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Development of an Abaca Fiber Automated Grading System Using Computer Vision and Deep Convolutional Neural Network

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Abstract—**This study introduces a device that can be used in classifying the eight normal hand-stripped of the abaca fiber applying the concept of Convolutional Neural Network (CNN)-MobileNetV2 algorithm. In this study, 100 sample images of abaca fiber for each class were used in training for a total of 800 sample images. The gathered data were split into a training and validation dataset using an 80/20 ratio in which 80% of the collected samples were used to train the network and 20% of it was used to validate if the trained model is within acceptable values. Using the Raspberry Pi 4, the device was made possible. Raspberry Pi 4 is a microcomputer that supports functional applications through the integration of hardware and software components. Upon testing, the developed system obtained an overall accuracy of 85%. The implementation of this device would be of great help to abaca fiber traders, producers, and Grading and Bailing Establishments.**

Index Terms – Convolutional Neural Network, MobileNetV2, Raspberry Pi 4

I. Introduction

Abaca (*Musa textilis*) is a plant native to the Philippines which is also known as Manila hemp in international trade [1]. Depending on the various features of the fibers, abaca fibers can be classified into 13 grades of which eight from it are in normal grade, one in wide strips, and four in residual. The quality of the abaca fiber has a significant aspect, so grading the fiber is considered to be an important factor in the global market [2].

A recent study about the abaca fiber grading process in [3] achieved a promising result in classifying different fiber grades using CNN-VGGNet16 architecture. Studies also showed that computer vision and CNN have been widely used in the food industry especially in quality inspection of different fruits for over a decade. In [4], the authors presented a detailed overview of the uses of computer vision in fruit classification and grading. Different kinds of fruits were graded considering the external properties of fruits such as color, texture, size, shape, and even the fruit's visual flaws. In their paper, computer vision was integrated into different kinds of machine learning approaches such as K-NN, SVM, ANN, and CNN. A similar concept was applied in [5] wherein computer vision was applied for grading and sorting Alphonso mangos which yielded 83.3% of accuracy rate and were also utilized in [6] for sorting and grading mangoes based on their physical appearance and size. Similar conclusions for the effectiveness of CNN for grading were manifested in [7], wherein they presented automation in grading fruits and vegetables according to the fruits and vegetable size, shape, and color. Their study yielded a 97.9% accuracy rate in grading apple, bell pepper, orange, and tomato.

Another grading system using computer vision was presented in [8], for automation in grading cashew kernels. Their study highlights the importance of having all the external features of cashew kernels such as color, texture, size, and shape for the efficiency of the grading process. Furthermore, authors in [9] provided an improvised algorithm using deep CNN for a computer vision-based grading system for Cashew. Their study emphasizes the importance of CNN for having the ability to extract the features of the images in which the researchers considered that as an advantage compared to the existing algorithms. This image processing concept was also proved to be beneficial in [10-13], for real-time classification in Peru, broccoli grading system, mangosteen defective detection, and classification and classification of cacao beans quality after the post-harvest procedures. This is also helpful in building a portable device capable of plant identification using raspberry pi [14], a digital goniometer using raspberry pi that was used for instantaneous measurement of elbow and knee joint angles [15], detection of valgus (knock knees), and varus (bowlegs) diseases [16]. CNN was also integrated with [17] for Cloud-based Signature Validation.

While there are already lots of studies about computer vision and CNN digitalizing classifications, at present, classification of abaca fiber grade is being done through visual inspection and the province is still lacking a device that can help in grading the abaca fiber. Hence, the purpose of this study.

The main objective of this study was to develop an automation process in grading abaca fiber using the concept of Computer Vision and CNN. In order to achieve this, specific goals are laid: (1) Develop an image acquisition device with raspberry pi 4 and raspberry pi HQ camera (2) develop a system model using MobileNetV2 architecture for classification and integrate it into the hardware components (3) test and evaluate the system's accuracy and recall based on machine learning matrix.

Upon completion, the developed device can is useful in providing an additional or alternative way of grading the abaca fiber in Catanduanes. Also, it will help improve the socioeconomic status of Grading and Bailing Establishment's available on the island due to its automation nature. Lastly, this study can be a gateway for future researchers because it can give them ideas to innovate and to improve for a more advanced design that will meet the requirements for more advanced technologies. It can serve as an educational guide and motivation in making their project research.

The research focused on the design, development, and systems evaluation of automation in abaca fiber grading. The abaca fiber that was used for training and testing was limited only in eight normal grades hand stripped of the fiber due to the availability of the fibers in the province. The limitation of this study falls only in the province of Catanduanes. Furthermore, the prototype setup was used only in the evaluation and testing of the project.

II. MATERIALS AND METHODS

This section presents the conceptual framework, materials, software and hardware resources needed, and the methods that are laid to attain the objectives of the study.

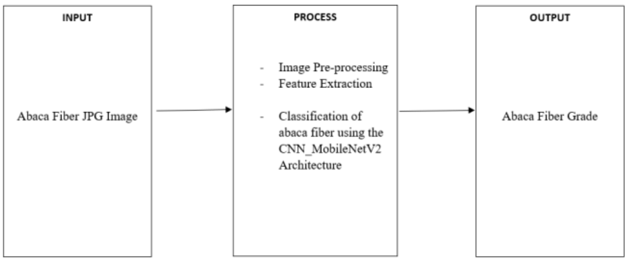

Fig. 1. Conceptual Framework of the System

Figure 1 presents the conceptual framework of the system. The different abaca fiber with their corresponding grades serves as an input. These inputs will be captured using the developed device. The captured image is then fed to the developed system which is responsible for image pre-processing, feature extraction, and classification of the uploaded images. Once the process is complete, the predicted grade is displayed.

A. Hardware Development

The hardware development focused on creating an image acquisition device that was used for gathering data and testing the system. The CAD design of the image acquisition device shown in Fig. 2 and the actual device which is shown in Fig. 3 has a dimension of 14x14x18 as its length, width, and height.

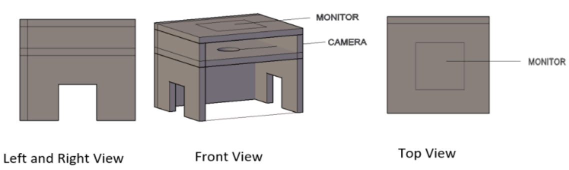

Fig 2. Device Drawing Design Consideration

Fig 3. Actual Image of the Device

For the microcomputer that will perform the image classification, the raspberry pi 4 was integrated into the device along with the raspberry pi HQ camera, ring light, and a raspberry pi LCD monitor. Fig 4 shows the system's block diagram of the device which also denotes how the hardware components relate to each other.

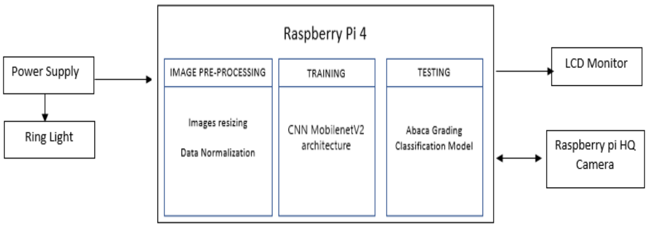

Fig. 4. System Block Diagram

The specifications of the integrated major materials are as follows: Raspberry Pi 4 quad-core Cortex-A72, 64 bit S0C @ 1.5GHz with memory RAM of 8Gb, 12.3 Megapixels raspberry pi camera with a sensor resolution of 4056x3040 pixels, and a 5 inches 800x480 HDMI LCD Screen display for raspberry pi.

B. Data Gathering

Using the developed device, the proponent manually collected a sample of different fiber grades. The fiber samples were obtained through a request to the sole Grading and Bailing Establishment in Catanduanes which is the Manila Hemp Trading Corporation. The abaca fiber part wherein the sample was taken is demonstrated in figure 5.

Fig. 5. Location of the Capture Images

A total of 800 data samples were taken, 100 samples for each class. The grading of the sample fiber was performed by a licensed PhilFIDA inspector. The samples of eight different fiber grades taken are shown in figure 6.

Fig. 6. Sample Image of Abaca Fiber with their grade

TABLE I. HAND-STRIPPED NORMAL GRADE OF FIBER [3]

Grade		Description				
Name	Alphanumeric Name	Fiber Strand size(mm)	Color	Stripping	Texture	Extracted From
Mid Current	EF	0.20-0.50	Light ivory to a hue of very light brown to very light ochre	Excellent	Soft	Inner Leaf sheath
Streaky Two	S2	0.20-0.50	Ivory white, slightly tinged with very light brown to red or purple streaks	Excellent	Soft	Next to outer leaf sheath
Streaky Three	S3	0.20-0.50	Predominant color-light to dark red or purple or a shade of dull to dark brown	Excellent	Soft	Outer Leaf Sheath
Current	I	0.51-0.99	Very light brown to light brown	Good	Medium soft	Inner and middle leaf sheath
Soft Seconds	G	0.51-0.99	Dingy white, light green and dull brown	Good	Medium soft	Next to outer leaf sheath
Soft Brown	H	0.51-0.99	Dark Brown	Fair	Medium Soft	Outer leaf sheath
Seconds	JK	1.00-1.50	Dull brown to dingy light brown or dingy light yellow	Fair		Inner, middle and next to outer
Medium Brown	M1	1.00-1.50	Dark Brown-almost black	Fair		Outer leaf sheath

The table 1 explained the description of the different grade of the abaca fiber in terms of its color, stripping quality, texture, and where it is extracted from.

C. Software Development

For software development, the proponent focused on the training on the neural network model that will facilitate the classification of the abaca fiber grade. The Convolutional Neural Network architecture applied in this study is the MobileNetV2 presented in figure 7.

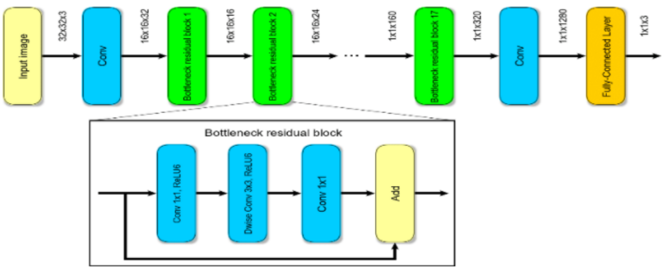

Fig 7. MobileNetV2 CNN Architecture [19]

MobileNetV2 is a lightweight CNN architecture that works well on mobile devices, it pays attention to the reduction of the required memory and has low memory requirements for hardware conditions [18] which is perfect for this project as the proponent is using raspberry pi. MobileNetV2 is also a known for its feature as an effective feature extractor for object detection, segmentation, and classification [19]. Studies also show the efficiency of MobileNetV2 for classification and how it outperforms other CNN architecture [20-22].

Figure 8 demonstrates the block diagram of the training. The training implemented the 80/20 ratio, wherein 80% of the gathered samples were used for the training of the neural network while the remaining 20% was used to verify that the accuracy of the trained model is within acceptable values. Since MobileNetV2 has its own pre-processing function, the training images were pre-processed the way mobilenetv2 expects it to be. The RGB pixels value of the training data is scaled to -1.0 to 1.0 instead of 0-255.

Data augmentation was also applied wherein the data were flipped and rotated to make more training data. The data is then fed to the based model of the network using the pre-trained model of mobilenetv2.

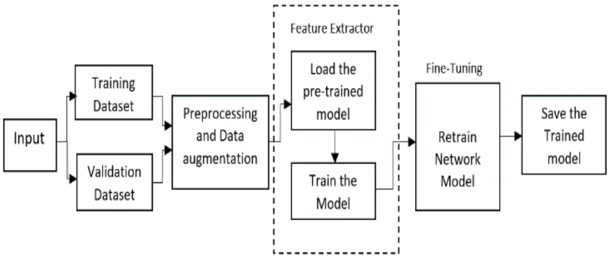

Fig. 8. Block Diagram of Training

The training use softmax as an activation function. Fine-tuning is then applied by unfreezing the top layers of the MobileNetV2 model. Then the model is retrained with the same learning rate and optimizer.

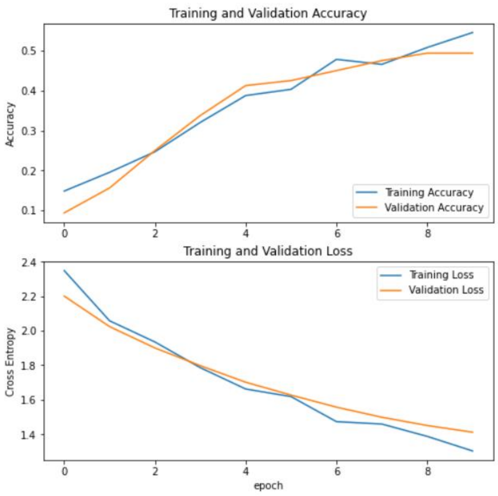

Fig. 9. Plot of Training and Validation Accuracy and Loss

A global average pooling and drop-out were also applied in the CNN training phase.

Figure 9 shows the result of the first based training which shows the training and validation accuracy and training and validation loss after the based training. Figure 10 on the other hand demonstrates the result after the fine-tuning was applied and the model was retrained. The model achieved a 90% training accuracy and 85% validation accuracy.

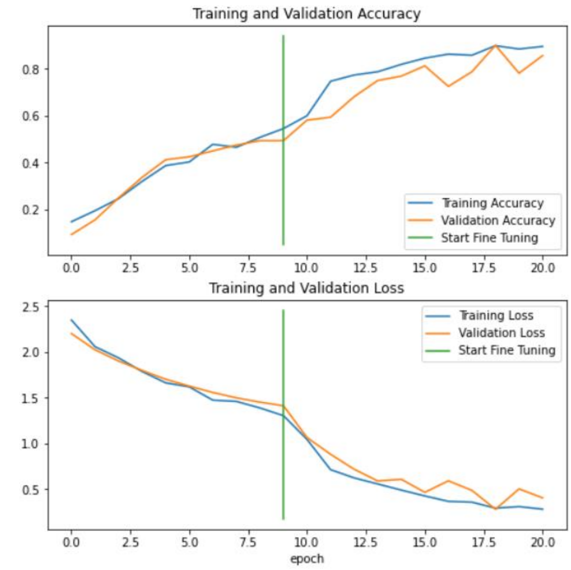

Fig 10. Training and Validation Accuracy and Loss after Retraining

The developed model is then saved to integrate it into the testing model. This testing model was integrated into the device and was used to test the functionality of the system.

D. Device Testing

The generated model in the training phase was integrated into the testing system in the device. With the working device, the proponent requested again to Manila Hemp Trading Corporation for a sample to be used for the testing. The certified PhilFIDA inspector who graded the training fiber was also requested as well to grade the abaca fiber that will be used in the testing.

In device testing, the first step is to take a sample image of abaca using the hardware prototype. The captured image is then uploaded to the developed testing system. Once the upload is done, the abaca fiber grade predicted or classified will be shown.

Table 2 presents the sample data for each class from the testing. To determine the performance of the developed device, a total of 200 samples were used in which every class has 25 samples.

The result is then plotted in a confusion matrix, from this, the accuracy rate and recall for each class can be acquired using the formula:

$$\text{Accuracy} = \frac{Sum\ of\ correct\ prediction}{Total\ number\ of\ samples} \qquad (1)$$

The system accuracy rate given in (1) is calculated using the formula sum of all correct predictions divided by the total number of the samples.

$$\text{Recall} = \frac{Correct\ Prediction\ for\ each\ class}{Total\ number\ of\ sample\ per\ class} \qquad (2)$$

The equation in (2) is the recall for each class which can be computed by dividing the correct predictions for each class and the total number of sample per class.

TABLE II. SAMPLE DATA FOR EACH CLASS FOR TESTING

Image Number	Actual Grade	Predicted Grade	Remarks
1	EF	EF	Correct
2	EF	EF	Correct
3	EF	EF	Correct
4	EF	EF	Correct
:	:	:	:
25	EF	EF	Correct
26	S2	S2	Correct
27	S2	EF	Fail
28	S2	S2	Correct
29	S2	S2	Correct
:	:	:	:
50	S2	S2	Correct
51	S3	S3	Correct
52	S3	S3	Correct
53	S3	S3	Correct
:	:	:	:
75	S3	S3	Correct
76	I	I	Correct
77	I	I	Correct
78	I	G	Fail
:	:	:	:
100	I	I	Correct
101	G	G	Correct
102	G	G	Correct
103	G	G	Correct
:	:	:	:
125	G	G	Correct
126	H	H	Correct
127	H	M1	Fail
128	H	JK	Fail
:	:	:	:
150	H	H	Correct
151	JK	JK	Correct
152	JK	JK	Correct
:	:	:	:
175	JK	JK	Correct
176	M1	M1	Correct
177	M1	M1	Correct
178	M1	M1	Correct
:	:	:	:
200	M1	M1	Correct

III. RESULTS AND DISCUSSION

Table 3 presents the confusion matrix which is derived from the summary of results in table 2. Based on the results, 170 out of 200 testing samples were correctly classified by the developed system.

Under these conditions, the system achieved an overall accuracy of 85% which indicates that the used algorithm was sufficient enough to support an accurate classification of the abaca fiber grade.

TABLE III. CONFUSION MATRIX BASED ON TABLE 2

N=200	SYSTEM PREDICTED GRADE							
		EF	***S2***	***S3***	***I***	***G***	***H***	***JK***	***M1***
ACTUAL	***EF***	25	0	0	0	0	0	0	0
	S2	9	16	0	0	0	0	0	0
	S3	0	0	25	0	0	0	0	0
	I	0	0	0	20	5	0	0	0
	G	0	0	0	0	25	0	0	0
	H	0	0	0	0	0	9	9	7
	JK	0	0	0	0	0	0	25	0
	M1	0	0	0	0	0	0	0	25

The developed system model holds a classification model that is reliable enough for an actual use for the classification of abaca fiber grade.

TABLE IV. RECALL FOR EACH CLASS BASED ON TABLE 3

Abaca Fiber Grade	Recall
EF	100%
S2	64%
S3	100%
I	80%
G	100%
H	36%
JK	100%
M1	100%

Table 4 presents the recall for each class, grade EF, S3, G, JK and M1 achieved a 100% recall while grades S2, I, and H recorded a recall of 64%, 80%, and 36% respectively. Grade S2 is sometimes mistakenly classified as EF, I for G, and -grade H as either JK or M1.

The sample output of the system is presented in figure 11. The sample figure shows the predicted grade of abaca fiber belonging to class EF and M1.

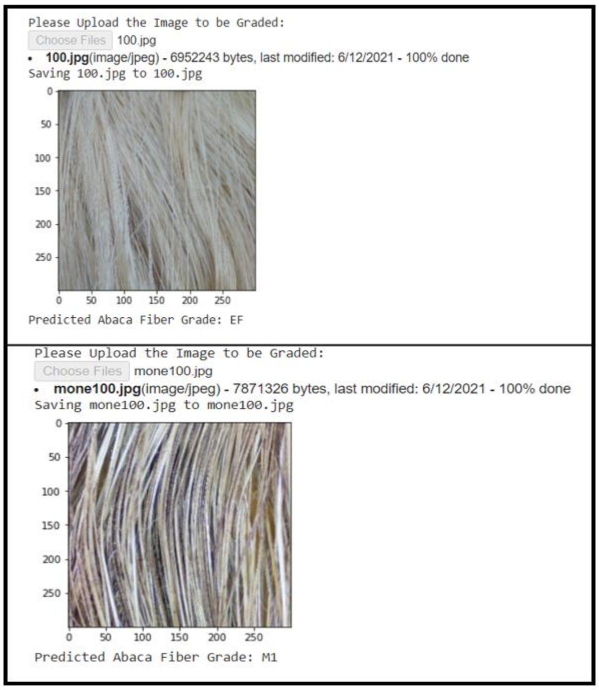

Fig. 11. Sample Result of System Prediction

IV. CONCLUSIONS AND FUTURE WORKS

Based on the conduct of the functionality test, the proponent was able to develop a device that can be used in grading the eight normal hand-stripped abaca fiber with the use of CNN-MobileNetV2 architecture which yielded an accuracy rate of 85%. Although the developed system was able to predict and classify almost all the abaca fiber grade, there are abaca fiber grade which yielded a low recall, thus using other algorithms to see whether this system could be improved would be recommended. Lastly, the algorithm and procedures applied in this study could be applied in grading the abaca fibers belonging to the residual and wide-strip classes.

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