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Research Article

Artificial intelligence (AI) application on plastic bottle monitoring in coastal zone

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Abstract: Plastic bottle is using everyday causing critical problems to environment, especially sea environment. A large number of plastic bottles come back to continent from sea by wave and stuck at coastal zone. Plastic waste in general or plastic bottle in particular has bad effects on coastal ecology. Artificial intelligence (AI) is widely applied in many fields, including environment. In this research, we developed a plastic bottle waste detection AI model by using Python, Yolo3, TensorFlow, ImageAI to detect and monitor plastic bottles in a coastal zone. Thousands of photos have been used to train the AI model for increasing detection accuracy. An AI model for plastic bottle detection has been built. The AI model then was applied to monitor plastic bottle waste in a coastal zone. The results showed that AI could detect plastic bottles from video sources better than from photo sources. The AI detected 68.52% sample bottles from photo sources while it could detect 100% a single bottle and 96.05% multiple bottles from video sources. Color bottles were detected better than transparent bottles. The research found that AI is an efficient tool to monitor plastic bottle in a coastal zone. It can automatically monitor and detect plastic bottles at a beach or floating bottles on sea surface.

Keywords: plastic bottle, AI, artificial intelligence, plastic monitoring

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1. Introduction

Plastic waste is now one of critical environmental problem in the world. It threatens to both environment and habitat. Marine environment is a major victim of this menace [1]. When plastic debris enters into oceans, it causes damages to ecology, aesthetics, and economy [2]. Recent study reported that, more than 300 million metric tons of plastics are generated every year [3], in which 8 million metric tons of plastic waste have been released into the ocean [4]. Plastic bottle is widely used in households. Almost all bottled–water are used plastic bottles [5]. Used plastic bottles are generated everyday. About 600 billion plastic bottles are released every year in the world, and only about 47% is collected [6]. Uncollected plastic bottles go into water, soil, and sediment environment. Used plastic bottles also move to river and oceans. Uncollected plastic bottle waste moves from ocean back to continent by waves causing environmental problems to coastal zone. Therefore, monitoring plastic bottle waste in the environment is an important work of environmental management.

Artificial Intelligence (AI) application is growing rapidly recently. AI has been applied widely in medical [7], production [8], security [9], transportation [10], telecommunication [11]. In the environmental research, AI has been applied to model the formation of methane gas hydrate [12], to monitor soil water content [13], to estimate gas production rate in reservoirs [14]. It is lack of knowledge in applying AI to monitor environment, especially in monitoring plastic bottle waste in coastal zone.

TensorFlow is the most popular deep learning math libraries created by researchers at Google [15]. Tensorflow has been applied in machine learning [16–18], object detection [19–21]. Tensorflow works well with Python, a high level programing language, to build AI application [22]. You Only Look Once (YOLO) is a deep learning model, real time object detection system [23–24]. YOLO was used to localize and recognize license plate [25–26] or human action [27], to detect surface defects of steel strip [28]. The combination of Python, TensorFlow and Yolo3 help to build an AI for object detection application more accurately.

Analytic hierarchy process (AHP) was developed by Saaty [29]. It is a good tool to perform multi–criteria analysis. AHP has been widely applied in choosing groundwater potential zones [30], selecting mobile health [31], and analyzing oversize cargo transportation [32]. AHP also was used in machine learning to perform decision making [33]. Therefore, AHP is a good method to analyze multi–criteria.

With the lack of knowledge about applying AI to monitor plastic bottle waste, this research has 3 objectives that include: (1) to build an AI model to detect plastic bottle waste; (2) to apply developed AI to monitor plastic bottle waste in a coastal zone; (3) to compare between the AI application and human ability in monitoring plastic bottle waste.

2. Materials and methods

2.1. YOLO algorithm

The YOLO divides input image into GxG grids. If the center of a detecting object falls into a grid cell, the object is detected by that grid cell. Each grid cell predicts N bounding boxes and confidence scores for those boxes. Each bounding box has 5 predictions: x, y, w, h, and confidence. The x, y coordinates represent the center of the box relative to the bounds of the grid cell. The w and h are predicted relative to the whole image width and height. The confidence prediction represents the Intersection over Union (IOU) between the predicted box and any ground truth box. Each grid cell also predicts C conditional class probabilities. Finally, the predictions are encoded as an $G \times G \times (N*5+C)$ tensor. The best results for YOLO V.1 on Pascal Visual Object Classes is 7x7 grid cells predicts 2 bounding boxes, PASCAL VOC has 20 labelled classes so C = 20. Therefore, YOLO prediction is a $7 \times 7 \times 30$ tensor (Figure 1) [34].

YOLO V3 is much deeper and more accurate than the other two versions. YOLO V3 is able to get more meaningful semantic information during the training process. However, YOLO V3 takes more time to train and detection of very close objects still has some limitations [35].

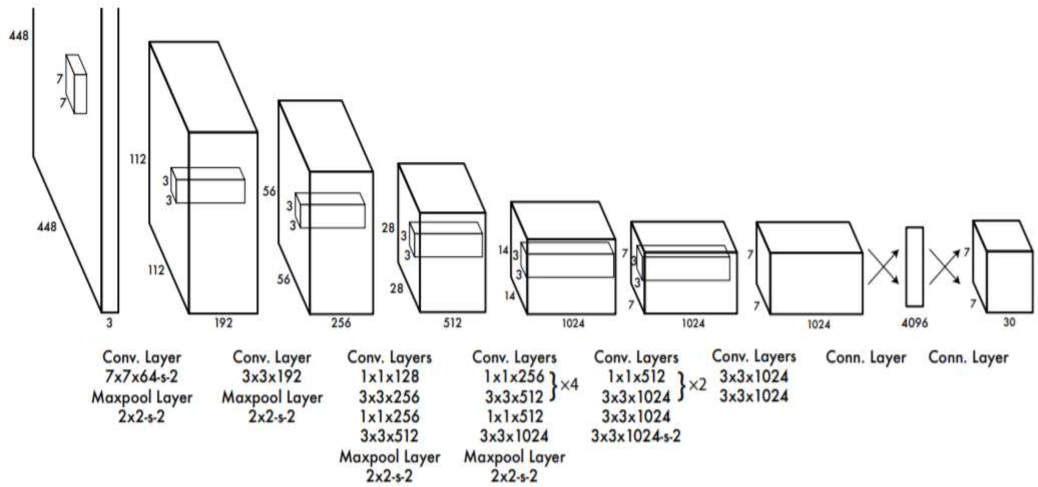


Figure 1. Structure of YOLO V1 [34].

2.2. Programing language

In this research, we used Python programing language (version 3.6), TensorFlow math libraries (version 1.15), YOLO real time object detection model (version 3) to build an AI for plastic bottle waste detection. For faster Python coding, we used ImageAI (version 2.1.5), an open–source python library developed by Moses Olafenwa and John Olafenwa. It helps to build systems and applications with self–contained computer vision and deep learning capabilities [36]. ImageAI requires dependencies: TensorFlow, OpenCV, Keras installed via pip under Python 3.6 environment.

2.3. Dataset preparation

To prepare a dataset for training the AI model, we used the Pascal Visual Object Classes (VOC) to label 1125 images. The dataset contains a list of each individual plastic bottle annotated from every single image in the plastic bottle dataset. Two labels set in the dataset were bottle and plastic. These labels helped machine learning objects and remember in its database. Then we created a folder for our dataset. In this parent folder, we created two child folders: train and validation folder. In the train folder, create images and annotations sub–folders. We put about 80% of our dataset images in the images folder and put the corresponding annotations for these images in the annotations folder. In the validation folder, we put the rest of your dataset images in the images folder and put the corresponding annotations for these images in the annotations folder.

We used LabelImg software to annotate the dataset with the Pascal VOC format. The Pascal VOC format uses XML files to store details of the objects in individual images (Figure 2).

Figure 2. Labeled images followed the Pascal VOC format.

2.4. Initiate the detection model training

To ensure that our trained model have better detection accuracy, we used transfer learning from a pre–trained YOLOv3 model in the training and the ImageAI. A personal computer (PC) was used for training with the GPU NVIDIA GeForce GTX 1060 6GB and use 2 Ram 16Gb DDR4 3000Mhz to ensure the training speed with large epoches. The processor was AMD Ryzen 5 2600X Six–Core Processor, 3800 MHz, 6 cores, 12 logical processors. The model trainer will run in CUDA developed by NVIDIA. The trained model was run under 100 epoches, batch size equal to 2 due to the maximum capacity of the GPU.

2.5. Evaluate the model

During the running process, new models were saved based on the decreasing in the validation loss. In most cases, the lower the loss, the more accurate the model will be detecting objects in images and videos. However, some models may experience over–fitting and still have lower losses. To ensure we picked the right model for highest accuracy, we used ImageAI to evaluate and calculate the mAP of all the trained models saved in the dataset/models folder. The higher the mAP, the better the detection accuracy of the model.

2.6. Samples

To evaluate the developed AI model as well as its ability in monitoring plastic bottle waste in coastal zone. We took 70 sample photos (dimensions 1276 x 956) and recorded 20 videos (frame width 1920, frame height 1080, frame rate 30.01 frames/second) at different places of coastal zone in Halong City, Quang Ninh, Vietnam. Photos and videos were divided into different background environmental categories: uniform environment and noise environment; single bottle and multiple bottles in a photo or video. The research flowchart is showed in the Figure 3.

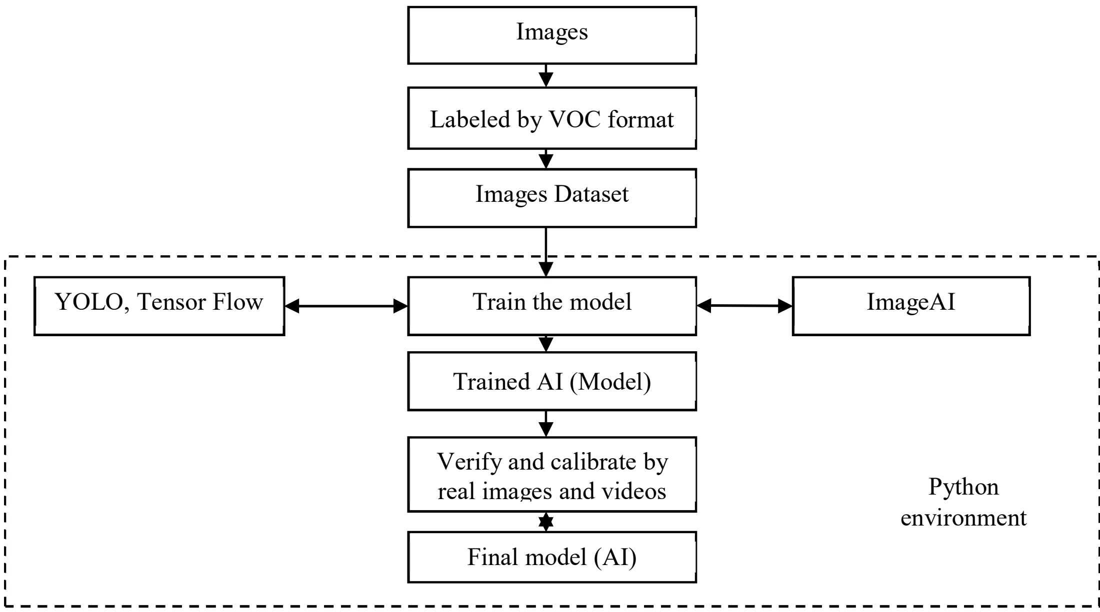


Figure 3. Research flowchart.

2.7. Multi–criteria analysis

To compare between human and AI in detecting plastic bottle waste, we selected 7 criteria to compare under the condition of industrial revolution 4.0 that include: automation, low initial cost, low operation cost, connecting ability, accuracy, 4.0 compatibility, large scale application. The pair comparison of these criteria was performed by the AHP to determine the weighting values of each criteria and between human and AI.

3. Results and discussion

3.1. Plastic bottle waste detection model

After training the AI plastic bottle detection model, we selected the most appropriate model with highest mAP equal to 0.1916, the lowest loss 3.015. The selected model was used to detect real images and videos to evaluate the detection accuracy.

3.2. Plastic bottle waste monitoring from photos

3.2.1. One plastic bottle in a photo

When a bottle appeared clearly in the photos, it could be easily detected in both uniform background (Figures 4a, 4c, 4d, 4k), and noise background (Figures 5a, 5b, 5d, 5f). These photos had high contrast between environmental backgrounds and bottles. When the contrast was low, the bottles were not well detected (Figures 4i, 5c, 5h). Color of background environment also affected to the detection. If the color of bottles are similar to background color, it is not only hard to detect by human but also by the AI model (Figures 4i, 4h). In average, the developed AI model could detect 68.52% of plastic bottles in the photo samples. The AI model could detect bottles even the original shape of bottles changed (Figures 4b, 4f) or submerged in sand and water (Figures 4g, 4h, 4j, 4l). In very noise environment, the bottles were well detected when the color of background environment differ from color of bottles (Figures 5a, 5b, 5g, 5i).

3.2.2. Two or more plastic bottles in a photo

In the case of two or more plastic bottles appeared in the photos, the detection ability of the AI is 63.33%. The results showed the significant decrease in detection percentage in noise environment dropped to 50%. Bottles located at the corner of the photos, the AI model could not well detect (Figure 6i). Opposed to bottles located at the center or near center of the photos, the AI model could well detect (Figures 6b, 6f).

Figure 4. Detection in different kind of plastic bottles in uniform environment.

Figure 5. Detection in different kind of plastic bottles in noise environment.

Figure 6. Detection of multiple plastic bottles in a photo.

3.3. Monitor plastic bottle waste from videos

When a single bottle appeared in a video frame, the AI could recognize 100% samples of both uniform and noise background (Table 1). Comparing with single bottle in photo sources (68.52%), bottles in video sources could be detected better. In the case of the color of bottles are similar to background color, AI could detect them from video sources (Figures 7i, 7j), while the AI could not detect them from photo sources (Figure 5h). When the data sources are images, the frames of the images are static. If the AI can not detect the bottles at the first time, it is finitely can not detect them. However, when the data sources are videos, the frames of images are dynamic. If the bottles can not be detected at the first time, they can be recognized when the image frame changed.

In the case of multiple bottles in a video frame, the AI could recognize 96.05% bottles in the video samples. In which the AI could recognize 95.65% bottles in the uniform background environment. In the noise background environment 94.44% bottles could be detected. Bottles in the video sources appeared in the different positions (close, far, corner, center of the videos), and shapes.

Table 1. Plastic bottles detected from videos sources by the AI.

Background	Detected	Not detected	% detected
Single bottle in a video frame			
Uniform	6	0	100%
Noise	6	0	100%
Multiple bottles in a video frame			
Uniform	44	2	95.65%
Noise	17	1	94.44%
Total	73	3	96.05%

Figure 7. Detection of plastic bottles in videos (screenshot from videos).

3.4. Comparison between statuses of plastic bottles

The appearance of bottles at different status, different location affects the detection ability of the model. The model can detect clear bottles easily than a part of bottles being covered, sunk or shape changed. 72.29% of clear plastic bottles in the photos could be detected (Figure 8), however the model could only detect 50% unclear plastic bottles in photos (Figures 4e, 4g, 4h, 4i, 4j, 4l, 5d, 5e). While 98% of clear plastic bottles and 78.56% of unclear plastic bottles could be detected from video sources. The detected results showed that colored bottles could be detected better than transparent color bottles. This could be explained by the color bottles could be easily distinguished with background environment than transparent color bottles.

3.5. Comparison between human and AI in monitoring plastic bottle waste.

The weighting values of compared criteria is shown in the Figure 9. In the 7 criteria, accuracy is the most important (0.345) one for both human and AI. Combining 7 criteria in the calculation to compare between human and AI in monitoring plastic bottle waste, weighting values of AI and human are 0.625 and 0.375. Therefore, in the trend of industrial revolution 4.0, the application AI in monitoring plastic bottle waste is better than human. Paired comparison among criteria showed that the criteria: large scale, 4.0 compatibility, connecting ability, automation, and low operation cost, the AI application performs better than human. While accuracy, and low initial cost human performs better than the AI.

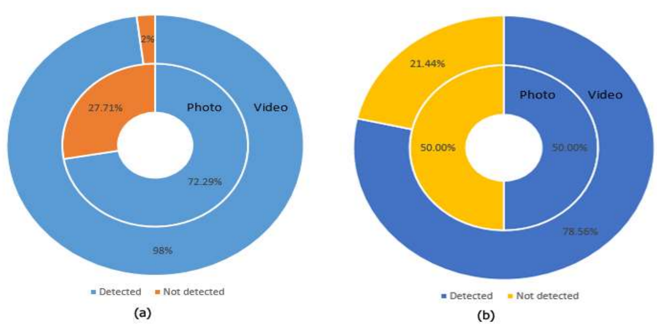
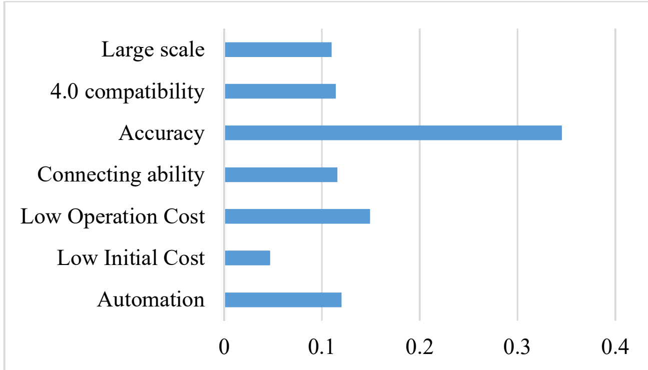
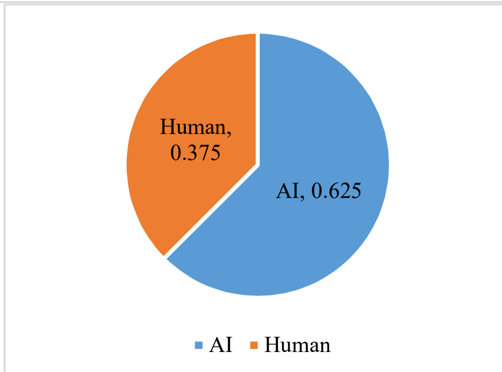


Figure 8. Comparisons between statuses of plastic bottles–clear (a) and unclear (b) in photos and videos.





(a) (b)

Figure 9. Weighting values of compared criteria (a) and human and AI (b).

4. Conclusion

In this research, an AI for detecting plastic bottle waste has been successfully developed. The AI model has been tested and verified the accuracy with real practice samples. The detection results showed that the AI could detect 100% of single plastic bottle and 96.05% multiple bottles in a video in both uniform and noise background environment. The detection accuracy of the AI with photo source was 68.52%. The percentage of detection for clear and unclear plastic bottles in videos were 98% and 78.56% respectively. While clear bottles from photos accounted for 72.29% and unclear bottle is 50%. Color bottles were detected by the AI better than transparent bottles. Under industry revolution 4.0, the application of AI in monitoring plastic bottle waste at coastal zone was determined more efficient than human force. In the further research, the AI model can be applied to detect plastic bottles from satellite data.

Author Contributions: The AI model was built and trained by H.T.D., A.D.T. The real plastic bottle images and videos were taken and recorded by H.T.D., L.A.P.T., T.H.P. The video and image samples were analyzed by H.T.D., A.D.T. Finally, the paper was written by H.T.D., A.D.T.; commented by L.A.P.T., T.H.P.

Conflicts of Interest: The authors declare no conflict of interest.

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