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MỤC LỤC

APPLYING COMPUTER VISION FOR INSPECTING QUALITY OF BOTTLE AND FOREIGN OBJECT DETECTION

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Abstract: For manufacturers as well as consumers, a product with a defective bottle or the existence of foreign objects is unacceptable. This article refers to the application of computer vision as a field of artificial intelligence to the automatic of foreign object detection and the quality of bottle. The inspection is carried out at all areas including body, mouth and bottom of the bottle. For experiment of this research, the python programming language is incorporated with an open source library (OpenCV). The training of system must be ensured that computer vision works so that it is closest to human vision which means building on simulating how the human brain works, known as neural network. Input data after going through the preprocessing process will be measured and diagnosed by the computer based on the trained knowledge, thereby determining the quality of the current product. The results obtained will be shown on a Graphical User Interface to facilitate the extraction and operation.

Keywords: *Computer vision, OpenCV, Bottle inspection, Foreign object detection, Neural network.*

I. INTRODUCTION

The influence of foreign bodies in products can be very large and very negative, which is why manufacturers require strict inspections to promptly detect foreign objects and defects of the product. However, it is difficult to guarantee the reliability and adapt to the requirements of modern production lines using the traditional way of manual detection [1]. In addition, manual inspection by humans is increasingly revealing many disadvantages such as low stability depending on their health and psychophysiological factors, low performance, increased operating costs. Therefore, applying an automated inspection system will help solve these problems.

There are many technological solutions applied in the process of checking bottles today. If only to detect metal foreign bodies, one can use metal probes. If it is necessary to check for defects in body shape, cracks, defects, digital cameras are used at the locations to be checked,... each of those technology solutions usually only addresses a certain requirement [2,3]. There are several surface defect detection algorithms such as: bottle mouth inspection based on the recommended ELM (Extreme Learning Machine) algorithm [4] and the detection rate can reach 99. 41%; the classification of bottle defects and the recognition of bottle mouth defects by SVM (Support Vector Machine) [5] has a detection rate of 91.6%. In addition, there are many other techniques used such as the detection of bottle wall defects based on the Fuzzy C Means Clustering algorithm; detection of bottle bottom defects based on Wavelet transform; surface defect detection based on Blod analysis [6,7],... However, the use of these algorithms to check bottles is still difficult and difficult to apply directly in practice, especially for bottles with non-slip ribs at the bottom of the bottle. Therefore, in the defect recognition of bottle bottom, because the antiskid veins of bottle bottom influence the detection accuracy [1]. At the same time, if you want to process multiple requests at the same time, the greater the number of objects collecting input data, plus the processing of the algorithm becomes more complex. This makes the automated inspection system cumbersome, slow processing speed at high cost.

At present, some big companies such as Heuft, Krones, Miho in Germany and Filtec in America, have made empty bottle inspection systems applicable to beverage and beer production lines [8]. The study of empty bottle inspection systems mainly focuses on how to improve the accuracy, speed and reliability of detection. However, these systems are only applicable to certain standards in the US and EU beer and beverage industries [8]. Such systems are difficult to apply in the beverage industry in Vietnam if it is not improved in algorithms and configurations.

To solve the problems as mentioned above, computer vision is a new field and has the ability to apply effectively in many different fields, especially the beverage industry. The application of computer vision and artificial intelligence integrated into the control system allows the creation of an intelligent control system. This system can receive images obtained with multidimensional data sets for analysis and processing according to the intention set by humans. Work is started from the image preprocessing process; the results obtained will be measured and diagnosed by the computer by comparing with the "knowledge" that has been "trained", thereby identifying the object to be monitored. When "training" the system, it must ensure that computer vision works in a way that most closely resembles human vision. called Neural Networks. Convolutional Neural Networks (CNNs) are one of the most efficient models available today [11,13].

This paper focuses on the research and application of computer vision, artificial intelligence and integration into control systems to detect and remove glass bottles on the bottling line with defects (incompleteness on the body of the bottle, mouth and bottom of the bottle) and foreign objects that exist inside the bottle (e.g. pieces of metal, glass, mineral stone, wood, bone, hard plastic, rubber,...). The rest of the article is sorted as follows. Part II presents the application of computer vision to check the quality of bottles and detect foreign bodies in the body of bottles. Experimental model and experimental results of automated systems that automatically identify and remove defective glass bottles are presented in Part III. Part IV is the conclusion.

II. THE PROPOSED METHOD

CNNs are one of the most common deep Neural Networks [14]. The name derives from the fact that CNNs have the application of linear operations between matrices called convolutions. CNNs has multiple layers; including convolutional layer, non-linear layer, pooled layer, and fully connected layer [14]. In this study, CNNs were used to "train" the system to recognize the objects to be detected.

There are mainly two types of object detection methods that are based on CNNs: two-stage schemes (also named R-CNN series object detection) and one-stage schemes, where the two-stage schemes combine region proposals with the CNN network to detect objects. In the one-stage schemes, the object detection is transformed into a regression problem to perform end-to-end detection [9]. Although two-stage method has higher accuracy than one-stage method, the one-stage method has faster detection speed than two-stage method [10]. Many CNNs-based model architectures have been built, of which YOLOv5 is one of the new architectures, a new approach to object discovery [11]. The block diagram of the YOLOv5 architecture is presented in Fig. 1. This architecture has fast processing speed with high accuracy, suitable for object detection tasks in practice.

YOLOv5 has multiple versions, in this study selected the version with an inference rate per image of 8.2 ms and the mean average precision value of 45.2 mAP. The system is planned to be built with two checking chambers, the first has 3 cameras to check for cracks on the bottle; the checking chamber 2 includes a camera to check for bottle bottom faults, bottle mouth faults and foreign objects. The actuators are connected to the microcontroller circuit linked to the computer to control the entire operation of the system. Fig. 2 shows the overall connection diagram of the system, and Fig. 3 shows the design diagram of the experimental model.

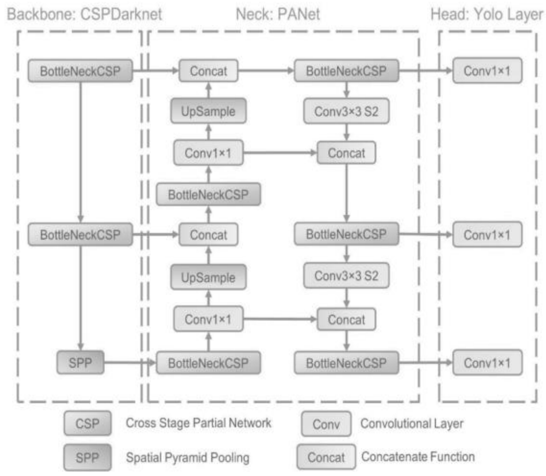

Fig. 1. The network architecture of Yolov5. It consists of three parts: (1) Backbone: CSPDarknet, (2) Neck: PANet, and (3) Head: Yolo Layer. The data are first input to CSPDarknet for feature extraction, and then fed to PANet for feature fusion. Finally, Yolo Layer outputs detection results (class, score, location, size) [12]

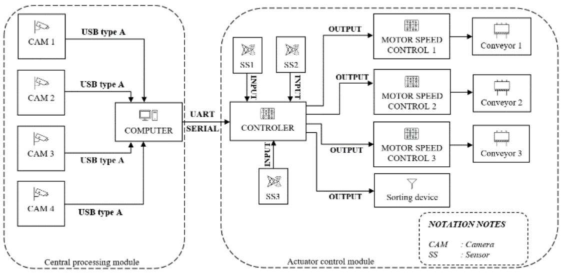

Fig. 2. Connection diagram of the system

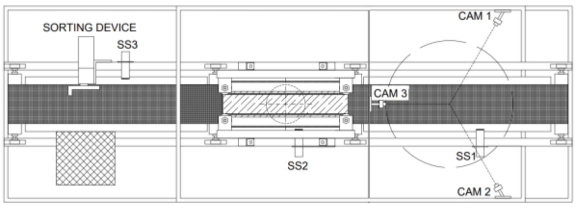

Fig. 3. Design diagram of the empirical model

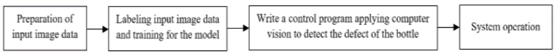

Fig. 4. Stages of implementation of the study

To train the system, we must first prepare an input data source consisting of 2500 images of bottles to be tested, the size of each image is 640 x 480 pixels, divided into two datasets for two checking chambers. This is an extremely important step and has a great impact on the accuracy of the system. The more different images of the subject are used for training, the more "intelligent" the system after training will be, from which it is easier to "see" the object during operation. An overview of the stages of the study is shown in Fig. 4. The images data will be labeled before being included in training for the model. The experimental model has two checking chambers. Checking chambers 1 has two layers of labels built, including: "chai" and "nut_vo"; checking chamber 2 has three layers of labels: "mieng_chai", "di_vat" and "bien_dang". Labeling is required to ensure that the bounding box covers just enough around the object to be detected, helping to increase the accuracy of the object detection process. After being labeled, the dataset is fed into training the model. The experimental process shows that the more repetitions of training, the higher the ability to accurately identify the object, and with the number of repetitions of 300 times or more, the ability to accurately identify the object does not change too much. Fig. 5 shows the model's training.

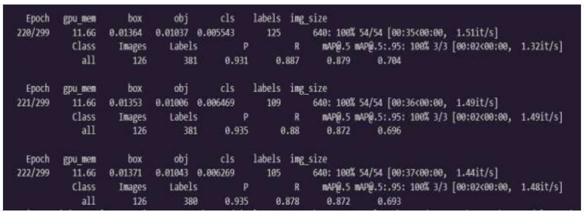

Fig. 5. Model training process

```
void loop()
{
  analogWrite(LPWM,240);
  analogWrite(RPWM1,150);
  if (digitalRead(CB1) == 0)
    {
      if (lock == 0)
        {
          lock = 1;
          delay(750);
          analogWrite(RPWM1,0);
          delay(300);
          Serial.println(1);
          lock = 0;
          delay(3000);
          analogWrite(RPWM1,150);
        }
  lock = 0;
    }
```

Fig. 6. Codes in microcontroller circuitry

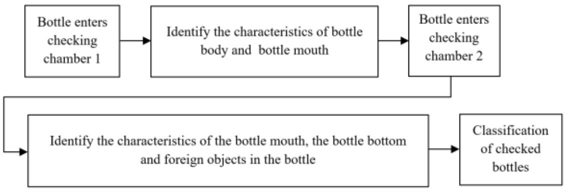

Fig. 7. System's operation progress

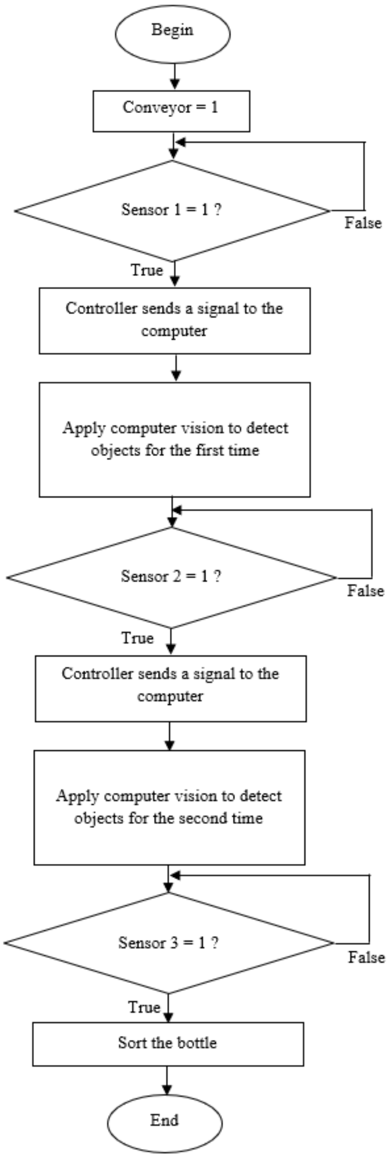

Fig. 8. Flowchart algorithm of the system

The results obtained from the training are used as a data source for the inspection of the bottle. The system is controlled through programming programmed in the microcontroller circuit and on a computer. Fig. 6 shows a program segment programmed in a microcontroller circuit. The programming language used to build computerized control programs is Python, which uses computer vision command libraries to build a flexible, fast, and accurate control algorithm. An overview diagram of the system's operational progress is shown in Fig. 7, and the proposed algorithmic diagram to perform this work is shown in Fig. 8.

One of the most used libraries in the control program is the open source OpenCV-Python library, abbreviated under the name "cv2", commands that manipulate images applied from this library. Fig. 9 and Fig. 10 show the commands used in Python.

In our study, the images collected from the cameras are RGB color images, converted to grayscale image format during image preprocessing, to help clarify object contours and features to be extracted , thereby overcoming the problem of missing small objects. To accurately detect errors, it is recommended that the diagnostic process be repeated twice for one bottle. The detected object will be marked with bounding boxes and the class name of the corresponding error. After the bottle is diagnosed, the obtained result contains many parameters, the program will extract the error code characteristic parameter to determine the fault nature of the bottle. If the bottle is defective, the bottle identifier will be updated to a vector of dimensions (1 x N), where N is the number of detected defective bottles, to serve the process of classifying the bottles after inspection. .

The bottle sorting stage after being diagnosed is a combination of a computer and a microcontroller circuit. Both of these components are set at a data rate of 9600 bps, communicating through the serial communication port. Corresponding to each task is a separate code used for communication, accompanied by a "key code" to determine the correct time of data transmission, avoiding the case of transmission at the wrong time or uncontrollable batch transmission.

Because the system has a combination of multiple cameras, the data processing process on the computer needs to apply threading techniques to be able to collect data simultaneously. Fig. 11 shows the application of threading techniques in this study.

The results of the inspection are presented on the graphical user interface as shown in Fig. 12 to make it more convenient for the operation process. To perform this step, the image frame coordinates parameter is extracted as a "Records", and the collected image must be converted to the Python Imaging Library (PIL) domain before being displayed to the GUI for the reason that GUI design support commands are only compatible with PIL images.

```
import threading
import cv2
import torch
import time
import serial
import numpy as np
import pandas as pd
from  tkinter import *
from threading import Thread
```

Fig. 9. Declare some libraries that use python programming language

```
        cv2.rectangle(im0, (x1, y1), (x2, y2), (255, 255, 255),2)
        cv2.putText(im0, name, (x1 + 3, y1 - 10), cv2.FONT_HERSHEY_DUPLEX, 1,
(255, 255, 255), 2)
```

Fig. 10. Application library "cv2"

```
detections_img0 = model(im0, size=640)
detections_img1 = model(im1, size=640)
detections_img2 = model(im2, size=640)
anh1 = threading.Thread(target=in_anh1(detections_img0, im0))
anh2 = threading.Thread(target=in_anh2(detections_img1, im1))
anh3 = threading.Thread(target=in_anh3(detections_img2, im2))
anh1.start()
anh2.start()
anh3.start()
```

Fig. 11. Apply threading techniques

```
lable_1 = Label(root, text = "cam 1")
lable_2 = Label(root, text = "cam 2")
lable_3 = Label(root, text = "cam 3")
lable_4 = Label(root, text = "cam 4")
```

Fig. 12. Create the Graphical user interface

III. EXPERIMENTS

After the experimental implementation process, we have successfully built a model, meeting the requirements of the study. The operation of the system achieves positive results with high accuracy, the ability to detect objects accurately. The training was repeated 300 times, with 290 layers of the YOLOv5 model, each time 16 data images were included in the training simultaneously, resulting in batches of post-training data stored for the operation of the system. Fig. 13 shows batches of data obtained after training. Fig. 14 and Fig. 15 represent the experimental model we designed. Fig. 16 shows the results shown on the graphical user interface, and Fig. 17 is a composite of the labels assigned to the object.

Fig. 13. Illustration of trained data batch

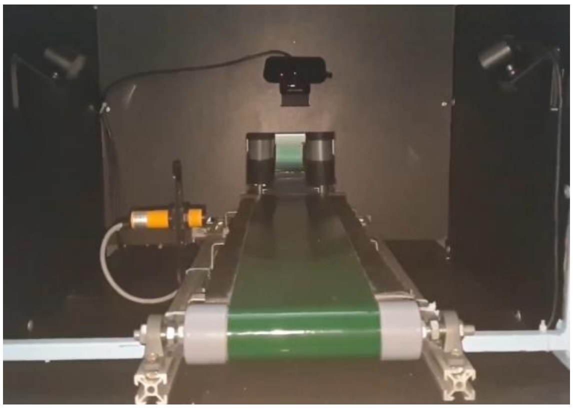

Fig. 14. Checking chamber 1

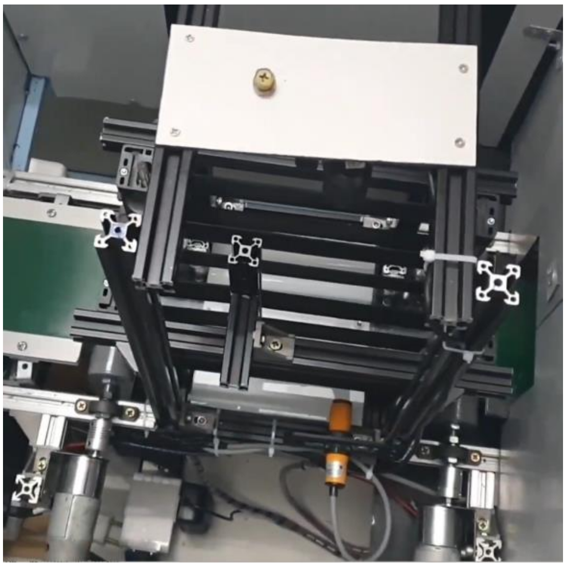

Fig. 15. Checking chamber 2

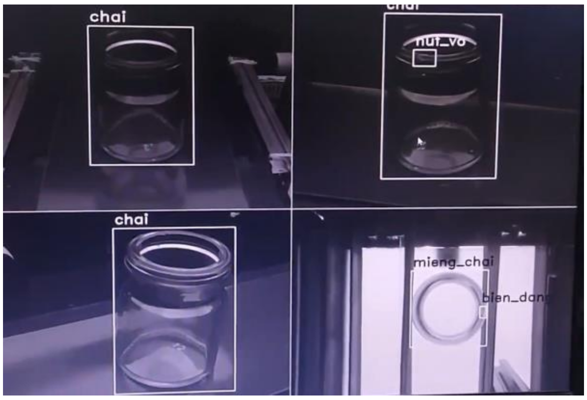

Fig. 16. Results displayed on GUI

Note that previous algorithms mainly only detected errors on the surface of the bottle, but in this study, with the transparent bottle object, the system was able to detect errors not only on the surface but also inside the material that makes up the bottle, with test speed for a fast object, can achieve up to 18ms. At the same time, this is a non-destructive inspection process, which will ensure the safety of the inspected object, suitable for all professions, especially in the production of food and beverages.

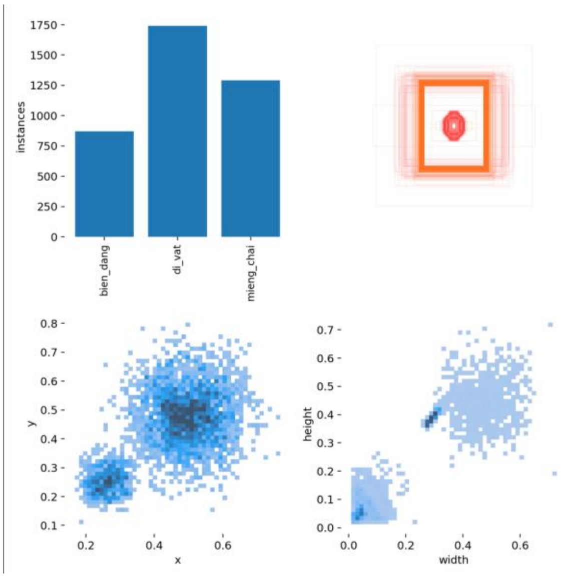

Fig. 17. The labels of the training process

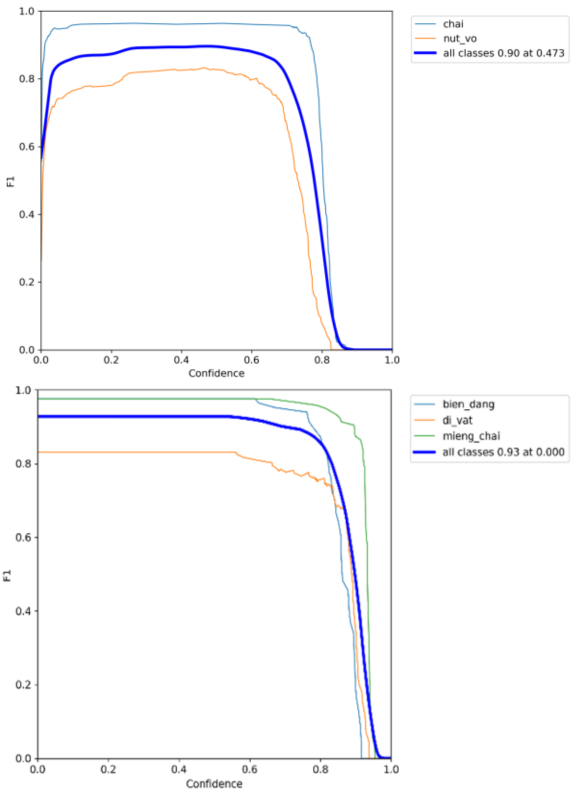

Fig. 18. F1_curve

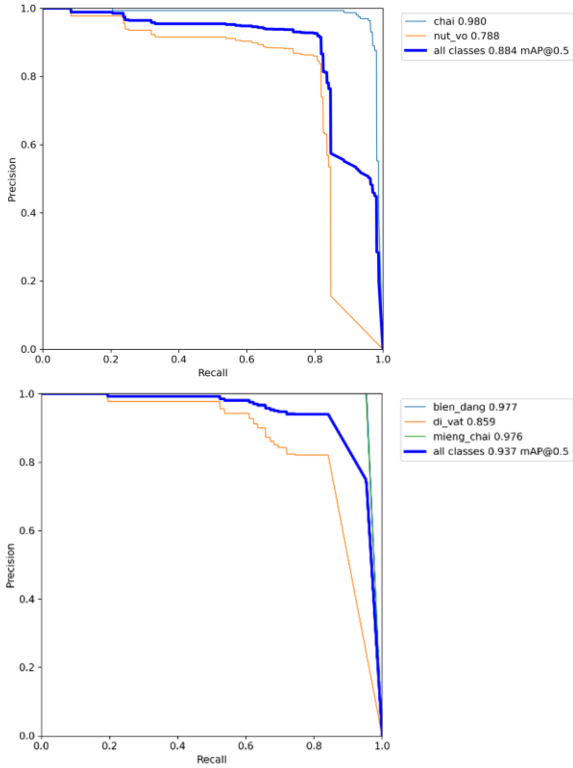

Fig. 19. PR_curve

According to the F1_curve graph in Fig. 18 as can be seen, for the test training in checking chamber 1, in the confidence interval from 0.05 to 0.85, the value of F1 is maintained at a high level above 0.8 (for all classes), and reaches a maximum value of 0.90; for the test training stage in checking chamber 2, in the confidence interval from 0.0 to 0.95, the value of F1 is maintained at a high level above 0.8 (for all classes), and reaches a maximum value of 0.93, proving that the efficiency of the achieved model is high and is maintained in a large confidence interval.

On the other hand, on the graph PR_curve in Fig. 19 showing a correlation between precision and recall shows that precision remains high as recall increases despite changes in confidence thresholds over a wide range. The mean average precision value (mAP) at the Intersection Over Union (IoU) threshold of 0.5 was achieved at 0.884 for identification in checking chamber 1 and 0.937 for identification in checking chamber 2, respectively, which is a high result demonstrating the high accuracy of the entire system.

IV. CONCLUSION

Inspecting the quality of bottle and foreign object in bottle is one of the important stages in modern production lines, it has a direct impact on the speed, accuracy and productivity of the whole factory. This report studies the application of computer vision to the inspection process, so that it is possible to comprehensively inspect the areas of the bottle in the same stage, helping to shorten working time as well as minimize the layout of space in the actual factory.

To do this, it is important first that the data source used for the "training" process be carefully selected so that it contains all the situations in which the object occurs. After the model is trained, it is necessary to extract the appropriate characteristic parameters for each task. The experimental results show that the algorithm proposed in this paper can improve the efficiency and accuracy of detecting defects and foreign bodies in bottles and can be applied in practice.

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