Eye-Smoker: A Machine Vision Based Nose Inference System of Cigarette Smoking Detection using Convolutional Neural Network

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ABSTRACT

In the Philippines, at least 16 million Filipinos reported smoking cigarettes amid the campaign against tobacco products due to various concerns about their adverse health effects. Due to health, environmental and safety concerns, the President of the Philippines issued Executive Order 26 s. 2017, imposing nationwide ban on smoking (use of tobacco including e-cigarettes) in all public places in the Philippines. Despite the implementation of this order, many are still seen smoking in prohibited smoking areas. A smoke detector can be helpful in this situation. This study proposed smoker detection system that use a deep learning algorithm that can detect people that are smoking cigarettes. The study used Pascal VOC format and LabelImg tool for annotating the datasets. Training, validation and evaluation of the system is done by presenting images, videos and live detection using webcam of a camera. Overall, the system produced 90% testing accuracy.

Key words : deep Learning, machine vision, smoking detection, smoking alarm, yolo v3.

1. INTRODUCTION

Cigarette Smoking is the single leading cause of preventable death in the world today, according to the World Health Organization [1]. Among the 1.1 billion smokers globally, 80% of these smokers live in low-and middle-income countries [2]. In the Philippines, at least 16 million Filipinos reported smoking cigarettes amid the campaign against tobacco products due to various concerns about their adverse health effects [3].

Cigarette smoking has many serious effects to the environment and to the human [4]. According to the study, cigarette butts top list to the most common coastal trash [5]. Cigarette butts are toxic waste, their chemical content can contaminate our water ways, ground soil, and may be harmful to wildlife [6]. While discarded lit cigarettes can cause fires that may result to property loss and deaths [7]. Due to health, environmental and safety concerns, the President of the Philippines issued Executive Order 26 s. 2017, imposing nationwide ban on smoking (use of tobacco including e-cigarettes) in all public places in the Philippines [8]. Despite the implementation of this order, many are still seen smoking in prohibited smoking areas. A smoke detector can be helpful in this situation [9].

The purpose of this study is to identify the smokers within in the area. A smoke detection device that; can detect smokers on prohibited smoking areas and; that can be installed in a large public prohibited smoking area.

In recent years, some researchers have proposed smoking image detection methods based on image recognition technology [10]. Study of [11]-[15] used also the power of deep learning as a tool for object detection. With this, the objective of this study is to create a smoker detection system using deep learning (YOLOv3) that aims to use visual medium (images and videos) for detecting. This study would benefit both the government and the private sector from the strict implementation of non-smoking regulations in prohibited smoking areas. This will also be beneficial for researchers working on the same or similar topic.
The focus of the study is limited to the detection of the cigarette to recognize a possible smoker. It does recognize other forms of smoke from e-cigarettes, smoke-pipes and the likes.

2. METHODOLOGY

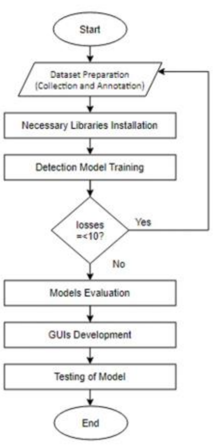


Figure 1: Flowchart Diagram of the System

In this section, the systematic steps in formulating a detection system is presented. Fig. 1 shows the flowchart diagram of the system.

2.1 Smoking Cigarettes Dataset

The study gathered images with people smoking cigarettes. The dataset shown in Fig. 2 are different photos of smokers. The study used Pascal VOC format and LabelImg tool for annotating the datasets. The study used 300 images, 70% for training and 30% for evaluation.

Figure 2: Smoking Cigarettes Dataset

2.2 Libraries Installation

The following codes are used to install the needed libraries:

- !pip install opencv-python==4.1.2.30
- !pip install keras==2.3.1
- !pip install tensorflow==1.14.0
- !pip install tensorflow-gpu==1.14.0
- !pip install imageai -upgrade

2.3 Training of Detection Model

The study used the transfer learning from a pre-trained YOLOv3 model in the training to improve the accuracy of trained custom models. To attain the accuracy of =>90%, losses must be =<10. Shown in Fig.3 is the complete code for training.

```
from imageai.Detection.Custom import DetectionModelTrainer

trainer = DetectionModelTrainer()
trainer.setModelTypeAsYOLOv3()
trainer.setDataDirectory(data_directory="smoke")
trainer.setTrainConfig(object_names_array=["smoking"], batch_size=4, num_experiments=50, train_from_pretrained_model="/content/gdrive/My Drive/Colab Notebooks/pretrained-yolov3.h5")
trainer.trainModel()
```

Figure 3: Training Code

2.4 Evaluation of Models

Low losses do not always guarantee high accurate models. Therefore, it is necessary to evaluate the mAP (mean Average Precision) of the trained models. Higher mAP means higher accuracy of the detection model. Shown in Fig.3 is the code for the evaluation of the model.

```
from imageai.Detection.Custom import DetectionModelTrainer

trainer = DetectionModelTrainer()
trainer.setModelTypeAsYOLOv3()
trainer.setDataDirectory(data_directory="smoker")
trainer.evaluateModel(model_path="smoker/models", json_path="smoker/json/detection_config.json", iou_threshold=0.5, object_threshold=0.3, nms_threshold=0.5)
```

Figure 4: Evaluation Code

2.5 GUI Development

A graphical user interface (GUI) is a means to communicate to a computer application using graphical symbols instead of typing the instructions in. In this study, an available GUI code was used. There are some modifications with GUI to make it suitable for the system.

2.6 Testing of Model

The study used the trained model with the highest mAP value. Custom object detection was tested by presenting 30 different images and 3 different videos. Live detection testing was conducted using laptop's webcam.

3. GRAPHICAL USER INTERFACE

Figure 3-3 shows the GUI of the smoker detector. There are 3 icons in there: webcam icon for live testing, camera icon for importing images, and video icon for importing videos.

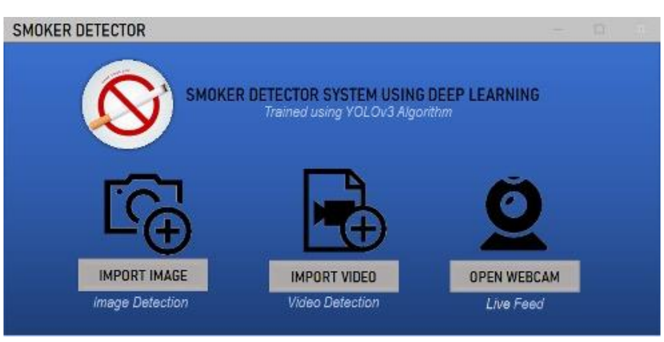


Figure 5: Smoker Detector GUI

4. RESULTS AND DISCUSSIONS

A. Training and Validation Results

There is a total of 50 epochs and the results ranges from 63% to 98%, Based on the data the most accurate trained model that can be used is from epoch number 48, with training accuracy of 98.10% and a validation accuracy of 98.22%, which are the highest value as shown in Figure 7.

Figure 6: Training Results

B. Evaluation of Model

In total, there are 30 models generated. Based on the gathered results, the trained model from epoch number 28 has the highest mAP value as shown in Figure 8. Therefore, this model will be use for the system.

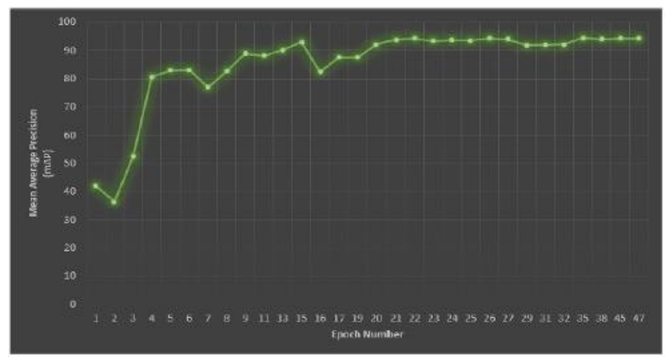
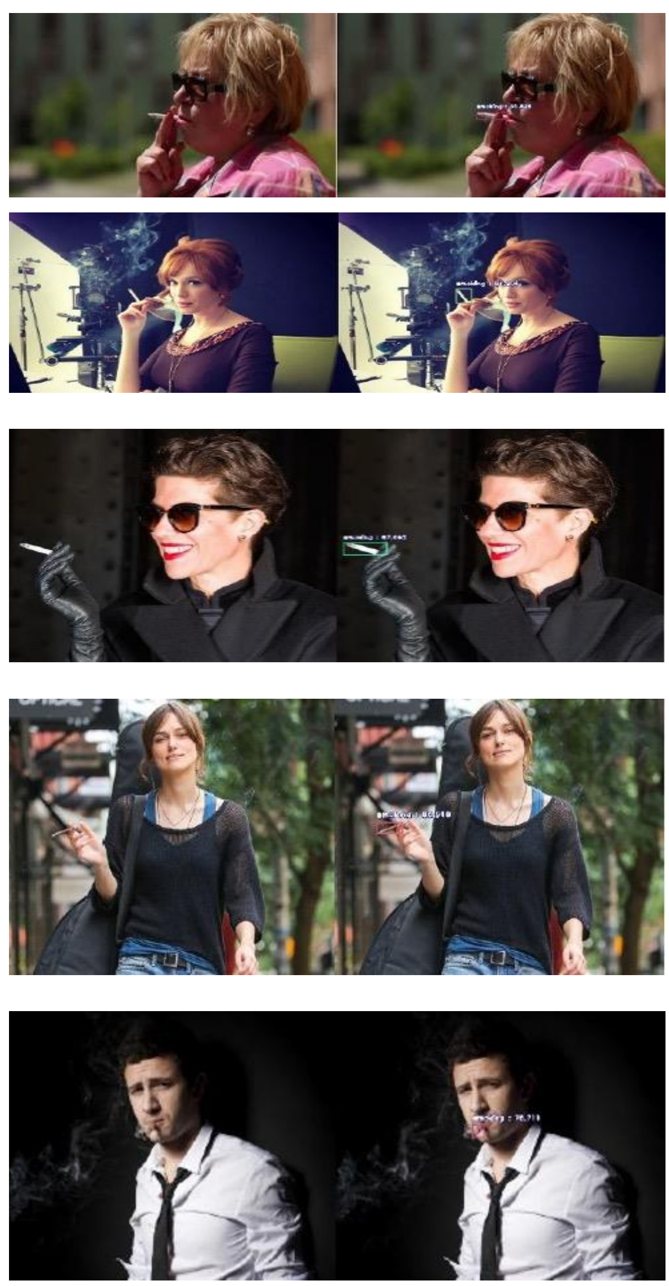


Figure 7: Evaluation Results

C. Testing Results

C.1 Image Testing

Fig.8 shows the testing of images before (left side) and after (right) being presented to the detection system:



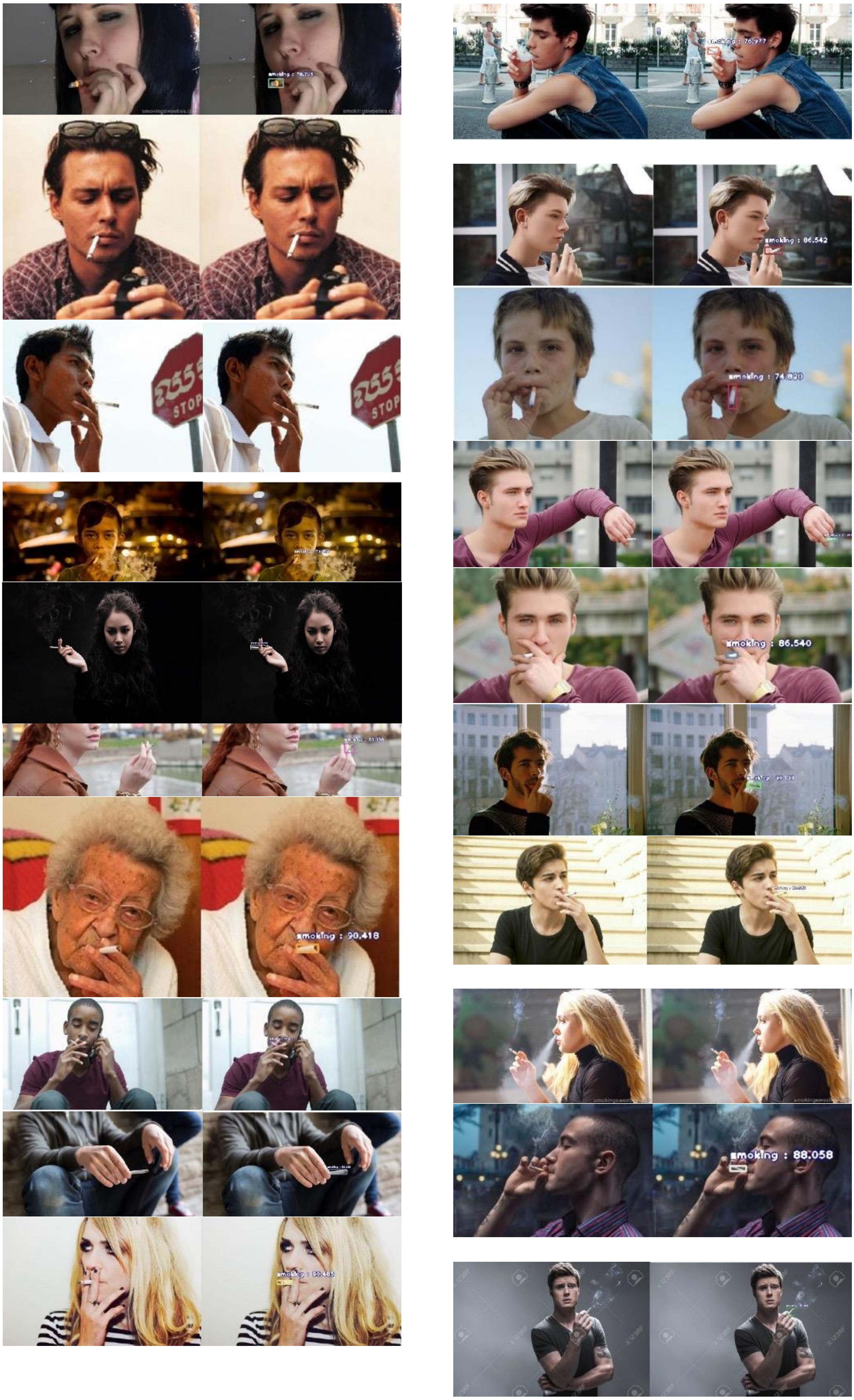

STOP
STOP
smoking : 90.418
smoking : 86.542
smoking : 74.820
smoking : 86.540
smoking : 88.058

Figure 8: Image Testing

Out of the 30 images presented for testing, 27 of them are correctly detected. Using the formula for accuracy:

$$\text{Accuracy} = \frac{\text{Number of Samples Recognized Correctly}}{\text{Total Number of Sample}}\ x\ 100\%$$

$$\text{Accuracy} = \frac{27}{30}\ \text{x}\ 100\%$$

$$\textbf{Accuracy = 90\%}$$

C.2 Video Testing

Fig .9 are the screenshots of video testing. It shows the success detection of cigarettes in the video. On this part, there instances that the cigarette was not easily detected due to the angle of the cigarette and the quality of the video (blurredness sometimes confuses the system).

Figure 9: Video Testing

C.2 Live Detecting using Webcam

Fig .10 is the screenshot of the live testing. Same as the video testing, several times that the object is not detected due to the angel of the cigarette and quality of the video.

Figure 9: Live Detection Testing using Webcam

5. CONCLUSION AND FUTURE WORKS

The study proposed a system that can detect smokers in an area. The system used a deep learning algorithm and it is optimized to detect people that are smoking cigarettes. In addition, the study conducted model training and testing of collected datasets (images and videos) with respect to smoking cigarettes as specific detection target. Model training and validation results ranges from 63% to 98%, considering the most accurate trained model can be used is from epoch 48, that has a 98.10% training accuracy and 98.22% validation accuracy. The experimental results show that the generated detecting system has higher average accuracy.

The study is limited to the detection of the cigarette to recognize a possible smoker. Any other forms of smoking like e-cigarettes, smoke-pipes and the likes will be unrecognize. Improvement of this study could be done in future. First, by adding image datasets of other forms as aforementioned, and second, application of the system in a hardware for a more complete setup.

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