection of interior color, compartmentalization, and defects in cocoa beans for effective classification of cocoa beans. However, due to its subjective nature, this method is limited, resulting in discrepancies in classification, which is time- and labor-consuming. A total of 1400 datasets of cocoa beans classified into 14 classes using an artificial neural network (ANN) model obtained accuracy, precision, recall, and F1 size of 85.36%, 85%, 83%, and 83% [32]. In 2020, Adhitya conducted research on the classification of cocoa beans based on quality using the Gray Level Cooccurrence Matrix (GLCM) method with classification types including simmered, non-dimmer, fragmented, mold cocoa beans, and damaged cocoa beans with accuracy results of 99.49% and 99.75% [33].

The aim of this study is to predict and detect the dryness level of cocoa beans dried by a dryer using a dataset trained in the model training process. This research results in a model's design and construction to classify cocoa beans accurately using CNN technology. This can help confirm whether the drying equipment is following the sunlight drying process accurately.

**Dataset Condition**

In this study, the data set used is a data set that has been collected using a camera without taking it from another source. Previous research only showed types of cocoa beans datasets in the form of dried beans with those that are dimmed, non-dimmer, fragmented, fungal beans, and damaged beans [33].

This study's datasets relate to the condition of dried and undried cocoa beans. The data set of dried cocoa beans includes 1440 samples of cocoa beans that have already gone through a drying process where this drying phase covers the weight of the beans, the color of the beans that are brownish or even thick, and the shape of the dried cocoa beans is somewhat scratchy compared to the undried cocoa beans, as well as the reduction in the water content of the cocoa. The undried cocoa beans are taken directly from the cocoa cut off from the tree. In the data collection phase, the image of the cocoa beans produced has different pixel values; then the image will be adjusted to the image input on the model of 640 × 640 pixels with the background on the cocoa beans having a white background using HVS paper. Then, this data set will be the reference for drying cocoa beans using a dryer so that it can be known whether the cocoa beans dried with the tool are already suitable or not.

**YOLO Architecture Model Design**

The model is trained using a previously designed structure at this stage. During the training process, the models learn from the existing data. This involves running 100 epochs, with each epoch training on the entire dataset in a single pass, using a batch size of 8. This means that the data is divided into 8 individual parts for processing.

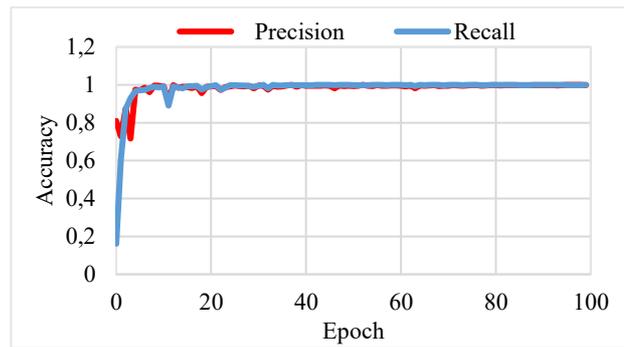


Figure 8. Accuracy Value Graph of Precision and Recall

Figure 8 shows the accuracy value of precision and Recall. Precision is the number of true positive predictions divided by the total number of positive predictions. Precision is used to measure how many of the positive values predicted by the model are true positives. The results of training with precision show that the value obtained at epoch 1 is 0.8088 and the value at epoch 100 is 0.9969. The lowest value generated was 0.8088 at epoch 1, and the highest value generated was 0.9998 at epoch 96.

Recall is the ratio of the model's success in predicting positive values. Recall also detects how capable the model is of predicting data compared to actual data. The recall value obtained at epoch 1 is 0.1613; at epoch 100, it is 1. The lowest value generated is 0.1613 at epoch 1, and the highest value generated is 1 at epoch 95.

The model training results include the following values: metrics, box, cls, and dfl values. The metrics section is divided into two parts: mAP50 and mAP50-95. Metrics mAP50 is the average precision value calculated at a 50% cutoff level.

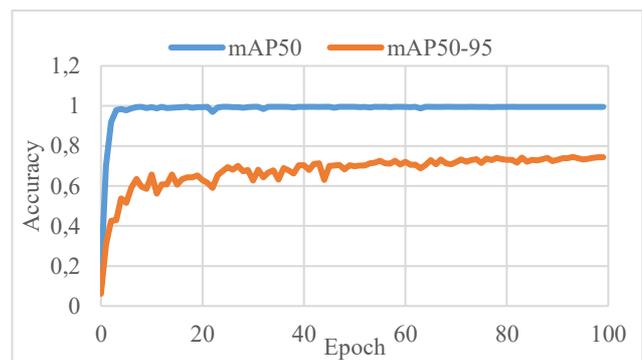


Figure 9. Accuracy Value Graph of mAP50 and mAP50-95 metrics

Figure 9 shows the model training results of mAP50 and mAP50-95. The model training mAP50 shows that the lowest value for the mAP50 metric was 0.1531 at epoch 1. The highest value for the mAP50 metric was 0.995 at the 100th epoch. The model, the mAP50-95 metrics, measures the average precision within the cutoff range of 50% to 95%. The lowest value generated in the mAP50-95 metrics was 0.06115 at epoch 1, and the highest value generated was 0.7433 at epoch 100.

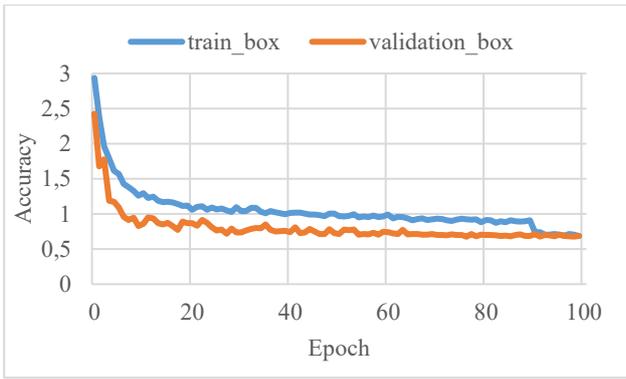


Figure 10. Train and Validation Value Graph of box

Figure 10 shows the train and validation of the box. Box, or bounding box, is one of the components in the object detection process that refers to the bounding box used to mark and delimit objects in an image. bounding objects in the picture. Each box includes an object identified through training the object detection model. Each bounding box is weighted by the likelihood that it will classify an object or not. The results of box training in the training process show that the lowest value is 0.6863 at the 100th epoch, while the highest value is 2.9374 at the 1st epoch. 2.9374 at epoch 1. In the validation data, the value of the box's lowest bounding box is 0.6785 at the 99th epoch, and the highest value of the validation data is 2.9374 at the 99th epoch. 99th epoch, and the highest value of box validation data is 2.429 at the 1st epoch.

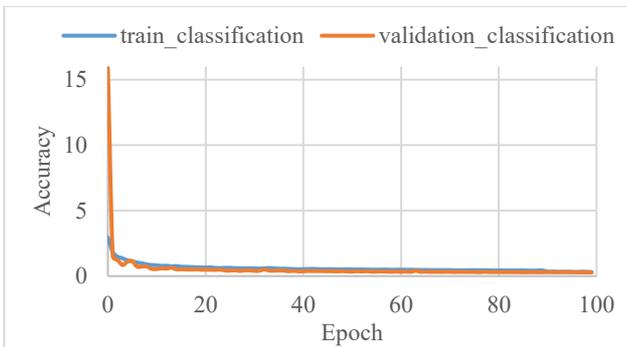


Figure 11. Train and Validation Value Graph of classification

Figure 11 shows the training and validation of classification. Classification is the process of training a model in YOLO, which refers to the object classification process performed. After determining the bounding box, YOLO uses a neural network to classify the objects. Classify the objects in the box from CLS model training (classification). In the training process, the lowest classification value is 0.2463 at the 94th epoch, while the highest value in the CLS training process is 4.146 at the 1st epoch. In classification validation, the lowest classification value is 0.2843 at the 100th epoch, and the highest value of classification validation data is 15.88 at the 1st epoch. Epoch to 1.

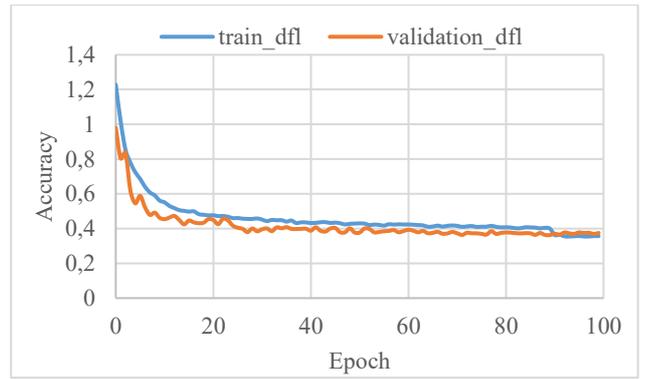


Figure 12. Train and Validation value Graph of the default anchor box

Figure 12 shows the default anchor box's train and validation value graph. The default anchor box, or anchor box, is a model training process in YOLO that refers to the anchor box used in the YOLO algorithm. An anchor box is a bounding box with a predefined size and ratio. The anchor box predicts a more accurate bounding box for each object in the image. The lowest value obtained in the training process is 0.3239 at the 94th epoch, and the largest is 1.228 at the 1st epoch. The lowest value of the default anchor box was 0.3628 at the 90th epoch, and the highest value of the default anchor box validation data was 0.9794 at the 1st epoch.

Table 2. Test result on the cocoa bean model

Wet Cocoa Beans	Dried Cocoa Beans
	
	
	

## Model Testing

Following the successful training of the model, which achieved excellent accuracy and low loss, testing was conducted using data from cocoa beans dried in a drying container. The aim was to assess whether the dryness level of cocoa beans dried in a container meets the standards for cocoa beans dried under sunlight by farmers. The test results for the cocoa bean model are presented in Table 2.

## Analysis of Result and Evaluation

In this study, an assessment is conducted to measure and determine the effectiveness of the cocoa bean model developed using one of the metrics, the confusion matrix—the confusion matrix results for the YOLO. The confusion matrix is displayed in Table 3, and the matrix result is in Table 4.

Table 3. Confusion matrix on YOLO Architecture with cocoa bean dataset

	TP	FP	FN
Wet	310	1	0
Dry	0	309	4
Background	0	0	0
	Wet	Dry	Background

Table 3 shows the confusion matrix with the test data of 620 consisting of 310 undried cocoa beans and another 310 for dried beans. It shows that the prediction value for 'undried' is 310, indicating that the model trained to detect the object of 'undried' cocoa beans can detect the actual 310 images out of a total of 310 images by the system. The detection rate for the dried part is 309, indicating that the machine learning model trained to detect the dried cocoa bean entity can recognize the object in 309 images out of 310 images. The background class is a special category that defines a region in an image with no entities requiring detection.

Table 4. Matrix result

	Accuracy	Precision	Recall
Wet	99,8%	99,6%	100%
Dry	99,8%	98,7%	99,6%
Background	99,8%	0%	0%

Table 4 shows the accuracy value obtained for wet cocoa, which is 0.998, and dry cocoa, which is 0.998. Precision for wet cocoa is 0.996, dry cocoa is 0.987, and background is 0. The values obtained from this model explain that the method used is suitable and the resulting model is also desired. These results prove previous research by Adhitya, where the percentage is around 99%, so this research uses the appropriate method.

## CONCLUSIONS

This study successfully developed a YOLO-based model to classify dry and wet cocoa beans with an impressive accuracy of 99.8%. Using color and shape as classification parameters, the model effectively evaluates the dryness of cocoa beans processed using artificial dryers compared to traditional sun drying. The results demonstrate the potential of CNN technology in improving the quality assessment of agricultural products. Future research should consider incorporating additional factors such as damaged or moldy beans and exploring alternative CNN

architectures, such as VGG16 or ResNet50, to enhance detection efficiency and broaden the model's applications.

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