VOL. 16, NO. 19, OCTOBER 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

COINIC-PH: A PHILIPPINE NEW GENERATION SERIES OF COIN INTELLIGENT CLASSIFICATION INFERENCE APPROACH FOR VISUALLY IMPAIRED

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ABSTRACT

Object detection experiences widespread use in many technology-related fields nowadays. This paper uses computer vision to execute object detection of the new series of coins of the Philippine peso. Compared to the coin designs of the previous series, these coins are much more identical to each other, which can be hard to distinguish for people with bad eyesight. Through the use of object detection, these coins can then be classified into their respective amounts just by an image or video sample. The machine learning model used in this paper performed sufficiently, with it being able to distinguish the one, five, ten, and twenty-peso coins from each other from image and video samples.

Keywords: Philippine coin, object detection, deep learning, machine vision, yolov3.

INTRODUCTION

In this technology-driven era, computer vision plays a large role in making people's lives much more convenient [1]. Since this technology can virtually be applied to any field which would utilize any sort of computer, its widespread use could be symbiotically related to its exceptionally fast improvement over time [2]. Through the use of computer vision, object detection can be done [3]. Object detection can be used to detect practically any object, provided that there is a dataset for it [4]. Within a myriad of datasets that can be used for object detection, this paper has chosen one particular type of dataset to focus on-money.

Since many powerful, readily-accessible deep learning models can be easily used nowadays [5], this paper utilized this technology to propose a possible solution for a problem that has plagued the Philippine citizens for quite some time now. While the designs for the new Philippine peso coins remain to be a matter of debate whether it is a step in the right direction or not, the fact remains that some people have more trouble classifying these new coins than the old ones due to the similarities to their designs [6].

Harnessing the power of object detection through image and video samples [7], this paper proposed a solution that could potentially help reduce the impact of this long-standing problem. Being able to classify coins through computer vision could help the automation of processes that involve having to recognize and classify money through visual means [8].

An accurate coin detection system can be embedded into many technologies and could inspire innovations to bloom [9]. This is important even more so in this modern age, where more and more things are slowly being modernized and digitalized as time goes on, of course, processes and systems relating to money are not strangers to this modernization either [10].

It does not mean, however, that this paper does not have its scopes and limitations. While the system could potentially incorporate all the coin designs that were released by the Bangko Sentral ng Pilipinas (BSP) throughout Philippine history, such large scope is impractical for a study of this scale. Moreover, the BSP also releases limited-edition coins, in which it would be hard to get a hold of related datasets. Therefore, the dataset used for this paper is limited to the one, five, ten, and twenty-peso coins-the coin designs which are the most commonly used.

RELATED LITERATURE

Coins are an integral part of the world's currencies and economies it has been used to purchase goods and services for countless generations [11]. According to the Washington Post, the quality and usability of coins cannot be compared with banknotes [12]. In recent years, there have been many vision techniques aimed at detecting and recognizing objects in images or real-time. Some of these are human detection, facial recognition, and much more. One of the applications of this computer vision technique is coin detection [13]. This coin detection has been important to devices that use coins such as videoke machines, vending machines, and gaming machines in arcade parks or casinos. Coin Recognition is a complicated process in artificial intelligence and computer vision due to its numerous rotations and a large shift in input patterns. Coin detection and recognition in noisy and cluttered images also pose a great challenge [14].

Zambanini and Kampel presented an automatic image-based ancient coin classification method that utilizes the SIFT flow algorithm [15]. In their research, the

VOL. 16, NO. 19, OCTOBER 2021 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

classification system contains 24 classes of early Republican coinage which achieved a 74% classification rate. While their research is useful to the field of archaeology, in particular, applying the same concept while utilizing recent computer vision technologies could generally describe the objectives of this paper. Conn and Arandjelović (2017) even used a similar approach to use this technology in the field, which focused on making the image preprocessing and normalization more reliable so that it can be useful for use in the wild by archaeologists and collectors [16].

On the other hand, the study of ZiHe Qiu et al, developed coin detection using radius ratio, feature constraint, and relative position constraint to obtain the region of the coins in the image [17]. They also design a CNN for multi-classification that uses the network to generate recognition results and they achiever 87.15% experimental results for natural images. While Modi and Bawa developed a coin recognition system based on ANN and by using MATLAB with a testing result of 97.74% recognition rate [18].

This study also aims to develop a coin detection system using a pretrained CNN. Further discussion of this paper is discussed in the next section.

METHODOLOGY

Figure-1 shows the block diagram of the study. These are the steps or procedures used in developing the system.

In preparation for the dataset to be used in this study, a total of 324 raw images are used that is composed of the front and back image samples of the one, five, ten, and twenty peso coins of the Philippine New Generation Currency coin series as shown in Figure-2. These images are then annotated or labeled using the software LabelImg, this is done by creating bounding boxes to the object in the image to make its shape recognizable, and then these images will be uploaded to a free online computer vision dataset manager called Roboflow. Three types of image augmentations are then used in the individual images, resulting in a total of 796 images in the dataset from the 324 raw images. It is then randomly split into 70-20-10 percent parts for training, validation, and testing respectively.

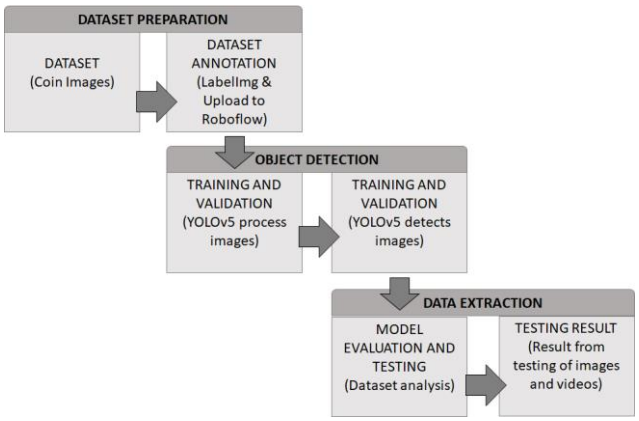

Figure-1. Block diagram of the system.

Once the dataset is ready, this will be trained using Google Colab, an impressive platform for deep learning processes, and YOLOv5, a pretrained algorithm. Released in June 2020, YoloV5 offered faster inference times and training iterations compared to its previous version. To start the process, Roboflow will be linked to Google Colab for the retrieval of the dataset. Dependencies and libraries will be installed and after that, the dataset will be trained. The dataset is trained 500 times (500 epochs) that took 6 to 8 seconds per epoch which resulted in a total training time of only 51 minutes. Train-loss and validation loss are generated for each epoch in every detected object and keep its predicted weight. Datasets are trained multiple times to improve the detection.

Figure-2. Sample of Philippine New Generation Currency (NGC) coin series datasets.

A model will be generated in each epoch and this will be evaluated. The performance of the model will be based on its generated mean average precision (mAP). The model with the highest mAP indicates that the model has high detection accuracy and this will be used in the system. For the last step, the model is tested using the images and video samples. The model is tested first by using an image of the coins. The output of the testing must be an image with a bounding box and detection accuracy as shown in Figure-3, then this will be tested on sample video.

Figure-3. Sample image testing result.

RESULTS AND ANALYSIS

The study used 324 raw images of coins and generated 796 images after using three types of augmentation. For the training, the study conducted 500 experiments (epoch). As shown in Figure-4, the graph describes the val loss of the model. The X-axis defines the number of an epoch, while the Y-axis defines the loss value. From the first to the 50th epoch, the value of Val loss dropped drastically while it continued to remain low for the remainder of the training. On the other hand, Figure-5 shows the mean average precision of the model generated on each epoch. The mean average precision is the most descriptive in assessing the performance of the model. At around 300 epochs, the model has consistently reached the value of 0.9 in the mAP, which means the extra 200 epochs in the training only served miniscule improvements. Nevertheless, even with the small dataset and above-average number of training epochs, the model did not exhibit overfitting indications.

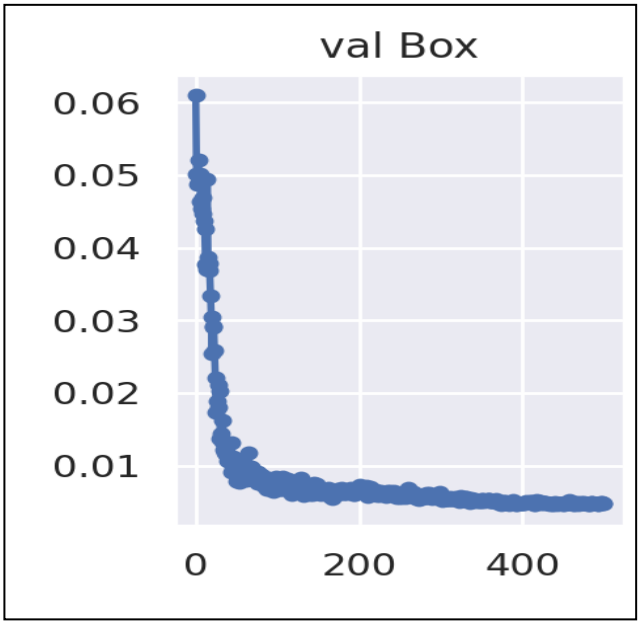

Figure-4. Training and validation (X = Epoch; Y Axis = Val_Loss).

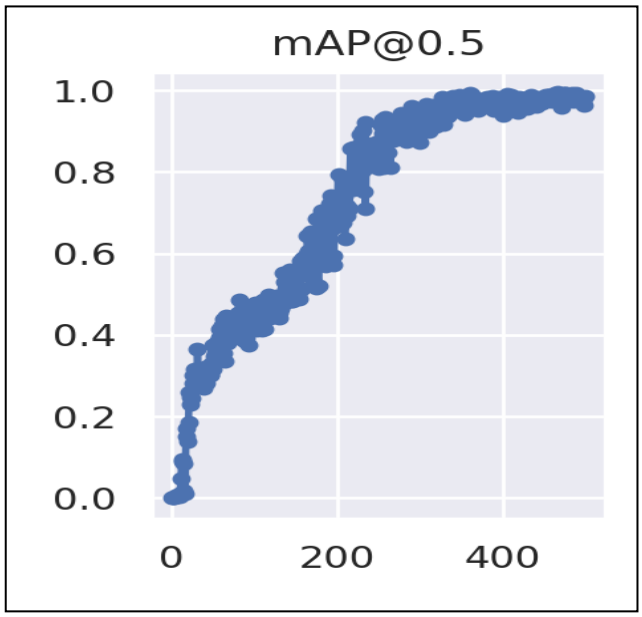

Figure-5. Model evaluation (X = Epoch; Y Axis = mAP Value).

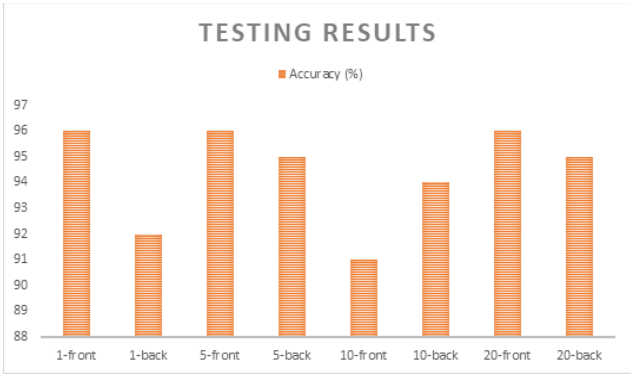

Figure-6. Testing results.

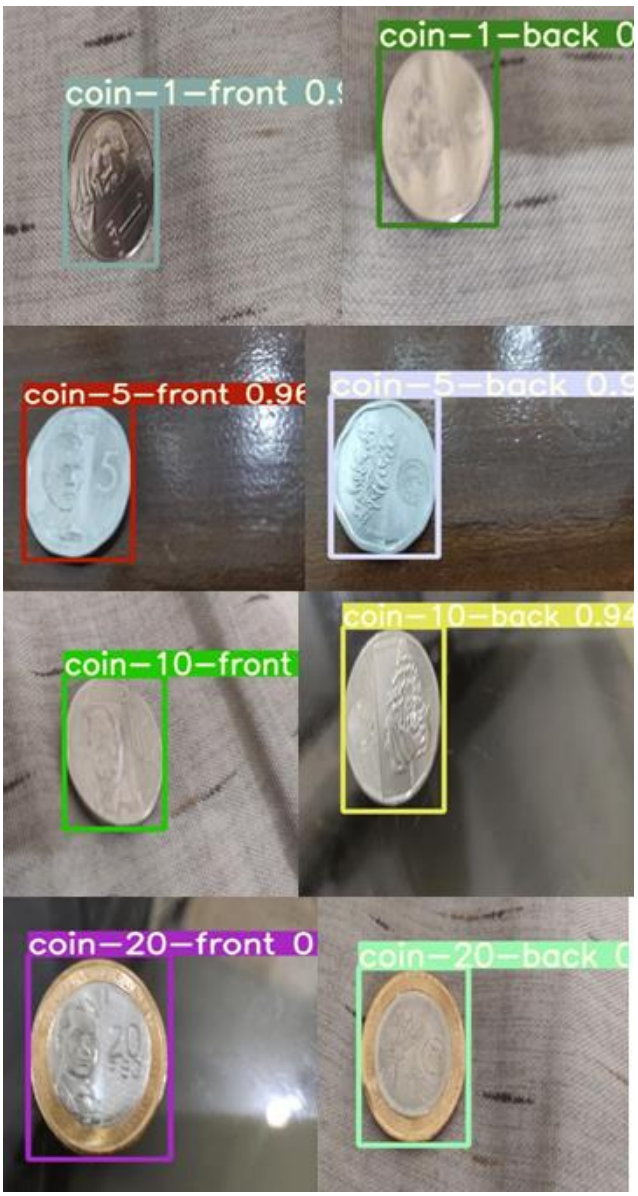

Figure-7. Testing results (accuracy percentage).

CONCLUSION AND FUTURE WORKS

Being a technology with countless possible applications, computer vision successfully enables the detection of objects through image or video samples. In this research, the detection and classification of the presence of coins in a given sample of an image or a video are studied. Through Roboflow, the YoloV5 model, and the Google Colab technology, these tools have worked together to successfully output wanted results.

The effective inference of the model allows for many possibilities in terms of technological advancements. While the accuracy of the model slightly suffers when using video inference as compared to image inference, the system is still perfectly usable and would continue to improve as the size of the dataset and the power of the training model improves. While this paper only served to test the model in a cloud system, its effectiveness would not diminish when importing it as a part of other technologies and systems.

With the number of possibilities that coin detection can be applied or integrated into other technologies, at the same time, there would be further improvements that can be made basing on this research. For instance, this research only used the model YoloV5, particularly the version YoloV5s-YoloV5's smallest and base model. Using other Yolo versions or even other models entirely could potentially give a different result, which would provide information on what model is the best for this particular dataset.

Future researchers that would eventually base on this paper should also consider expanding the content of the dataset, adding more sample images and even classes. This paves the way to more potentially useful innovations that involve coins. For instance, integrating coin detection into bill detection systems would help build a system related to the cash handling of one particular currency. This allows for automated and embedded systems that can handle cash without the need for manual human observation.

In conclusion, improving the scale of the system's capabilities in both quantity and quality would make the model usable from experimental environments to actual, real-world system applications. Not only the software used of course, but by also improving the hardware, researchers should see an obvious increase in performance when using this particular object detection model.

ACKNOWLEDGMENTS

The author would like to express deep and sincere gratitude to the computing resources and the support of the Digital Transformation Center of STEER Hub at Batangas State University.

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