EyeBill-PH: A Machine Vision of Assistive Philippine Bill Recognition Device for Visually Impaired

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***Abstract*— The value of money can be quickly grasped by the fact that virtually all economic, social, and other tasks are carried out and done using money. With dramatic shifts in global growth and other total human needs, the value of money is rising day after day. Money is an important asset that will allow you to run your life. The exchange of goods for products is an older custom, and you cannot buy something you want without any money. It's straightforward to use money, you just have to glance at the currency instantly, pull the appropriate sum of cash out, and that's it. But that may become a challenging job for those who cannot see. Among the most significant issues facing visually impaired people is the identification of money, particularly for paper currency. In this study, it focuses on this problem and is based on a machine vision technique called object detection. The study used Raspberry Pi 4 as a microcontroller, Pi Camera as its capturing device, and a speaker for audio in announcing the detected bill. EyeBill-PH has been done with an overall testing accuracy of 86.3%.**

Keywords—bill recognition, visually impaired, machine vision, deep learning, raspberry pi.

I. INTRODUCTION

Money's value can be quickly understood from the fact that almost all cultural, social, and other tasks are carried out and done using the currency. The value of money is rising day by day with dramatic shifts in economic growth and other general human needs [1]. Money is considered to be the ultimate key to overcoming all economic woes. It's straightforward to use money, you just have to look at the currency instantly, pull the appropriate sum of cash out, and that's it. However, this may become a challenging job for those who cannot see [2]. The word "blind" is a very broad term. If you're legally blind, you may be able to see reasonably well with a pair of corrective lenses. What a blind person can see depends a great deal on how much vision they have [3]. A person with total blindness won't be able to see anything. But a person with low vision may be able to see not only light but colors and shapes too. However, they may have trouble reading street signs, recognizing faces, or matching colors to each other. If you have low vision, your vision may be unclear or hazy [4]. Based on the 2017 data of the Department of Health, over two million people in the Philippines are blind or suffering from poor vision. The DOH stated that an additional 332,150 people are bilateral blind in the world, while the total number of people with bilateral low vision has already exceeded 2,179,733 [5]. Some of the key challenges experienced by individuals with visual impairments are the failure to identify paper currencies owing to the resemblance of the various types of paper texture and thickness. The task of technology is, therefore, to find a response to this problem to allow blind people to feel secure and comfortable in financial transactions [6].

In the Philippines, both currency amounts have the same measurements. This implies that blind persons cannot differentiate between one denomination or another. Blind people physically arrange a currency unit in a specific way. For e.g., a bill of 20 pesos might be left unfolded. A bill of 50 pesos can be folded width-wise and a bill of 100 pesos can be folded lengthwise. Folding money differently is a reasonable option for easily understanding a particular bill's value, but it needs anyone the blind individual believes in defining the currency for them to stop getting tricked or scammed by someone. There are instances that blind people want to live independently and this includes taking up public transportation, going to work and going to the market to buy their groceries, folding money differently is a good solution for them to pay but it is a challenge to make sure that they received an exact amount for change, blind people get fooled as they often received the inadequate amount of money [7].

The objective of this study is to have a high accuracy in detecting the amount of money. Considering that the target user is blind people, it is not easy for them to take a picture or provide an exact input to the application. The existing solution also works by using a smartphone which is not easy for the blind to use and operate and this greatly affects its accuracy. Another objective is for the study to develop a system that can complete its function without the need to rely on an internet connection to be highly utilized by the blind. The study also aims to develop an algorithm that will be able to identify the Philippine peso bill.

The lack of identification devices motivated the need for a device that can be used as a bill identifier. Banknote identification, though, poses a major challenge for individuals who are blind / visually challenged. The visually impaired population depends on various artificial aids to allow them to

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live an ordinary life in a modern complex society. In this respect, the recognition of currency notes is of vital importance and several currency recognizers have been created [8] - [15]. Some others used machine vision-based deep learning for general object detection such as [16]-[21]. Nevertheless, it is strongly desired to provide a lightweight, accurate, and cost-effective recognizer tailored for local currency notes.

The study will be used by the blind or visually impaired in identifying the amount of the bill. This part includes the other details of the project which refers to the problem or issue that the researcher wants to study as well as constraints that impact the researcher's ability to effectively study the scope of the project. The scope and limitation of the project would be to determine the currency of the Philippine bill released only by the Bangko Sentral ng Pilipinas. Bills released by other countries can't be recognized by the device. Additionally, the device won't be able to recognize the commemorative notes released by the BSP as well as the Philippines coins. Also, the device will only recognize the current Philippine bill released by the BSP as of the year 2020.

II. METHODOLOGY

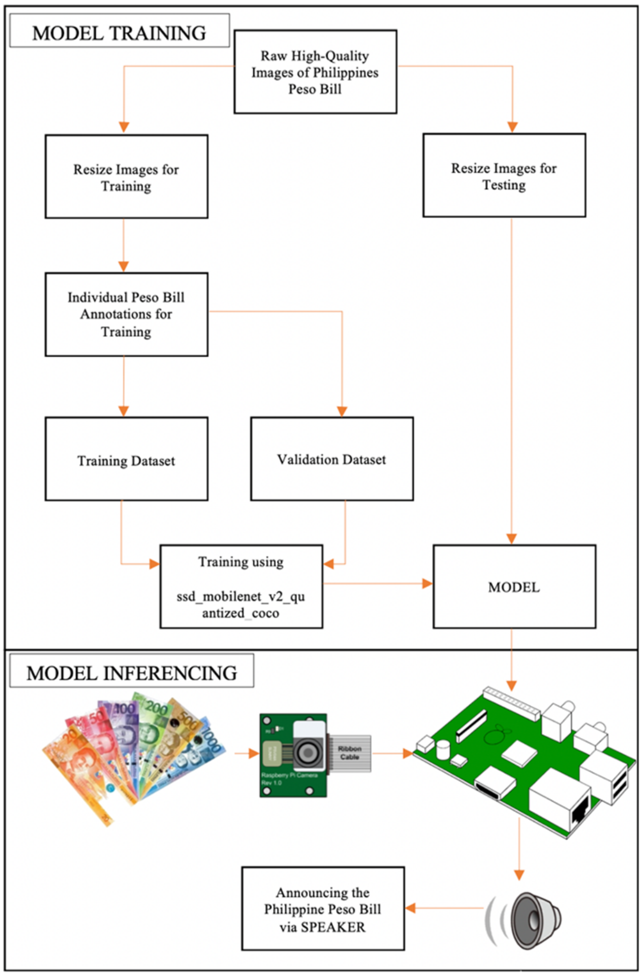


Fig. 1. EyeBill-PH Methodology

Multiple schemes were introduced in different articles [8] - [15]. Through the performance, though, one will infer that neither of these systems is fully effective and that the intended people are blind or visually disabled, they may consider it impossible to utilize such methods. Therefore, the study created a system that recognizes the variations in each bill as shown in Fig. 1, taking into consideration numerous different features. The study designs a device in a manner that is both compact and reliable.

A. Raw High-Quality Images of Philippines Peso Bill

The study gathered raw high-quality images of the Philippine peso bill which includes 20, 50, 100, 200, 500, and 1000 peso bills. Additionally, the front and back parts of each bill have also been captured. The study gathered 500 front and 500 back images for each peso bill with a total of 1000 images for each bill.

B. Resize Images for Training

The images have been resized for training using OpenCV as shown in Fig. 2. The recommended size of each image for the system is 300 x 300.

Fig. 2. Resized Images for Training

C. Individual Peso Bill Annotation for Training

Each peso has been annotated using labellmg as shown in Fig. 3. The label of each bill corresponds with the actual amount of the bill. The output is an XML file that includes the coordinates of the annotated images.

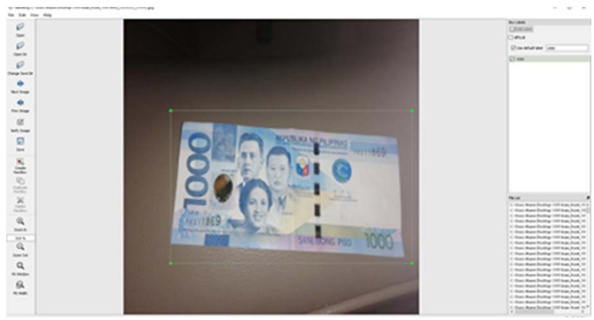
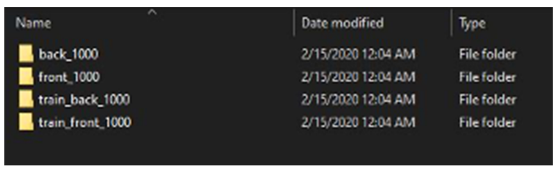


Fig. 3. Image Annotation using labellmg

D. Splitting Process

- *Training Dataset:* Create a folder and named it "train_back_amount" and "train_front_amount". 80% of the total dataset of each bill should be placed in this folder. Fig. 4 shows that these images have been used for the training of the model.
- *Validation Dataset:* The remaining 20% of the images of each bill has been used for the validation of the trained dataset.



Name	Date modified	Type
back_1000	2/15/2020 12:04 AM	File folder
front_1000	2/15/2020 12:04 AM	File folder
train_back_1000	2/15/2020 12:04 AM	File folder
train_front_1000	2/15/2020 12:04 AM	File folder

Fig. 4. Splitting Process for a 1000 Peso Bill

E. Training using ssd_mobilenet_v2_quantized_coco

The ssd_mobilenet_v2_quantized_coco which is an existing model has been used for the training. The study performed transfer learning using the said model. The training process as shown in Fig. 5 has been completed after when the loss per step is consistently below 2.0.

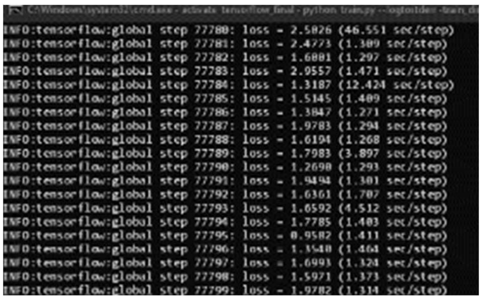


Fig. 5. Training Process

F. Model

Fig. 6 shows the output files are tflite_graph.pb and tflite_graph.pbtxt but to use this model on Raspberry Pi, it has been converted to detect.tflite file, the study used bazel for this process. After this, the creation of a labelmap.txt file containing all the classes has been needed for the output.

Fig. 6. Output Files

To execute the bazel process, Fig.7 shows this command can be used:

```
bazel run --config=opt tensorflow/lite/toco:toco -- --
input_file=%OUTPUT_DIR%/tflite_graph.pb --
output_file=%OUTPUT_DIR%/detect.tflite --input_shapes=1,300,300,3 --
input_arrays=normalized_input_image_tensor --
output_arrays=TFLite_Detection_PostProcess,TFLite_Detection_PostPro
cess:1,TFLite_Detection_PostProcess:2,TFLite_Detection_PostProcess:3 -
-inference_type=QUANTIZED_UINT8 --mean_values=128 --
std_values=128 --change_concat_input_ranges=false --allow_custom_ops
```

Fig. 7. Bazel Process Command

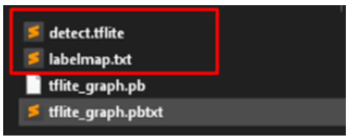


Fig. 8. The output of the Bazel Process Command

G. Detected Peso Bill Denomination

The Philippine Peso Bill which includes 20, 50, 100, 200, 500, 100 are now trained. The model can now be tested using a web camera or PI camera. Fig. 9 shows the initial testing from the model.

Fig. 9. Detected 1000 Peso Bill

H. Announce Denomination via Audio Speaker

Additionally, the device should be able to announce the denomination of the Philippine Peso Bill. The announcement of the amount should correspond with the actual amount of the bill.

III. Hardware Design

The study created a design of the prototype using a 3D Sketch online as shown in Fig. 10. During the process of creating the design, we will need to take into consideration the size of the case as it should fit the camera and the Raspberry Pi as well as the other materials needed for the project.

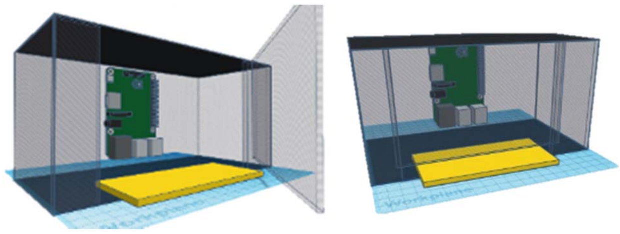


Fig. 10. Prototype 3D Design Layout

The study used acrylic glass for the case and was able to finish it but it will need some finishing touches. The size of the case is 7 inches for the height, 9 inches length, and 6 inches width. Fig. 11 shows the actual prototype.

Fig. 11. Actual Prototype with R-Pi, Pi-Cam, and Speaker

IV. Results and Discussions

A. Training Results

Classification /localization loss values are the result of loss functions and represent the "price paid for the inaccuracy of predictions" in the classification/localization problems (respectively). The loss value given is a sum of the classification loss and the localization loss. The optimization algorithms are trying to reduce these loss values until the researchers are satisfied with the results and considered the model 'trained'. Generally, the lower the score the better the model.

- *Classification Loss:* The X-axis represents the step's value reaching 6.5k while the Y-axis represents the number of classification loss as shown in Fig. 12.

Fig. 12. Classification Loss

- *Localization Loss:* The X-axis reaching 6.5k represents the steps while the Y-axis represents the number of localization loss as shown in Fig. 13.

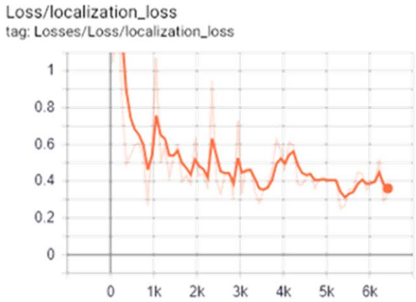


Fig. 13. Localization Loss

- *Total Loss:* The X-axis accounts for the number of phases while the Y-axis reflects the overall loss rate as shown in Fig. 14. The study used a loss function to assess how much the expected values deviate from the observed training data values. Changing the weights of the trainer made the loss minimal and that's what training is about.

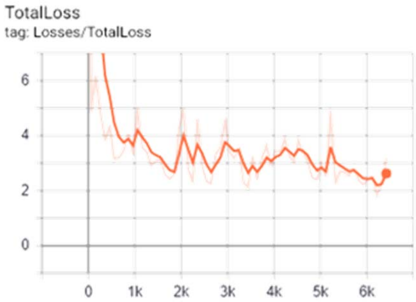


Fig. 14. Total Loss

B. Testing Results

The system works by inserting the bill inside the case. Through this, the device automatically detects the bill's denomination and produced a voice announcing the amount of the bill inserted. The device should be able to work without an internet connection.

- *20 - Peso Bill Testing:* Fig. 15 shows that the study has performed the testing with a 20-peso bill. 4 out of 5 tests were successful and the device was able to detect the 20-peso bill denomination.

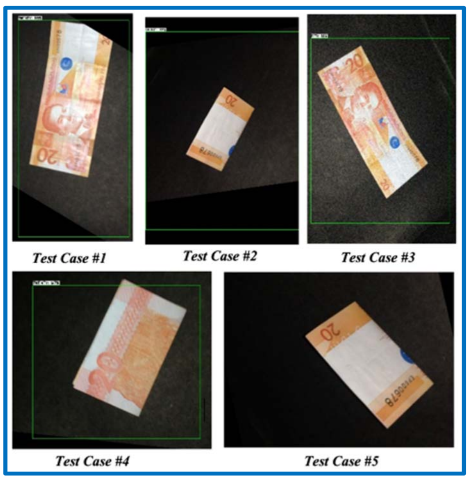


Fig. 15. ₱ 20 – Peso Bill Testing

TABLE I. ₱ 20 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
1	₱ 20.00	₱ 20.00	98 %
2	₱ 20.00	₱ 20.00	97 %
3	₱ 20.00	₱ 20.00	0 %
4	₱ 20.00	₱ 20.00	88 %
5	₱ 20.00	₱ 20.00	88 %
		Mean Average	**74.2 %**

The system was able to get a 74.2% success rate for a 20-peso bill as shown in Table 1.

- *50 – Peso Bill Testing:* Fig. 16 shows that the study has performed the testing with a 50-peso bill. 5 out of 5 tests were successful and the device was able to detect the 50-peso bill denomination successfully.

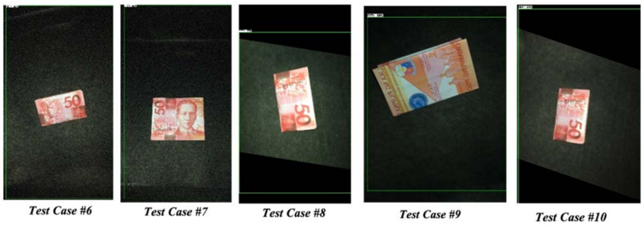


Fig. 16. ₱ 50 – Peso Bill Testing

TABLE II. ₱ 50 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
6	₱ 50.00	₱ 50.00	99 %
7	₱ 50.00	₱ 50.00	99 %
8	₱ 50.00	₱ 50.00	97 %
9	₱ 50.00	₱ 50.00	88 %
10	₱ 50.00	₱ 50.00	88 %
		Mean Average	**94.2 %**

The study was able to get a 94.2% success rate for a 50-peso bill as shown in Table 2.

- *100 – Peso Bill Testing:* Fig. 17 shows that the study has performed the testing with a 100-peso bill. 4 out of 5 tests were successful and the device was able to detect the 100-peso bill denomination successfully.

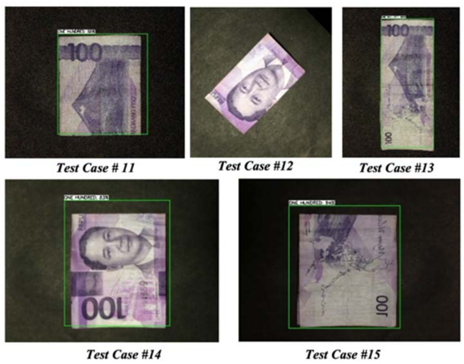


Fig. 17. ₱ 100 – Peso Bill Testing

TABLE III. ₱ 100 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
11	₱ 100.00	₱ 100.00	88 %
12	₱ 100.00	₱ 100.00	0 %
13	₱ 100.00	₱ 100.00	99 %
14	₱ 100.00	₱ 100.00	83 %
15	₱ 100.00	₱ 100.00	94 %
		Mean Average	**72.8 %**

The study was able to get a 72.8% success rate for a 100-peso bill as shown in Table 3.

- *200 – Peso Bill Testing:* Fig. 18 shows that the study has performed the testing with a 200-peso bill. 5 out of 5 tests were successful and the device was able to detect the 200-peso bill denomination successfully.

Fig. 18. ₱ 200 – Peso Bill Testing

TABLE IV. ₱ 200 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
16	₱ 200.00	₱ 200.00	83 %
17	₱ 200.00	₱ 200.00	99 %
18	₱ 200.00	₱ 200.00	92 %
19	₱ 200.00	₱ 200.00	83 %
20	₱ 200.00	₱ 200.00	88 %
		Mean Average	**89 %**

The study was able to get an 89% success rate for a 200-peso bill as shown in Table 4.

- *500 – Peso Bill Testing:* Fig. 19 shows that the study has performed the testing with a 500-peso bill. 5 out of 5 tests were successful and the device was able to detect the 500-peso bill denomination successfully.

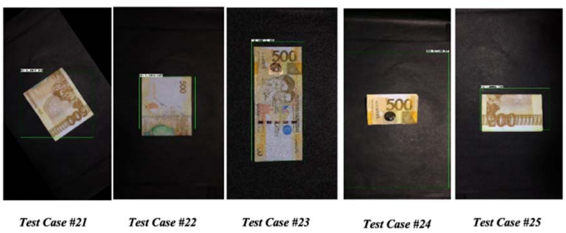


Fig. 19. ₱ 500 – Peso Bill Testing

TABLE V. ₱ 500 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
21	₱ 500.00	₱ 500.00	99 %
22	₱ 500.00	₱ 500.00	99 %
23	₱ 500.00	₱ 500.00	88 %
24	₱ 500.00	₱ 500.00	94 %
25	₱ 500.00	₱ 500.00	92 %
		Mean Average	**94.4 %**

The study was able to get a 94.4% success rate for a 500-peso bill as shown in Table 5.

- *1000 – Peso Bill Testing:* Fig. 20 shows that the study has performed the testing with a 1000-peso bill. 5 out of 5 tests were successful and the device was able to detect the 1000-peso bill denomination successfully.

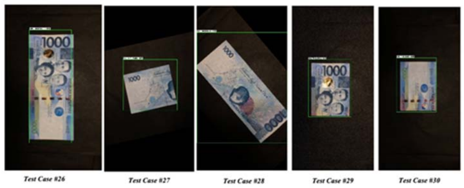


Fig. 20. ₱ 1000 – Peso Bill Testing

TABLE VI. ₱ 1000 – PESO BILL TESTING SUMMARY

Test #	Test Case	Expected Output	Detection Output
26	₱ 1000.00	₱ 1000.00	99 %
27	₱ 1000.00	₱ 1000.00	88 %
28	₱ 1000.00	₱ 1000.00	99 %
29	₱ 1000.00	₱ 1000.00	96 %
30	₱ 1000.00	₱ 1000.00	83 %
		Mean Average	**93 %**

The study was able to get a 93% success rate for a 1000-peso bill as shown in Table 6.

C. Overall Testing Results

The study was able to get an overall 86.3% success rate as shown in Fig. 21. The system has performed the testing with 5 tests for each denomination (20, 50, 100, 200, 500 & 1000). Overall, 30 tests were done. To conclude, the 100-peso bill got the lowest success rate of 72.8% and the 500-peso bill got the highest success rate of 94.4%.

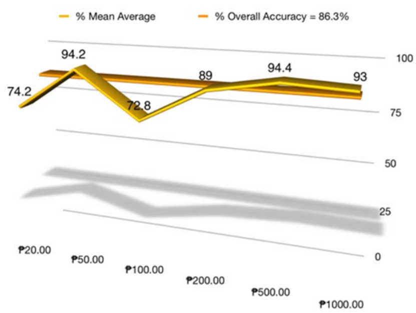


Fig. 21. Overall Testing Results

V. CONCLUSION

The study had presented an alternative way for blind people to identify the amount of a bill. The development of independent living skills like buying groceries and riding public transportation is important to everyone; however, this can become an issue to those who are blind and visually impaired as it is not easy for them to identify money, they are prone to scam and tricks. There are strategies and tools available to help them but they are still limited. The developed device is a tool that can help solve such problems. It will serve as a way for them to somewhat live, travel, and buy things independently without having second thoughts if they receive the right amount for a change. To recognize the currency notes, this system would also be of tremendous benefit to nearly 2 million visually disabled citizens in the Philippines.

Overall, the accuracy of the whole system produced by 86.3%. The system detection is having low accuracies when identifying the 20 – Peso bill (PHP. 20.000) and 100-peso bill (PHP. 100.00). Either or both of the following two changes can be required to fix this issue: First, by adding more datasets both in the 20-peso bill and 100-peso bill. Adding more datasets for each bill can be of help. Second, this can be overcome by increasing the preparation time by which more accurate results can be obtained resulting in more accurate classification. Work on this field is worthwhile. Additionally, future work includes introducing counterfeit notes.

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