A Vision Based System Design for Over-Sized Vessel Detecting and Warning Using Convolutional Neural Network

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Abstract. In this work, we aim to investigate the problem of automatically detecting, and warning of an oversize vessel traveling through the Water lock of the flood-holding system. First, the image processing technique based on camera vision using Convolutional Neural Network (CNN), which has the potential to detect the oversize included the length and width of the vessel, is used to help the sailors to prevent this vessel crashed into the Water lock. Second, a model named Oversized Vessel Detector (OVD) was built to detect the vessel in the streaming video and to calculate the size relatively accurately of the vessels based on the proposed math function. Then, the system automatically compares the estimated sizes of the detected vessel and allowable sizes of the flood-protecting system (FPs) to determine the oversize condition, and the result will be displayed on the monitor and warning with alarm devices when decided that the vessel is oversized. Finally, to show the effectiveness and implementation performance of the proposed approach, an experiment is carried out based on Raspberry Pi 4 hardware for coding all the mentioned algorithms.

Keywords: Water lock · Flood-protecting system · Oversized vessel detection · Convolutional neural network

1 Introduction

Climate change is a serious challenge to humanity, profoundly affects, and altogether changes the global social life, especially in marine countries including Viet Nam. Therefore, each country demands implementation climate to proposed change adaptation solutions. Ho Chi Minh City is at risk of flooding, even under normal climatic conditions. Related to responding to climate change, the proposed plan is to deploy a dikes system around the city and tidal sluices while ensuring water traffic. This system, named the flood-protection, used modern technologies [1–5] that involve two possible approaches: to ensure safety for nation waterway traffic system (including vessels and construction) and to adapt to climate change already.

Artificial Intelligence (AI) alongside the Internet of Things (IoT) and Big Data are the core elements of digital technology in the Industrial Revolution 4.0. in the world.

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Focus on the maritime industry, AI is studied and applied in many fields, most of which are automatic control [6, 7], transportation and Maritime safety assurance [8], video streaming [9, 10], and camera vision-based neural network [11, 12]. In general, AI has many positive and effective points, especially increasing safety in operating and managing marine transportation systems.

In this paper, we focus on the given possible approach, some studies [3–5] provided evidence of damages that happened when the monitoring systems are installed without insufficient alarm functions. The over-height vehicles (OHVs), usually a truck, crane, a double-decker bus, or boats try to travel through bridges or tunnels which have a height lower than the size of OHVs caused collisions for the general transport system, as same as the national water system. These collisions lead to traffic delays, damage to bridge structures, bridge foundations, and fatal harm to drivers. In the worst case, derailment, the immediate collapse of the bridge structures, and fatalities of road users can occur [5, 13]. Moreover, Shanafelt & Horn showed that OHVs were the leading cause of the damage (81%) for the prestressed concrete bridge over 5 years, and about 95% of the damage to the steel bridge in America is due to OHVs [9]. Therefore, the development of new technologies in traffic monitoring and warning systems is necessary at the moment.

Considering the designed models on the traffic monitoring, detecting, and warning system, many authors have studied and applied image processing algorithms to observe and coordinate traffic [1–4]. The authors presented a new method for preventing oversize vehicle collisions by using a camera, and the idea is an improvement to the existing laser projection method [1]. The camera mounted on the side of the road or bridge is used to replace the transmitter, receiver, and distance sensor. The camera is installed at the maximum allowable height of the bridge on all lanes in each traffic direction.

Related to the methods and technologies, the advent of modern improvements in AI and deep learning [1–3] has a significant in camera vision based on computer technology in recent years. Object detection is a computer technology linked to computer vision and image processing that deals with combination object classification and object positioning. Most recent research concentrated on designing the complicated network for object detection based on a neural network to intensify accuracies, such as single-shot detector (SSD) [4] and faster R-CNN [5]. Therefore, the performance of object detection models using deep learning methods has been improved a lot. However, limited by the amount of training data and high computational costs, these frameworks are difficult to be implemented practically.

Related to the hardware of the traffic monitoring system, the authors [14] used some instruments, a laser range sensor, a radar speedometer, and a digital camera, to build a vehicle's exterior contour identification and detection system. According to measured data from the vehicles on the highway, six characteristics, such as vehicle length, height, width, height variance, the ratio of peak length, and body length, are extracted [15]. Then, vehicles are classified into sub cars, mini-buses, trucks, buses, large rails, and large buses automatically using the BP neural network. Test results showed that the system is more effective at classifying existing outcomes, especially being able to differentiate between trucks and buses of similar shape more effectively. Deal with design a height limit warning system based on the road coordination of the vehicle, the proposed method in [16] applied directional coordination in the direction using the SSD algorithm mounted on the camera, vehicle network, GPS, and altimeter algorithm to assist the driver in assessing the height limit and informing the driver in advance. Therefore, a safe way to safely pass the high limit section for vehicles that ignore warnings and do not slow down or change lanes within a safe distance.

Based on the discussion aforementioned, the motivation of this paper is to design the automatic detection and warning of an oversize vessel traveling through the flood-protecting system, for the reasons as follows: 1) Due to climate change, the rising water level seriously affects people's life in Ho Chi Minh City. A new flood protection system is currently in the improvement, the development of the detecting and warning an oversize vessel system is necessary, 2) Selected the image processing technique based on camera vision using Convolutional Neural Network (CNN) has the potential to detect the oversize included the length and width of the vessel, 3) The experiment is carried out based on Raspberry Pi 4 hardware for coding all the mentioned CNN algorithms. The experiment results not only perform the effectiveness but also implement the performance of the proposed approach.

The rest of this paper is organized as follows. In Sect. 2, we introduce the motivation of the paper with the overview of current situation of flood-protection system of Ho Chi Minh City and some remarks. To design the OVD model based on camera vision using Convolutional Neural Network is presented in Sect. 3. Section 4 is dedicated to showing the experiment results, analysis, and evaluation of the proposed model. Finally, we conclude the paper in Sect. 5.

2 Motivation

2.1 Overview of Current Situation of Flood-Protection System of Ho Chi Minh City

Ho Chi Minh City has a dense river system, a system of rivers connecting and circulating to the East Sea of Vietnam. Moreover, the Saigon River water level is highly dependent on two factors: the seasonal rain discharge and the tidal influence. Then, the rivers discharge into the East Sea of Viet Nam, and the lower river limits are subject to tidal influence. Due to climate change, the rising water level seriously affects people's life in Ho Chi Minh City. A new flood protection system is currently in development and under construction, the actual pictures of the flood protection system under construction in HCMC are shown in Fig. 1. The flood-protection system is shown in Fig. 2 comprised six major floodgates including Ben Nghe, Tan Thuan, Phu Xuan, Muong Chuoi, Cay Kho, and Phu Dinh. The barrier widths of floodgates are in the range of 40 m to 160 m. The pumping stations were installed at Ben Nghe, Tan Thuan, and Phu Dinh floodgates, the respective capacities of 12 m^3/s, 24 m^3/s, and 18 m^3/s.

In the context of the gradual completion of the flood protection system, there will be a lot of ships and boats passing through the water locks of these structures caused collision. Therefore, the development of the detecting and warning an oversize vessel system not only assists to protect the system's structure but also helps vessels pass through safely.

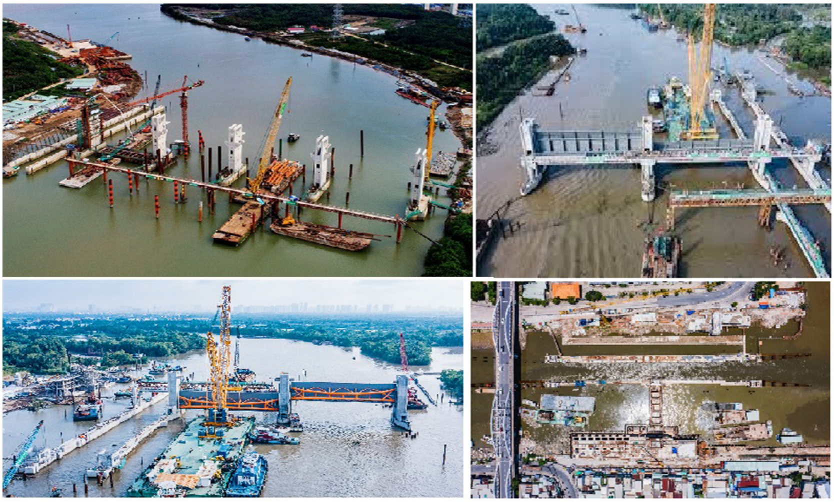


Fig. 1. The actual pictures of the flood protection system under construction in HCMC

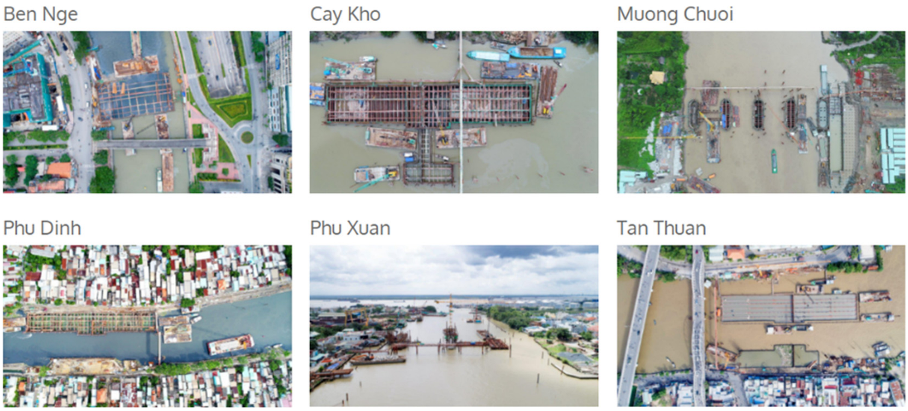


Fig. 2. The flood-protection system comprises six major floodgates in Ho Chi Minh City

2.2 Some Statistics Related to Bridges and Marine Construction Collisions Caused by Vehicles

In general, Network Rail reported 12,829 incidents in the transport system between 1995 and 2003 in the UK [17]. In their most recent statistics, Network Rail summarized approximately 1,708 bridge collisions in 2014, an increase of 9.9% over the previous year. Especially, bridges and marine construction collisions pose significant risks to the safety and operation of the transport infrastructure. In the United States, it is estimated that more than 7,000 bridges suffer a total of more than 5,000 collisions per year, resulting in more than $ 100 million in damage to public and private property [18]. According to the Federal Highway Administration (FHWA), collisions by vehicles or boats were the third cause of marine construction and bridges failures [19]. The marine construction structure crash issue is widespread globally with OH bridge collisions reported in Canada, Ireland, UK, Western Australia, Japan and 14 European Union Member States, all of which consider the collisions are a significant safety risk [20].

First of all, marine construction collapse is regularly a complex process that results from a combined effect of many different factors. Therefore, it is hard to identify the leading factor that has directly resulted in the destruction. Furthermore, to perform the field tests to study the collision of the vehicle to the marine construction is difficult due to safety concerns and cost issues (Zhang et al. 2013 [21]; Piran Aghl et al. 2014 [22]). In recent years, the progress of finite-element methods and computer technologies have provided useful devices for researchers to study marine construction collapse on a numerical basis. While experimental studies were conducted to understand the collapse status of structures of marine construction included bridges. Although much improvement is used for understanding the action and breakdown of marine construction, many challenging issues remain.

3 Oversized Vessels Detector Model Based on Camera Vision Using Convolutional Neural Network

In recent years, the Convolutional Neural Network (CNN) based methods have been used for ship detection [23], and land target detection [24], and CNN displayed a better achievement than the traditional methods. In [25], the authors divided the images into tiny patches, and then they used a pre-trained CNN model to classify those patches, after which the distribution patches are mapped again onto the original images. However, this method does not take the edges of targets into account to get a low target location precision. Moreover, the structure of Faster-RCNN improved the detection performance for small boats [26, 27].

In this paper, we aim to detect and analyze over-sized vessels automatically from the streaming videos. A comprehensive system is needed to identify the over-sized vessels, estimate the dimensions. The result is displayed and warned on the monitor and alarm devices. Therefore, we deal with using a CNN for detecting and analyzing over-sized vessels, and the overall framework of the proposed model shows in Fig. 3.

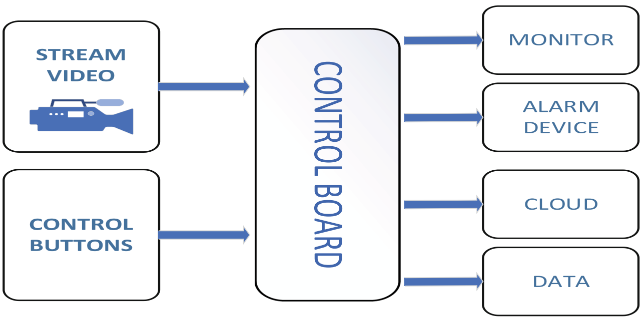


Fig. 3. The overall framework of the proposed model

To detect and estimate the size of a moving object. We selected SSD_Mobilenet_V2 to detect the vessels, and a motion interactive field method used to estimate the vessels' sizes. A framework for Oversized Vessel Detector (OVD) was created and showed in Fig. 4. The control board, selecting the Raspberry Pi 4, is the main computer used to code all algorithms, and the camera is directly connected to the control board and takes image data in the water lock. The signals are processed by using the improved convolutional neural network [4] for the vessel's image processing and detection. The OVD is designed based on the following sequence of steps:

Step 1: To detect the vessels from the streaming video using the improved cnn algorithm.
Step 2: To estimate the sizes of the detected vessel.
Step 3: To display an alert with alarm devices or monitor when the system decided that the vessel is oversized.
Step 4: To process and save the data to the local storages (SD card) and cloud storage.

3.1 Detecting the Vessels from the Streaming Video Using the Improved CNN Algorithm

We aim to develop the OVD model for real-time applications with extremely effectual configuration (GPU/CPU) for embedded systems (Raspberry Pi, Nano PC). Therefore, we select to build a model like SSDLite-MobileNet hybrid helped to achieve high accuracy while low computation time lies in the hybrid structure from SSD and MobileNet structure. Moreover, SSD (Structure of Single Shot Multi-Box Detector showed in Fig. 4) is an object detector that performs two main actions: Extract feature maps of features (from the video streaming) and apply convolution filters to detect vessels.

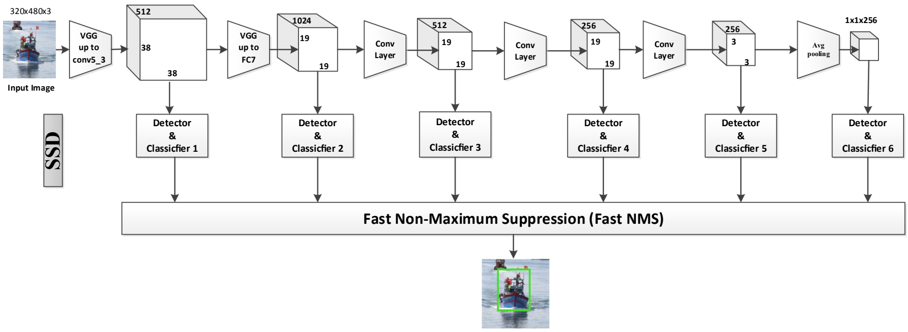


Fig. 4. Structure of single shot multi box detector used to detect the vessels

In this work, we use the loss function presented by Dang et al. [11]:

$$L(x,c,l,g) = \frac{1}{N}\left(L_{conf}(x,c) + \alpha L_{loc}(x,l,g)\right) \tag{1}$$

$$L_{loc}(x,l,g) = \sum\nolimits_{i\in Pos}^{N}\sum\nolimits_{m\in\{cx,cy,w,h\}} x_{ij}^{k}\, smooth_{L1}\left(l_i^m - \hat{g}_j^m\right) \tag{2}$$

where $\hat{g}_j^{cx} = (g_j^{cx} - d_i^{cx})/d_i^w$, $\hat{g}_j^{cy} = (g_j^{cy} - d_i^{cy})/d_i^h$, $\hat{g}_j^w = log(\frac{g_j^w}{d_i^w})$ and $\hat{g}_j^h = log(\frac{g_j^w}{d_i^w})$; L_{loc} is the localization loss caused by the parameter error between the predicted box and the ground-truth box.

$$L_{conf}(x, c) = -\sum\nolimits_{i\in Pos}^{N} x_{ij}^p log(\hat{c}_i^p) - \sum\nolimits_{i\in Neg} log(\hat{c}_i^0) \tag{3}$$

where: L_{conf} is the confidence loss, and α is set to 1 by cross validation. $\hat{c}_i^p = \frac{exp(c_i^p)}{\sum_p exp(c_i^p)}$; $x_{ij}^p = \{1, 0\}$ is an indicator for matching *i-th* default box to the j-th ground truth box of category *P*. The default boxes of each feature map computed as Eq. (4) [11]:

$$s_k = s_{min} + \frac{s_{max} - s_{min}}{m - 1}(k - 1), \mathrm{k} \in [1, \mathrm{m}] \tag{4}$$

The parameters are configured in detail: s_{min} is 0.2; s_{max} is 0.9; s_k is *0.1, 0.2, 0.375, 0.55, 0.725. 0.9* means *32, 64, 120, 176, 232, 290* pixels and some of them have an input resolution of *320* × *480* pixels.

Process of Building the Database of Images: We have taken photos of vessel types sailing on rivers in Ho Chi Minh City in Fig. 5, and some surrounding areas. In this work, we choose small vessels that match the allowed sizes of vessels to be sailed through the flood-protection system.

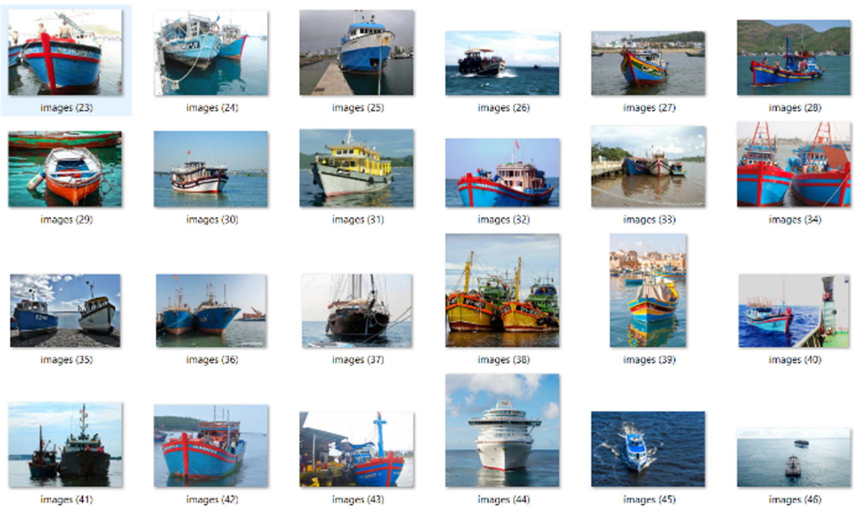
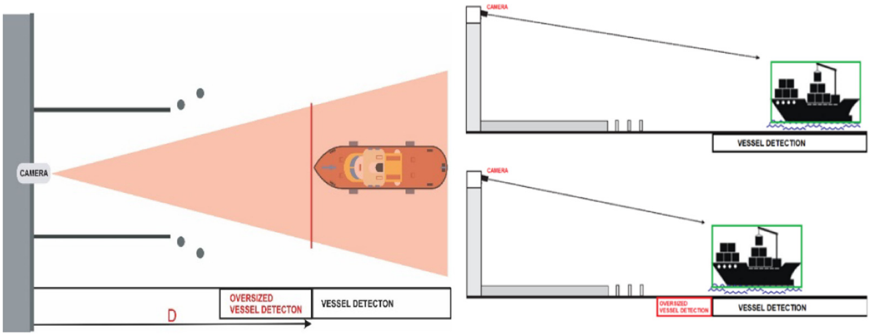


Fig. 5. Some images collected in Saigon river

We collected 450 pictures to train the recognition model, and the remaining 50 images were used to test in the designed model to hold it is within the allowed limit of memory of selected hardware. To conduct identity modeling training, the author chooses the TensorFlow framework as a template for the data. Known as a framework for building identity models, the TensorFlow APIs provides a full range of intuitive data computation, processing, and evaluation tools.



(a) (b)

Fig. 6. The camera recording area (a) and distance start to get an image (b)

Regarding the problem of the Camera recording area and starting distance to get the image from the video streaming, the camera usually mounted in the center of the water locks, as shown in Fig. 6. The distance to start working is dependent on the position and length of each flood-protecting gate. After identified the vessel, the TensorFlow APIs will intercept the images from the videos and record their locations in each frame. Finally, the identification process finished and moved on to the next step, estimating the sizes.

3.2 Estimating the Sizes of the Detected Vessel

The estimation of vessel sizes (including height and width) is used as the method of converting the object recognition frame height and actual dimensions. Suppose the camera recording area captures from video streaming an area a(m) wide and b(m) length, equivalent to an x * y (pixel) frame. The description of the camera's image frame at the gate of the water lock present in Fig. 7.

The object identification frame coordinates are located at the corners shown in the figure. Hence, we have the width and height of the vessel that can be calculated as follows:

$$Width\,(m) = (X_{max} - X_{min})\frac{\mathrm{a}}{\mathrm{x}} \tag{5}$$

$$Height\,(m) = (Y_{max} - Y_{min})\frac{\mathrm{b}}{\mathrm{y}} \tag{6}$$

Where: a is recordable camera frame width (meter), b is recorded camera frame height (meter), and x is frame width and y is frame height (pixel), respectively.

Therefore, we propose the Vessel sizes estimating algorithm in Table 1 as below:

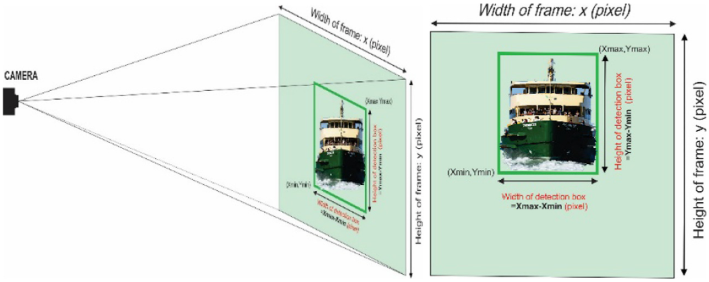


Fig. 7. Description of the camera's image frame at the gate of the water lock

Table 1. Proposed Vessel sizes estimating algorithm.

Vessel sizes estimating algorithm
Input: Bounding box (X_{max}, X_{min}, Y_{max}, Y_{min}), allowable limits of the construction (W_C;H_c)
Output: Vessel Sizes (W**idth**, H**eight**)
1. Creating computed starting position (when the vessel starts entering the virtual line area with preset position) *if (ymax in range(200, 220)[*]):* *self.**width**.setText(str(**width**) + " M")* *self.**heigh**.setText(str(**heigh**) + " M")*
2. Filtering noise detection frames if ***final_score ≥ min_score_thresh*** then proceed to measure the size.
3. Computing the sizes (pixel) of bounded box $width\_pixel = (X_{max} - X_{min})$ $heigh\_pixel = (Y_{max} - Y_{min})$
4. Creating the bounded box sizes (pixel)
5. Estimating the sizes of vessel (meter) following equations (5) and (6) ***width*** *= width_pixel *a /x* ***heigh*** *= heigh_pixel *b/y*
6. Comparing set thresholds to deliver notifications *if (**width > WC** or **heigh > HC**):* *self.Dangerous()* *else:* *if(**width** != 0 and **heigh**!= 0):* *self.Safe()*
7. Extracting parameters and writing to history file *log = 'Log.txt'* *with open(log, 'a') as logfile:* *logfile.write('Score:' + 'FPS: ' + '**width of vessel**: ' + str(width) + '; **heigh of vessel**: ' + str(heigh) + '; Stage: ' + s + '\n')*
8. End

where: WC is allowable width and HC is allowable height of the construction (meter), [*] noted for the starting position depend on each water lock designed.

4 Experimental Result and Discussion

4.1 Testing the Designed OVD in HCMC University of Transport LAB

a. The designed hardware of OVD   b. The tested model of OVD in HCMC University of Transport LAB

Fig. 8. The overall of designed hardware and tested in HCMC University of Transport LAB

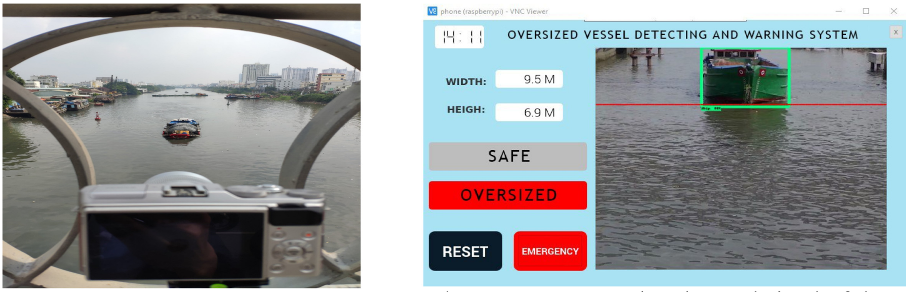
We build the embedding OVD system on the experimental model, which's structure and specification present in Fig. 8, a. This real-time system realizes the program directly into the Raspberry Pi 4 Model B. This model is the latest product in the popular Raspberry Pi range of computers. It offers ground-breaking increases in processor speed, multimedia performance, memory, and connectivity compared to the prior-generation Raspberry Pi 4 Model B+ while retaining backward compatibility and similar power consumption. For the end-user, Raspberry Pi 4 Model B provides desktop performance comparable to entry-level x86 PC systems.

- Broadcom BCM2711, Quad core Cortex-A72 (ARM v8) 64-bit SoC @ 1.5 GHz; 8GB LPDDR4-3200 SDRAM, 2.4 GHz and 5.0 GHz IEEE 802.11ac wireless, Bluetooth 5.0, BLE Gigabit Ethernet; 2 USB 3.0 ports; 2 USB 2.0 ports;
- Raspberry Pi standard 40 pin GPIO header (fully backward compatible with previous boards).

The OVD model are tested in HCMC University of Transport LAB (Fig. 8, b). Under ideal working conditions in the Lab, the OVD system showed the ability to identify the model vessel very accurately.

4.2 Testing the Designed OVD in Cay Kho Floodgates in Ho Chi Minh City

The OVD model are tested in Cay Kho floodgates in Ho Chi Minh City (Fig. 9, a), The vessel is in "oversize" condition in Fig. 9, b. Experimental results and evaluation are discussed in the next section.



a. Mounted the Camera on the designed position

b. Images captured and tested sized of the vessels

Fig. 9. Testing the designed OVD in Cay Kho floodgates in Ho Chi Minh City

4.3 Summary Experimental Results

Images captured through the Logitech C270 camera are then processed using the CNN based on object detection algorithms. The output is the processed image, extracted the frame around the detected object, and the confidence in percent. For vessels within the permissible sized limits, the system display is "Safe" (Fig. 10, (a)). On the contrary, "Oversize" is displayed (Fig. 10, (b)) in case of the system decided that the vessel height and width exceed the permissible traffic allowance of the water lock, a warning will be issued by a light and sound signal in the control room at the water lock. The monitor displayed parameters related to width and height and saved them in the history file. Hence, to confirm and turn off the alarm signals, the supervisor needs to press the "RESET" button on the monitor screen or physical button in the control room. Moreover, the warning actions will be decided by the monitoring specialist through the radio system.

a. The vessel is in "Safe" condition

b. The vessel is in "oversize" condition

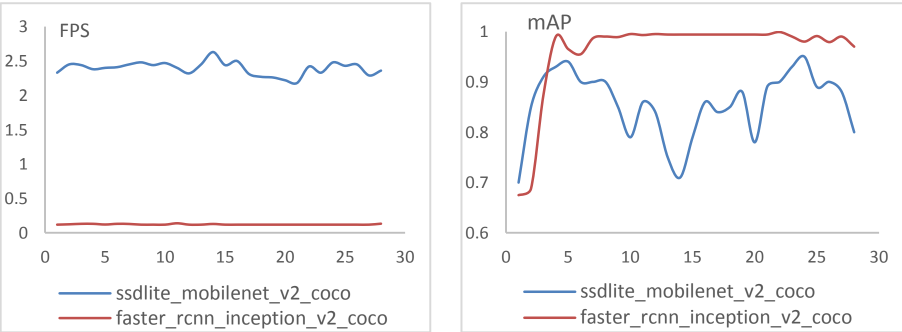
Fig. 10. Displayed the "safe" and warned "oversize" states of the vessel

Highly configurable models running on TITAN X GPUs produced processing speeds between 17 and 37 frames per second. However, when experimenting on COCO data sets and mean average precision (mAP) calculations on all object classes, the results only reached 21–28%. The experiment used the selected hybrid SSDLite-MobileNet algorithm, and the mAP of the system was firstly tested on the flood-lock model with laboratory working conditions to calibrate the vessel sizes. The high performance attained in the range of 86%–99% accuracy. Then, the experiment was directly tested in Caykho flood-lock in Ho Chi Minh City in normal working conditions, and the performance showed in Table 2, and the mAP achieved from 76% to 97% accuracy.

Table 2. Compare the testing performance of models in experimental

Model name	Test on GPU TITAN X		Real time on water lock area test on Raspberry Pi 4		Laboratory test on Raspberry Pi 4	
	Speed (ms)	COCO (mAP)	Speed (FPS)	(mAP)	Speed (FPS)	(mAP)
ssdlite_mobilenet_v2_coco	27	22	2.39	85	2.23	81
faster_rcnn_inception_v2_coco	58	28	0.12	96	0.12	90

This impressive result is achieved when installing the camera in the bridge in a convenient position while the hardware is a mobile device with only an ARM CPU and no integrated GPU. The highest processing speed is only approximately 3 FPS. The discussion of the experimental results focuses more detail in Table 1. The result showed that 2 models tested on our hardware (Raspberry Pi 4) using our method better than GPU TITAN X hardware (difference hardware) about speed (ms) and mAP. So that, the FPS speed of the test methods is indicated in Fig. 10, and mAP showed in Fig. 11. These results illustrated the good response rate for a monitoring system.



a. Compare processing speed of object detectors on system hardware

b. Compare the output reliability of object detectors on system hardware.

Fig. 11. Compared the FPS speed and mAP

4.4 Discussion

As for the detection task, the output reliability reached the highest with the Faster RCNN detector. However, it is not possible to meet on a monitoring system. Object detectors based on the hybrid SSD_MobileNet structure (in brown color) produce highly reliable results and meet processing speed requirements. Meanwhile, the results of SSD_MobileNetV1 (yellow) and SSD_MobileNetV2 (green) sets are almost equivalent, but the load time of the model is slow due to large capacity and actual output. There are still certainly deviations. Thus, the improved SSDLite_MobileNetV2 solution gave good results relating to quality, processing speed, fast model load time (stable running on Raspberry Pi 4), and has higher accuracy than the other solutions.

Regarding the FPS, the result presented in Fig. 10 is our experiment compared with the TensorFlow tool used Faster_RCNN_inception_V2_CoCo by the Google team. Extremely powerful hardware performs high FPS, but when considered on the whole COCO data set (about 40,000 images and 90 object layers), the (mAP) for a group of subjects) only attained 58%.

Related to the estimating process, the proposed OVD using a neural network with limited hardware tested in a water lock in the open space environment giving an intermediate accuracy average of about 80–90%. Moreover, the system needs more testing to evaluate the feasibility in real applications when we add extra size errors in the calculating and estimating process.

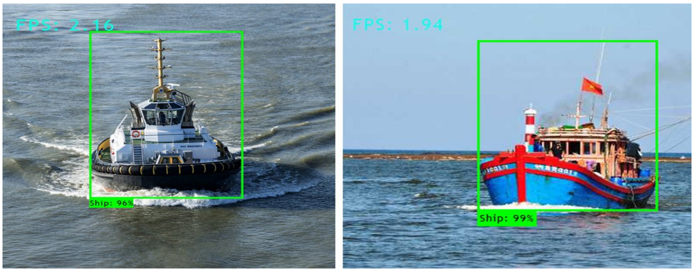


Fig. 12. Image processing and Vessels' sizes estimation

The results in Fig. 12 are shown with an identification processing level of about two frames per second while with the mobile device hardware only ARM CPU and no integrated GPU. This picture indicated an immeasurable response speed for a surveillance and vessel recognition system that does not require high speed as in the subject's goals.

5 Conclusion

In this paper, we studied and applied the CNN algorithm to design the Oversized Vessel Detector for the Flood-protecting system. The hardware used Raspberry Pi 4, an embedded single board computer with CPU smartphone level, limited RAM without CUDA GPU, for coding all the mentioned CNN algorithms. The experiment results not only perform the effectiveness but also implement the performance of the proposed approach.

The rising water level seriously affects people's life in Ho Chi Minh City due to climate change. Thus, the new Flood-protecting system is currently improving built to help the city clean, beautiful, and safer in the future.

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