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Research Article

Developing a Computer Vision Model to Classify Abaca Fibers Using YOLOv8

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ABSTRACT

Introduction: Abaca (Musa textilis), a banana species endemic to the Philippines, which is vital for the country's economy, supplying 87% of the global market. T he industry faces significant challenges in fiber classification, relying on a limited number of trained professionals to visually inspect fibers within a restricted timeframe, leading to inefficiencies and high costs. Although some automated systems using convolutional neural networks (CNN) have been developed, they are limited to processing single fibers at a time.

Objectives: This study aims to improve the classification process of abaca fibers. This study aims to create a deep learning-based classification model utilizing YOLOv8 architecture to accurately distinguish between various grades or types of abaca fibers based on their visual characteristics and conduct laboratory tests to evaluate the effectiveness of the classification and sorting system.

Methods: This study focuses on developing a YOLOv8 model for classifying grades S2 and S3 abaca fibers. Images were collected from two trading centers in Iligan City. These images were manually annotated, with the dataset split into training and validation sets. Then the images undergo preprocessing and augmentation including flipping, cropping, blur, and noise adjustment, which results in a 2,332 training images and 295 test images. The model was then tested on 40 new, unannotated images in a laboratory setting to evaluate its performance in classifying abaca fibers.

Results: The model performed well in detecting and classifying abaca fibers, achieving high precision, recall, mAP50 and mAP50-95. The training process showed positive results, with decreasing box loss in later epochs and a quickly dropping validation loss, indicating effective generalization. Although there were minor signs of overfitting and the losses stabilized around 1.0, the overall convergence of training and validation losses suggested reliable performance. The confusion matrix showed strong classification accuracy, with 136 correct predictions for Grade S2 and 132 for Grade S3 fibers, despite some false positives in images without fibers. In the final testing phase, the model successfully identified 35 out of 36 abaca fibers, demonstrating its strong classification abilities.

Conclusions: In conclusion, the researcher was able to create a model to classify grades S2 and S3 abaca fibers. The trained YOLOv8 model proved to be a robust model in classifying abaca fibers. Since the dataset uses a variety of settings, including the time of day and light source, the model was able to generalize well in classifying abaca fibers.

Keywords: Abaca fiber grade, Computer Vision, Deep learning, YOLOv8, Fiber classification

INTRODUCTION

Abaca (Musa textilis) is a banana species native to the Philippines. It is harvested for its fiber, which is extracted from its leaf stems [1]. It is traditionally used to create shiny fiber that is hand-woven into different indigenous textiles in the Philippines, such as t'nalak, as well as luxury fabrics known as nipís. The finer 5m-long fibers are utilized for weaving cloth, while the coarser fibers are employed in making mats and strong cordage [2]. The Philippines is the leading global provider of abaca, accounting for more than 87% of the world's abaca supply [3]. The Bicol region is the primary contributor, generating 34% of the country's production in June 2023. Catanduanes was named the "abaca capital of the Philippines" in 2022 due to its consistent leadership in the industry.

Table 1. Normal Grades of Hand-Stripped Abaca Fiber [15, 16]

Name	Code	Stripping	Source	Color	Strand Thickness	Texture
Mid Current	EF	Excellent	4	Light ivory to a hue of very light brown to very light ochre; frequently intermixed with ivory white	0.20–0.50 mm	Soft
Streaky Two	S2	Excellent	2, 3	Ivory white, slightly tinged with very light brown to red or purple streak	0.20–0.50 mm	Soft
Streaky Three	S3	Excellent	1	Predominantly light to dark red or purple or a shade of dull to dark brown	0.20–0.50 mm	Soft
Current	I	Good	3, 4	Very light brown to light brown	0.51–0.99 mm	Medium soft
Soft seconds	G	Good	2, 3	Dingy white, light green and dull brown	0.51–0.99 mm	Medium soft
Soft brown	H	Fair	1	Dark brown	0.51–0.99 mm	Medium soft
Seconds	JK	Fair	2, 3, 4	Dull brown to dingy light brown or dingy light yellow, frequently streaked with light green	1.00–1.50 mm	
Medium brown	M1	Fair	1	Dark brown to almost black	1.00–1.50 mm	

Note: For source: 1 = outer leafsheath, 2 = leafsheath next to the outer leafsheath, 3 = middle leafsheath, 4 = inner leafsheath.

Stripping is a step in the extraction process of abaca fiber that must be completed within the day after cutting the stem; otherwise, it will lead to a lower quality, faded fiber [4]. Abaca fibers can be classified into two types based on how the fibers are stripped. Hand-stripped fibers are fibers extracted using manually-operated stripping apparatus such as knives. On the other hand, machine-stripped fibers are extracted using a semi-mechanized device aided by an engine. Abaca fibers are sorted manually, usually through visual inspection by the fiber classifiers. Tables 1 and 2 outline how the abaca fibers are graded. The predominant feature that changes with each grade of the abaca fiber is the color. High-quality fibers typically have a lighter brown color compared to low-quality fibers. The classification process is done manually, which causes problems due to the nature of visual inspection. Manual quality control relies heavily on trained individuals to visually assess the external appearance of agricultural products such as fruits and determine their grade [5]. There is also a limited number of people who can classify abaca fibers. According to the data from PhilFIDA [6], there are only 230 fiber classifiers in 2023, the lowest number recorded. In Region X alone, there are only 12 fiber classifiers. Aside from that, the manual method of classifying abaca fibers is time-consuming and costly [7]. Montañez and Barrera developed a system to automate the classification of abaca fiber using a convolutional neural network (CNN) [7]. Meanwhile, Hong and Caya created a device that can be used to classify abaca fibers using the CNN algorithm [8, 9]. These studies focused on image classification of abaca fibers; thus the trained models cannot be used to classify multiple abaca fibers.

There have been huge advancements in object classification nowadays. One of the state-of-the-art classification models is You Only Look Once (YOLO) v8. There are five different variants of YOLOv8, each with a different number of parameters. These variants are named YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, and YOLOv8x, in ascending order of the number of parameters. A study by Cheng et al. focused on recognizing 15 types of fruits using the YOLOv8n model, resulting in an average accuracy of above 97% [10]. Other studies also used YOLOv8 for classifying fishes, ants, and plant leaf diseases [11–13]. Furthermore, Dave et al. compared the performance of YOLOv8m, YOLOv8l and YOLOv8x models in detecting wild animals [14]. The trained YOLOv8x model achieved the highest mAP at 94.3%, making it the most effective model in classifying wild animals.

Table 2. Normal Grades of Spindle-Stripped Abaca Fiber [15, 16]

Name	Code	Stripping	Source	Color	Strand Thickness	Texture
Mid Current	S-EF	Excellent	4	Light ivory to a hue of very light brown to very light ochre; frequently intermixed with ivory white	0.20–0.50 mm	Soft
Streaky Two	S-S2	Excellent	2, 3	Light ivory to very pale brown with very red or very light purple streaks	0.20–0.50 mm	Soft
Streaky Three	S-S3	Excellent	1	Light brown to dark red or light purple with occasional streak of very light green	0.20–0.50 mm	Soft
Current	S-I	Good	3, 4	Very light brown to light brown	0.51–0.99 mm	Medium soft
Soft seconds	S-G	Good	2, 3	Light brown with occasional streaks of very light green	0.51–0.99 mm	Medium soft
Soft brown	S-H	Fair	1	Brown to dark brown, intermixed with lighter colors in a substantial portion of fiber; sometimes, color approaches black	0.51–0.99 mm	Medium soft
Seconds	S-JK	Fair	2, 3, 4	Light dull brown to dingy light brown or dingy light yellow with occasional streaks of light green	1.00–1.50 mm	
Medium brown	S-M1	Fair	1	Brown or nearly black	1.00–1.50 mm	

Note: For source: 1 = outer leafsheath, 2 = leafsheath next to the outer leafsheath, 3 = middle leafsheath, 4 = inner leafsheath.

OBJECTIVES

Due to the problems with abaca fiber classification, the classification process takes a long time. As a result, moisture builds up in abaca fibers, ruining their quality. Thus, this study aims to create a system to speed up abaca fiber classification. Specifically, this study aims to:

1. Develop a deep learning-based classification model using YOLOv8 architecture to accurately identify different grades or types of abaca fibers based on visual characteristics.
2. Test the efficacy of the classification and sorting system through lab tests.

METHODS

As stated earlier, this study aims to train a model to detect grades S2 and S3 abaca fibers. The researcher focuses on using the YOLOv8 model for the detection system. The methodology of this study is divided into four parts: model requirements analysis, data gathering which involves gathering image data for the training, training of the model, and testing and evaluation of the trained model on unseen data.

Figure 1 presents the system architecture diagram, which involves the detection system and how it handles data for abaca fiber classification. Image of abaca fibers are taken through a web camera which are then saved to the computer. These images are then uploaded to Roboflow for pre-processing and dataset generation. Then, the YOLOv8 model is trained using the images in the dataset with the help of Ultralytics' YOLOv8 model and Ultralytics HUB. Finally, testing of the model on new images is done with the help of PyTorch. These images are then saved to the computer for results analysis.

The following items below guide the researcher in developing the research output. The overall model is limited for experimental purposes:

1. Image dataset is limited to grade S2 and S3 abaca fibers.
2. The images are taken near the camera.
3. Dataset testing is done in the laboratory using sample images.

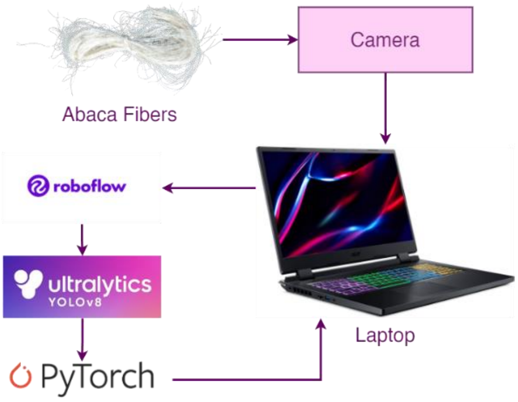

Figure 1. System Architecture Diagram

Acquiring of image data is done by capturing images of abaca fibers from two abaca fiber trading centers located at Barina-ut and Bayug, Iligan City. These fibers were harvested from Tandag City, Surigao del Sur and Lake Sebu, South Cotabato. These images were taken using a Logitech Brio 500 camera using the 1080p setting. The abaca fibers taken in this study are from Grades S2 and S3. The abaca fibers are bundled together, as shown in Figure 2. Images are captured in various lighting conditions and backgrounds, and turning on and off the HDR setting which allows the model to perform better during deployment. The initial dataset consisted of 879 images, including one to be used as placeholder for the test set.

Figure 2. Grades S2 (left) and S3 (right) Abaca Fibers

The images were uploaded to Roboflow and then manually annotated using their annotation tool as shown in Figure 3. Grade S3 fibers tend to have darker color with some black streaks compared to Grade S2 fibers. There are 407 images of Grade S2 and S3 fibers and 65 images with no fibers in the initial dataset.

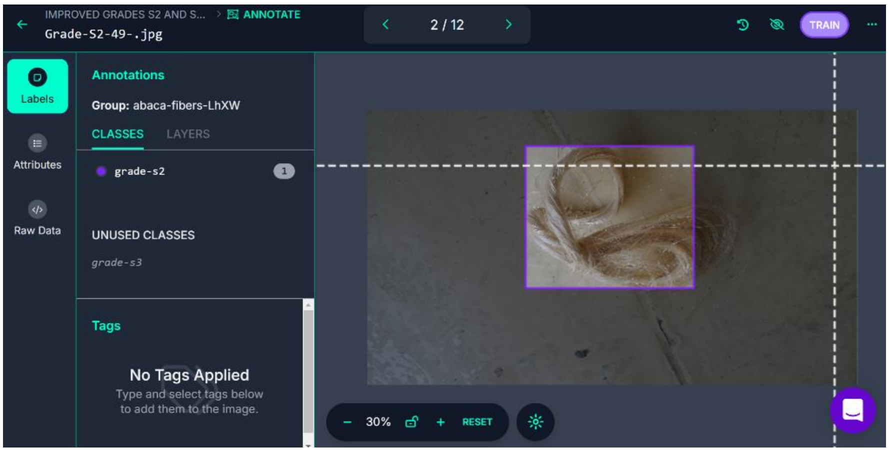

Figure 2. Annotating Grade S2 and S3 Abaca Fibers in Roboflow

To generate the dataset, the researcher first split the dataset into 583 images for the training set, 295 images for the validation dataset, and one image for the testing set. Since the testing of the model was used on new data, the researcher used only one image as placeholder for the dataset. The researcher also preprocessed the images by applying flipping, crop, blur, and noise adjustments. For each item in the training set, four images are generated. This results in a dataset of 2628 images, with 2332 images in the training set and 295 images in the validation set with a 89-11 split, as shown in Figure 4. If 10% of the images are added in the test set, this results in an approximately 80-10-10 split of training, validation, and test sets.

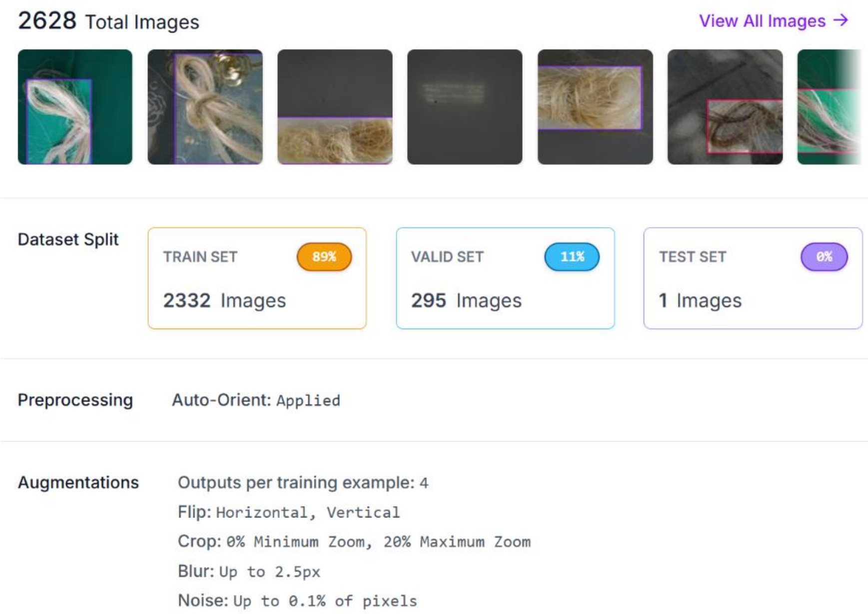

Figure 3. Image Preprocessing and Augmentation Using Roboflow

Before starting the model training, the dataset is first exported to Ultralytics HUB. The model training is linked to Ultralytics HUB for more accessible results visualization and resuming training if the training is interrupted. The researcher used the YOLOv8s model for model training. It uses a custom CSPDarknet53 backbone, which uses partial connections to improve accuracy and information flow between layers [17]. The architecture also used a novel C2f module for its feature extractor, which combines high-level semantic features with low-level spatial information, improving its detection accuracy, especially for small objects. This model has the second least number of parameters, as shown in Table 3 [18]. The model training is done on Google Colab using their T4 GPU, as shown in Figure 5.

Table 3. Comparison of YOLOv8 Modes [18]

Attribute	YOLOv8n	YOLOv8s	YOLOv8m	YOLOv8l	YOLOv8x
Parameters	3,011,238	11,136,374	25,857,478	43,631,382	68,154,534
GFLOPs	8.2	28.6	79.1	165.4	258.1
Layers	225	225	295	365	365
Overall complexity	Low	Medium	High	Very High	Highest

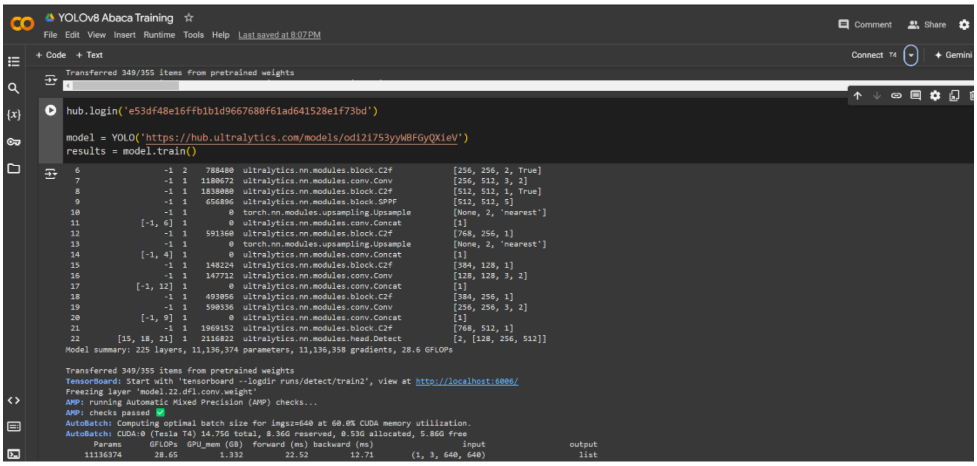

Figure 4. Training Abaca Fiber Classification Model

Then, in the testing phase, the trained model was tested on 40 unannotated images absent in training and validation sets. As stated earlier, this paper is limited to experimentation. Thus, the testing phase was done inside the laboratory.

RESULTS

To evaluate the performance of the trained model in classifying abaca fibers, the researcher analyzed vital metrics such as precision, recall, and loss values. These metrics provide insights into the model's capability of detecting and classifying abaca fibers.

One of the metrics utilized for evaluation is precision, defined as the ratio of correctly identified fibers (true positives) to the total number of identified abaca fibers (both true and false positives). Recall, another important metric, is calculated by dividing the number of true positives by the total of true positives and false negatives. In this study, the model achieved a recall of 98.2% and attained a precision of 98%.

$$\text{Precision}=\frac{\text{True Positives}}{\text{True Positives+False Positives}} \quad (1)$$

$$\text{Recall}=\frac{\text{True Positives}}{\text{True Positives+False Negatives}} \quad (2)$$

The mean average precision metric has two variants, depending on the Intersection over Union (IoU) threshold being considered. The mAP50 metric is calculated at an IoU threshold of 0.5, often used to assess model performance quickly. On the other hand, the mAP50-95 metric is calculated by finding the average of the mAP at IoU thresholds from 0.50–0.95. This metric allows for a comprehensive evaluation of the model's performance in various levels of detection difficulty. The model managed to achieve a mAP50 of 99.11% and a mAP50-95 of 91.93%.

The graph in Figure 6 shows how the metrics of precision, recall, and accuracy changes over time.

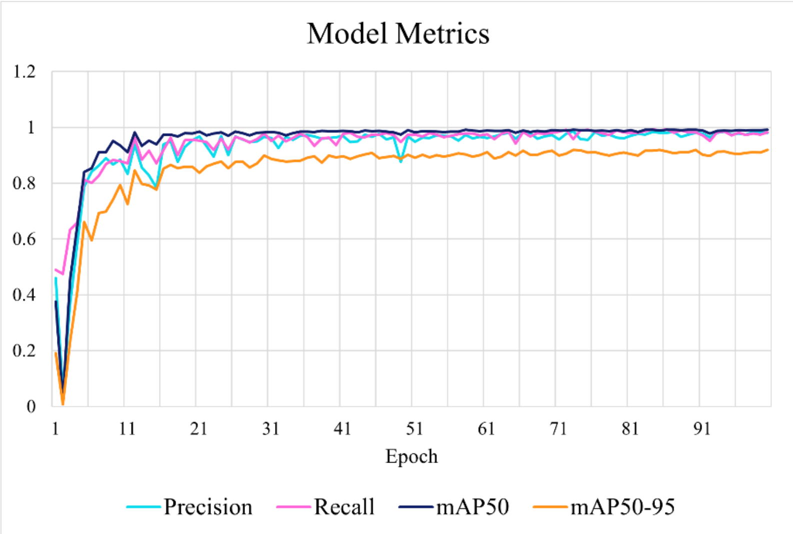

Figure 5. Metrics of the Trained Model

The box loss training commenced at 0.849 and exhibited a steady decline throughout the training process. In contrast, the validation loss initially peaked at 3.0 before quickly falling during the first ten epochs. Over time, both losses continued to decrease, with a slight dip in training loss observed during the final ten epochs. For class loss, both training and validation metrics showed sharp initial decreases, followed by a more gradual decline. This pattern indicates quick convergence and stable classification performance without any signs of underfitting. Meanwhile, the object loss validation metric began at a high value but rapidly decreased and stabilized, with training and validation losses converging around 1.0.

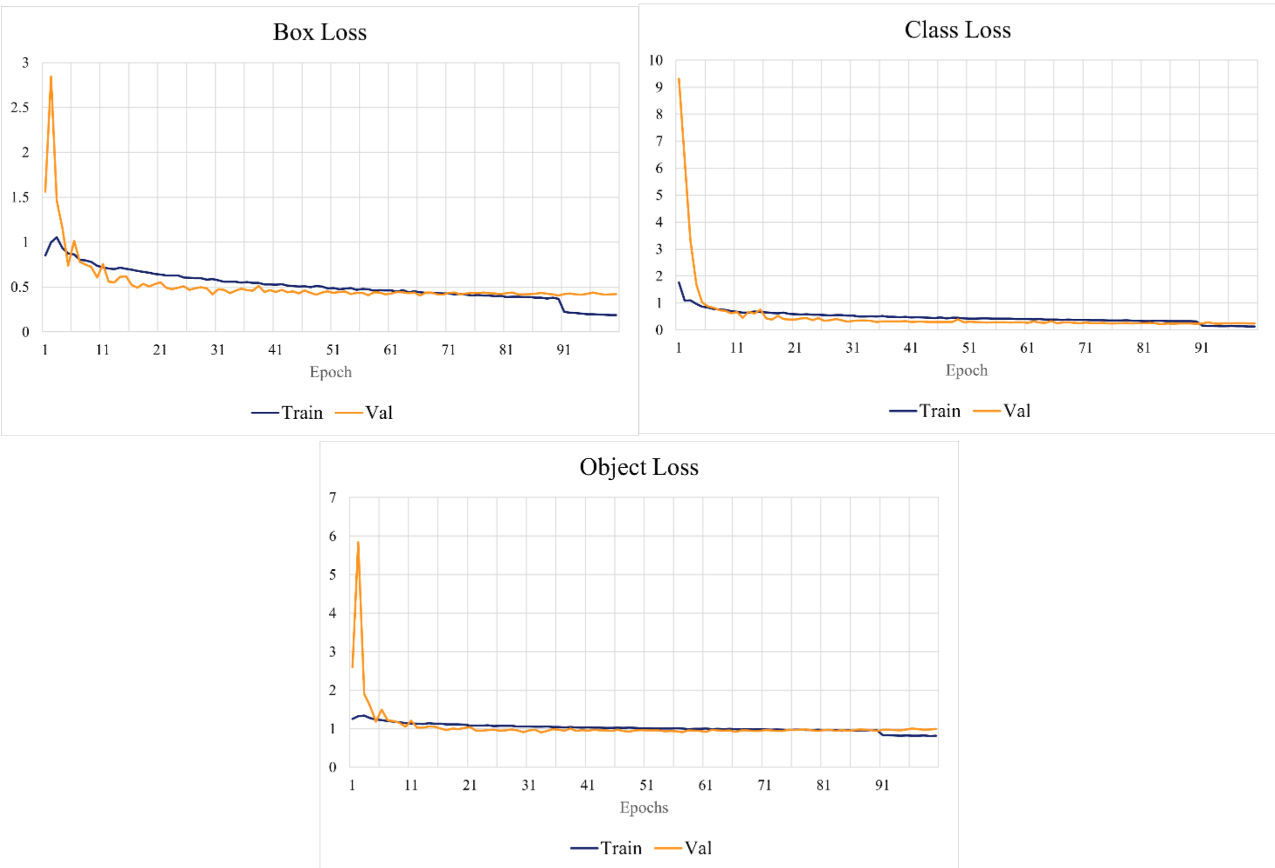

Figure 6. Box, Object, and Class Loss of the Trained Model

Figure 8 shows the confusion matrix of the trained model. Out of all the abaca fibers, 136 were accurately predicted as grade S2 while 133 were accurately predicted as grade S3. The grades of four abaca fibers were incorrectly predicted. There were nine false positives where the model finds an abaca fiber when there is only background. Two grade S3 fibers were incorrectly classified as grade S2 while one grade S3 fiber was not detected by the model.

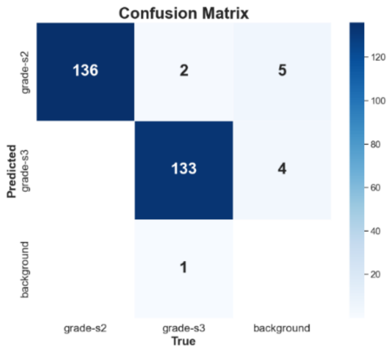

Figure 7. Confusion Matrix of the Trained Model

As stated earlier, the model was tested in a laboratory setting since this paper is only limited to experimentation. The researcher evaluated the performance of the model in detecting abaca fibers from 38 images, as shown in Figure 9. Of these images, 18 images were of grade S2, another 18 were of grade S3, and two images have no abaca fibers present.

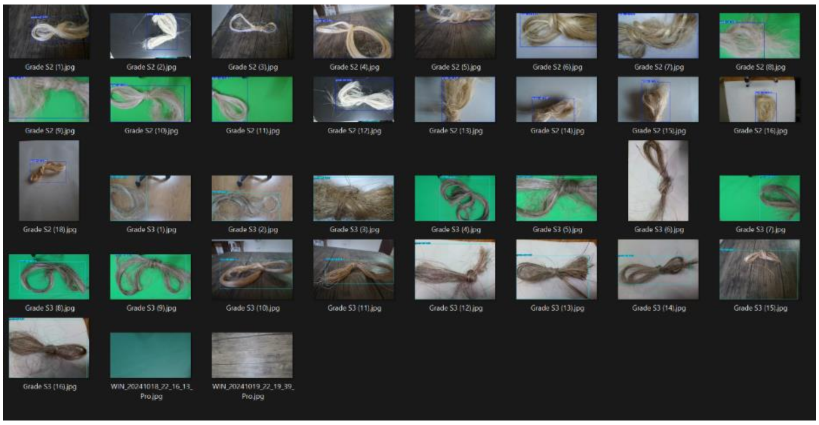

Figure 8. Testing Results

The results were filtered using the parameters conf = 0.5, agnostic_nms = true and iou = 0.2. This is done to reduce false positives, remove overlap between different classes and eliminate duplicates respectively. Figure 10 shows the confusion matrix of the test set. The model managed to classify 35 out of 36 abaca fibers.

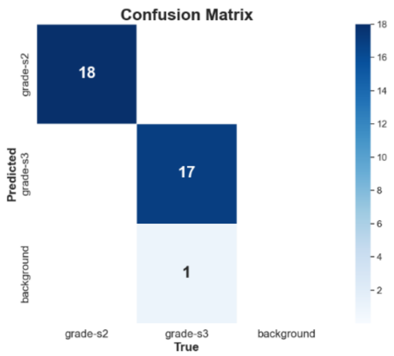

Figure 9. Test Results Confusion Matrix

DISCUSSION

After analyzing the results, the model managed to achieve exceptional precision and recall. The mean average precision (mAP) metric evaluated using mAP50 and mAP50-95 highlighted the model's robust capability in detecting and classifying abaca fibers in various scenarios.

The loss metrics analysis revealed important insights into the model's learning. The box loss slightly decreased in the last ten epochs, showing improved bounding box predictions. The validation loss dropped sharply after the early epochs, indicating good generalization to new data. While the training loss was a bit higher than the validation loss, this still showed effective processing of unseen data, though there were signs of minor overfitting. The model quickly learned to classify abaca fibers, with training and validation losses aligning well, indicating proper fitting and stable generalization. Object loss decreased rapidly and then stabilized, which shows that the model is performing well in detecting abaca fibers. Overall, the training and validation losses converged around similar values, which showed good generalization without significant overfitting. However, the losses stabilization around 1.0, which means there were minor errors in detecting abaca fibers.

The confusion matrix shows that the model performs well in classifying abaca fibers, with 136 correct predictions of Grade S2 fibers and 132 correct predictions of Grade S3 fibers. Most of the mistakes come from incorrectly detecting abaca fibers in pictures where there are none.

After the testing phase, the model managed to correctly identify classifying 35 out of 36 abaca fibers present in the test images, which shows its strong performance in classifying abaca fibers.

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