**LINKER: Journal of Computing and Technology**
Vol. 1, No. 1, (2020), pp. 8-12

LINKER: TJCT
Journal of Computing and Technology

**Research Article** **Open Access**

# ILL-Park: A Deep Learning Approach of Illegal Parking Detection

Cherry D. Casuat[1], Julie Ann B. Susa[2], Helcy D. Alon[3]

*Department of Computer Engineering, Technological Institute of the Philippines, Manila, Philippines[1]*
*Department of Computer Engineering, Technological Institute of the Philippines, Manila, Philippines[2]*
*Graduate School, Technological Institute of the Philippines, Manila, Philippines[3]*

*Corresponding author: e-mail address: ccasuat.cpe@tip.edu.ph*

***ABSTRACT***

*Illegal parking in the Philippines was prévalent, this is a critical problem in large, growing cities such as Metro Manila, Metro Cebu, Metro Davao, and other cities in the Philippines. Currently, the responsibility for detecting illegally parked vehicles has been left to law enforcement, which often requires manual inspection. The aim of this study is to detect public and private vehicles that are illegally parked on sidewalks and parked within the driving lane. To improve the efficiency of law enforcement for vehicle parking management, the researchers proposed an illegal parking detection based on an existing deep learning approach. Upon training Epoch 41/50 being the best model to be used having a 96.41 training accuracy and 92.13 validation accuracy.*

***Keywords –*** *Deep Learning, Illegal parking detection, Object detection*

## Introduction

The Illegal parking in the Philippines has become a serious problem as time goes by, for many urban areas in large and growing cities. The resulting effect on vehicle movement can cause issues in traffic congestion, air pollution, and public safety (Aljoufie,2016), (Yin et. al,2019) (Xun et. al,2016). Traditionally, the detection of illegal parking is achieved through manual inspection, which requires considerable human efforts from law enforcement and security personals.

Efficiently detecting illegal parking has attracted research attention from various domains. Considerable effort has been applied to the development of new algorithms designed to improve the performance of detection (He,2018) (Lee,2009), (Sarker,2015), (Xie,2017). Most of these attempts have used videos captured from fixed cameras (Lee,2009). To overcome the limitation of fixed camera coverage, recent studies used alternative data sources, such as biking trajectories, to detect illegal parking (He,2018). This study differs from these previous studies by using cameras that can be deployed on moving objects (e.g. patrolling vehicles, robots).

In a study on deep learning-based vehicle occupancy detection for open parking, a thermal camera was used in order to collect data from videos where frames from these videos are extracted for dataset preparation. To perform multi-object detection in vehicle detection, deep learning algorithms were used. Deep learning networks are used to evaluate layers and architectures on vehicle detection. With the collected data, compared are the template of parking spaces in identifying vehicle occupancy information.

Previous studies and researches on deep learning-based studies on vehicle detection and parking only detect areas where a vehicle is and where it can be parked. The detections done are for vehicles and spaces where vehicles can be parked.

In this study, vehicles are detected using deep learning. The detection focuses on vehicles parked on sidewalks and within the driving lane. The dataset prepared are from google street view where images are taken from Aparri Cagayan and some streets in Manila near the Technological Institute of the Philippines.

## Methods

This section illustrates the procedures in creating the detection system as shown in Fig.1.


Fig.1. Procedural Steps

*Dataset Gathering and Annotation*

In gathering the dataset for this project, google street view is used for collecting images of the streets where vehicles are seen. The dataset gathered consists of 300 or more images for detection. After gathering the dataset needed, the images are annotated for the AI to determine the vehicle parking classification whether the vehicle is parked or illegally parked or have been parked badly. Label image is used for annotating the images gathered in the dataset. As shown in Fig. 2 the annotated images are shown wherein vehicles are parked and shown in Fig. 3 and Fig. 4 are the annotation for vehicle labeled as bad-parking.

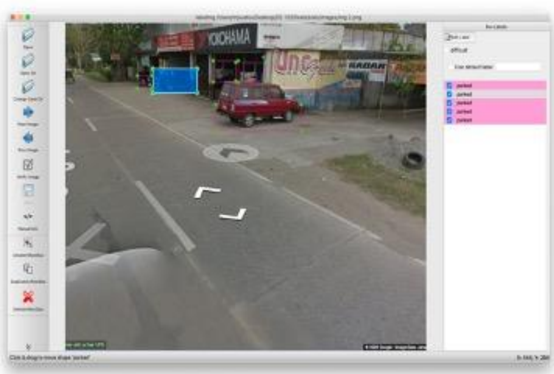

Fig. 2 Sample Properly Parked  Annotated Dataset

Fig. 3 Sample Bad Parking Annotated Dataset

*Training and Validation*

For training and validation, the dataset and annotated images are stored in the google drive for and are to be mounted at google colab as seen in Fig. 3 for dataset training and validation. The code that is shown in Fig. 4 determines the training loss and validation loss. The training and validation results are shown in chapter 3 and seen in summary is the training accuracy and validation accuracy in Fig. 5 having the highest training accuracy at 96.41 and validation accuracy at 92.13**.**

```
[ ] from google.colab import drive
    drive.mount('/content/gdrive')

    Mounted at /content/gdrive

[ ] cd gdrive

    /content/gdrive

[ ] cd My\ Drive

    /content/gdrive/My Drive

[ ] cd Colab\ Notebooks

    /content/gdrive/My Drive/Colab Notebooks

[ ] cd Midterm-Exam/

    /content/gdrive/My Drive/Colab Notebooks/Midterm-Exam
```

Fig. 4 Google drive mounted in google collab

```
from imageai.Detection.Custom import DetectionModelTrainer

trainer = DetectionModelTrainer()
trainer.setModelTypeAsYOLOv3()
trainer.setDataDirectory(data_directory="/content/gdrive/My Drive/Colab Notebooks/Midterm-Exam/midterm")
trainer.setTrainConfig(object_names_array=["parked","bad-parking"], batch_size=[illegible], num_experiments=[illegible], train_from_pretrained_model="/content/gdrive/My Drive/
trainer.trainModel()
```

Fig. 5 Sample codes

*Evaluation*

In evaluation and deployment, the trained models of the dataset are evaluated in google colab where the highest accuracy for training and validation is evaluated to an h5 file.

## Results and Discussions

This section presented the Training Validation Results, Evaluation of the Model Results, Graphical Interface, Testing Results.

### *Training Validation Results*

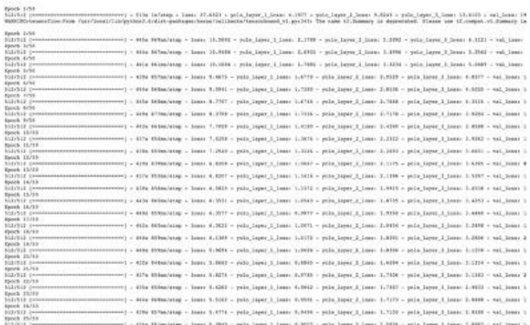

Fig. 4 Epoch from 1-25 Training Loss

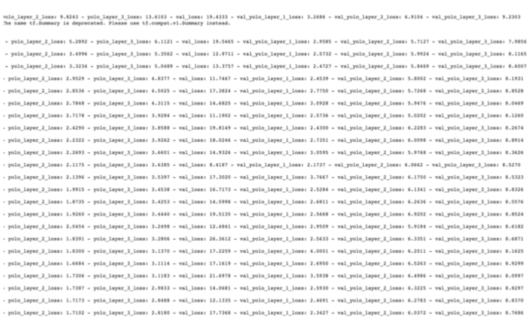

Fig. 5 Epoch from 1-25 Validation Loss

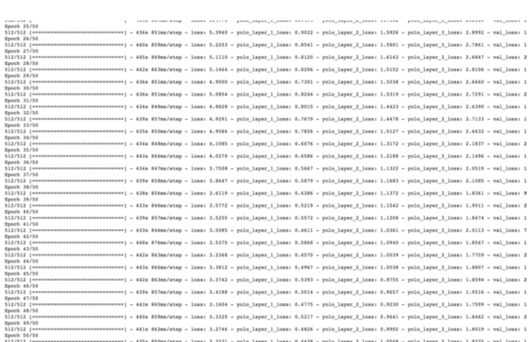

Fig. 6 Epoch from 25-50 Training Loss

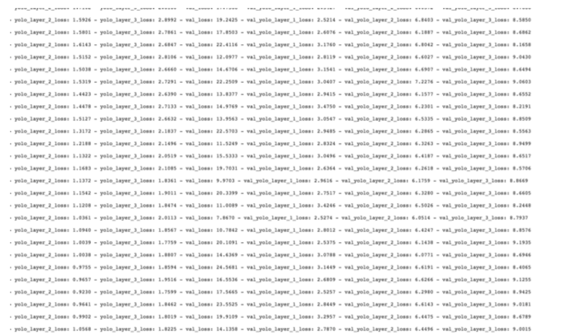

Fig. 7 Epoch from 25-50 Validation Loss

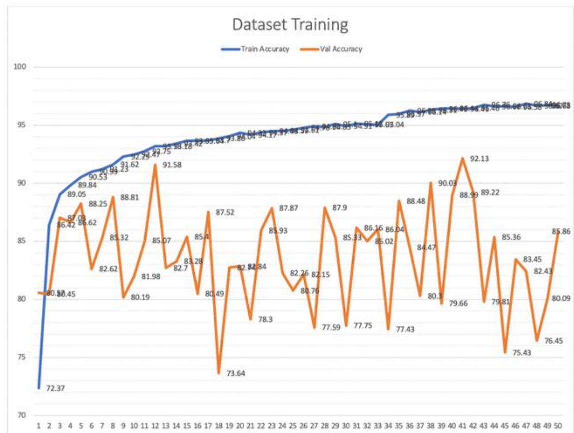


Fig. 8 Training and Validation Results. Dataset Training and Validation Line Chart for Training Accuracy and Validation Accuracy.

In Fig. 8 shows the line chart shows the highest accuracy for training and validation. Epoch 41/50 being the best model to be used having a 96.41 training accuracy and 92.13 validation accuracy.

### *Evaluation Model Results*

```
Model File:  midterm/models/detection_model-ex-010--loss-0007.661.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.0900
parked: 0.3412
mAP: 0.2156
===============================
Model File:  midterm/models/detection_model-ex-010--loss-0007.789.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1667
parked: 0.5632
mAP: 0.3650
===============================
Model File:  midterm/models/detection_model-ex-011--loss-0007.254.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.2349
parked: 0.6572
mAP: 0.4461
===============================
Model File:  midterm/models/detection_model-ex-011--loss-0007.404.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1018
parked: 0.3627
mAP: 0.2322
===============================
Model File:  midterm/models/detection_model-ex-011--loss-0007.518.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1637
parked: 0.3893
mAP: 0.2765
===============================
```

Fig. 9 Evaluation of Model. 09 to 11.

```
Model File:  midterm/models/detection_model-ex-008--loss-0008.380.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1827
parked: 0.7057
mAP: 0.4442
===============================
Model File:  midterm/models/detection_model-ex-008--loss-0008.617.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1804
parked: 0.4340
mAP: 0.3072
===============================
Model File:  midterm/models/detection_model-ex-009--loss-0007.706.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1514
parked: 0.6255
mAP: 0.3885
===============================
Model File:  midterm/models/detection_model-ex-009--loss-0007.797.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.2077
parked: 0.3935
mAP: 0.3006
===============================
Model File:  midterm/models/detection_model-ex-009--loss-0007.935.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1817
parked: 0.4967
mAP: 0.3392
===============================
```

Fig 9 Evaluation of Model 7 to 9

```
Model File:  midterm/models/detection_model-ex-006--loss-0008.930.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1057
parked: 0.4009
mAP: 0.2533
===============================
Model File:  midterm/models/detection_model-ex-006--loss-0009.005.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1014
parked: 0.4452
mAP: 0.2733
===============================
Model File:  midterm/models/detection_model-ex-006--loss-0009.094.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1503
parked: 0.5655
mAP: 0.3579
===============================
Model File:  midterm/models/detection_model-ex-006--loss-0009.158.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.1540
parked: 0.3660
mAP: 0.2600
===============================
Model File:  midterm/models/detection_model-ex-007--loss-0008.548.h5

Using IoU :  0.5
Using Object Threshold :  0.3
Using Non-Maximum Suppression :  0.5
bad-parking: 0.0985
parked: 0.3886
mAP: 0.2435
===============================
```

Fig. 10 Evaluation of Model 5 to 7

*Graphical User Interface*


Fig 11 Sample GUI

Fig. 11 presented the graphical user interface of the system. The system consists of (1) image where they could upload the images of a car parked, (2) Video to upload the video of those car parked, and (3) Webcam for live feed car parked in the sidewalks. The system will determine if the car parked is properly parked, badly parked, and illegally parked

## Conclusion and Future Works

To satisfy the requirement of 85 mAP and the objective of detecting illegal parking, the researchers concluded that for the object detection to become successful the training and validation needs to have an accuracy of at least 90 percent above and for the evaluation of models to have an mAP of 85 above. Upon training the epoch 41/50 being the best model to be used having a 96.41 training accuracy and 92.13 validation accuracy. Having attained this percentage the researchers concluded that detection will be successful. For future works, can be integrated with car plates detection to easily determine those who parked illegally.

## Acknowledgment

The proponents would like to thank MR. SUAVE Laboratory for the computing facilities, without those facilities this study will never be feasible.

## Authors Bio note

**CHERRY D. CASUAT** currently a Doctor of Engineering student from the Technological Institute of the Philippines. She is currently an associate professor in the Department of Computer Engineering, College of Engineering and Architecture, Technological Institute of the Philippines. Her current research interests include Employability Signals and Machine Learning.

**JULIE ANN B. SUA** is a graduate of the Master's Degree of Engineering in Education major in Computer Engineering. She is currently an Assistant professor in the Department of Computer Engineering, College of Engineering and Architecture, Technological Institute of the Philippines. Her current research interests include Signal Processing and Embedded Systems.

**HELCY D. ALON** currently a Master of Engineering student from the Technological Institute of the Philippines. Her current research interests include Data Science and Embedded Systems.

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