

AI-Based Detection of Legal Violation for Shared Electric Scooters

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Abstract—Recently, with the rise in the use of shared electric scooters, illegal operation of Personal Mobility (PM) is becoming a social issue. To address these issues, some local governments are implementing various measures, such as amending the Road Traffic Act to enhance traffic safety. However, most current crackdown methods rely on citizen reports, and their efficiency needs to be improved. This study focused on systematically managing and resolving the issue of illegal driving of shared electric scooters through the utilization of Artificial Intelligence (AI) technology. To this end, we developed an illegal driving detection system using You Only Look Once version 5 (YOLOv5) image recognition technology. This system detects electric scooters being illegally driven in real-time and determines the fine for the violation. Therefore, the developed system is expected to provide useful information to relevant organizations for efficiently managing and resolving the issue of illegal driving of shared electric scooters.

Keywords—Artificial Intelligence (AI), You Only Look Once version 5 (YOLOv5), Personal Mobility (PM), Automated Fare Collection (AFC), electric scooters

I. INTRODUCTION

Recently, Personal Mobility Devices (PMDs) have become a convenient mode of transportation for short distances, and the number of users is increasing every year [1]. According to the market research firm Grand View Research, the global Personal Mobility (PM) market is expected to grow at an average annual rate of 5.8% by 2028 from KRW 13 trillion in 2020, and the domestic market is growing at a faster pace. The Korea Transport Institute predicts that the domestic PM market will grow at an average annual rate of more than 20% [2]. Various traffic laws are being proposed by governments in each country to improve the convenience of personal mobility devices. As personal mobility devices become integrated into the transportation system, they have a positive impact on improving transportation mobility. However, negative aspects are also being raised. The biggest issue among these is that the majority of personal mobility device users violate traffic laws [3]. Typical traffic laws violated by PM users include not wearing a safety helmet, exceeding

passenger capacity, driving without a license, and driving under the influence of alcohol.

First, due to the low speed of the electric scooter and the small wheels, the risk of accidents and the degree of injury is higher compared to other means of transportation [4]. Consequently, if you do not wear a safety helmet [5], you may suffer more serious injuries. Therefore, the Korean government mandates the wearing of safety helmets through traffic laws. However, there is an issue that few users actually comply with the law [6].

Secondly, if the weight limit is exceeded, the steering becomes sluggish, reducing the ability to respond to situations. The excessive weight also makes it easier to lose balance even with a slight shake. As a result, the accident rate increases when two people are riding compared to riding with one person [7]. Additionally, most shared electric scooters have a weight limit of approximately 110 kg. When two or more people ride together, the increased weight on the electric scooter raises the risk of damage, such as functional failure or missing parts. This damage problem is directly related to the sustainability and safety issues of electric scooters. Therefore, only a limited number of people should ride the electric scooters [8].

Therefore, in this study, we aim to contribute to improving road safety and traffic flow by establishing a detection system for illegal acts that occur while riding an electric scooter. For this purpose, the You Only Look Once version 5 (YOLOv5) is used to detect non-wearing of helmets and multiple passengers boarding in real time. The existing Regions with Convolutional Neural Networks (R-CNN) [9] method divides the image into several pieces and analyzes the image using a Convolutional Neural Networks (CNN) model. Therefore, looking at one image was like analyzing multiple images. However, YOLO has the feature of skipping this process and viewing the image only once. It can achieve six times faster performance than the existing R-CNN. Afterwards, a system was developed to identify users and collect fines on the web. Maria DataBase (DB) was used as the database to automatically collect fines for illegal activities detected through the system, and Amazon Web Services (AWS) was used to transmit this data to the server.

The structure of this paper is as follows. Section II describes the proposed system. Section III explains the learning performance of the custom YOLOv5s model.

Afterwards, Section IV discusses the test results of the learned custom YOLOv5s model. Finally, Section V concludes this paper.

II. PROPOSED SYSTEM

This section describes the overall structure of the proposed system. We selected electric scooters as the target of the proposed system from various PMs. First, the conceptual diagram of the proposed system is presented in Fig. 1.

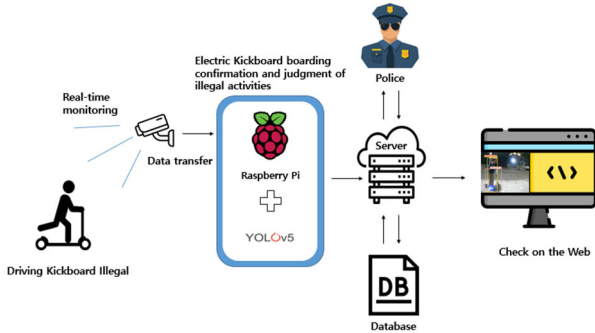


Fig. 1. Conceptual diagram of proposed system.

As shown in the figure, the proposed system can be divided into three main components. The first component is an infrared camera, which captures data by recording the road in real-time. The second component is the AI engine, which utilizes trained models to detect law-breaking behavior by PM users. Lastly, the third component involves transmitting the detection results from the AI engine to the database and police for issuing fines via a webpage. By entering user information on this webpage, you can view photos, timestamps, and fines of violations. The following subsections describe each function in detail.

A. Data Collection

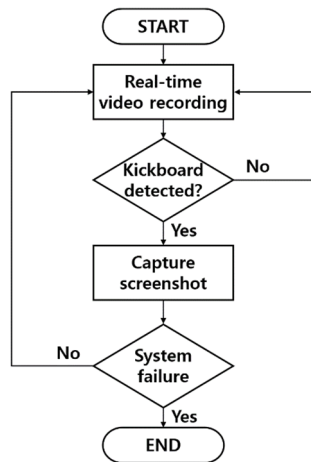


Fig. 2. Flowchart of data collection.

This subsection describes the first component of the system, which is the data collection. The key elements of the data collection are the camera and the driving Main Control Unit (MCU). In this study, the Raspberry Pi 4 was

used as the MCU to enable integration with an AI engine. A Raspberry Pi camera was used in this case for compatibility with the Raspberry Pi 4.

Data collection proceeds as follows. First, cameras installed on the road capture real-time images. Next, they capture the electric scooter as it passes by and save the screenshot. The saved screenshots are later input into the AI model to determine if the driver is driving illegally. The decision to use the electric scooter is determined by an AI model, as explained in the following subsection. The flowchart of the data collection process described above is presented in Fig. 2.

B. YOLOv5

This subsection explains the AI technology, which is the core of the proposed system. This study utilized YOLOv5 as an AI model to detect instances of law violations. The main feature of YOLOv5 is its utilization of a single neural network structure, which simplifies and speeds up its configuration. With these characteristics, it was judged to be suitable for processing real-time data. The detailed model of YOLOv5 includes s, m, l, and x. The YOLOv5s model is a lightweight model that offers a certain level of object detection performance while maintaining a high frame rate. Therefore, this study selects the YOLOv5s architecture, known for its fast real-time object detection capabilities and designed to facilitate detection with minimal labeling in typical environments.

Afterwards, customization of the YOLOv5s model was performed. The aim of this study is to determine whether an individual is using a scooter and to detect illegal activities performed by the rider. Therefore, two YOLOv5s models were applied sequentially. The first object recognition model is “RIDE”. Because this distinguishes between scooter riders and non-riders, only Ride is used as a class. The second object recognition model is “Violation”. The system captures photos of passengers from the “RIDE” model and detects violations of the law. For this purpose, a total of five classes were utilized. Each class is divided into Helmet and Non-Helmet depending on whether a helmet is worn, Kickboard to indicate the presence or absence of a electric scooter to prevent errors, and Person and People depending on the number of persons.



Fig. 3. Dataset labelling of RIDE detection model.

To distinguish the different classes mentioned above, data sets were collected from a real environment. The data was collected both during the day and at night to ensure

the model’s robust performance. The collected data was labeled using Roboflow [10]. For the “RIDE” model, the electric scooter rider was labeled throughout the entire image, as shown in Fig. 3. In the case of the “Violation” model, violations were labeled in the cropped image using the “RIDE” model, as shown in Fig. 4. The labeled dataset is utilized to train the YOLOv5s model. The learning performance is analyzed in detail in Section III.

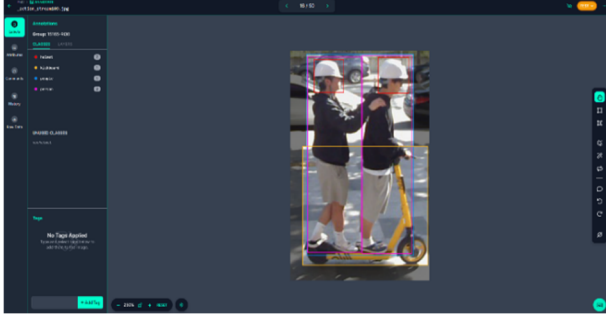


Fig. 4. Dataset labelling of Violation detection model.

C. Web Page

This subsection explains the detailed functions of the web page. As mentioned earlier, the webpage was implemented using AWS. The implemented web page hosted the web application by establishing a stable and scalable cloud computing environment using AWS EC2 instances. Users can access scooter enforcement information anytime, anywhere, and check real-time updated data. In addition, MySQL on AWS RDS was used to manage data, and AWS S3 was utilized to securely store images and files. A web page was developed based on the foundation mentioned above. Through this webpage, users can conveniently view and pay fines for scooter violations, check enforcement times, and access their law violation records. Additionally, users can check their law violation records through this webpage.

III. MODEL TRAINING PERFORMANCE

In this section, we present the results of training the YOLOv5s model using the previously constructed dataset. To evaluate the performance of the proposed YOLOv5s model, we utilize the F1-Score, Precision-Recall (PR) curve, and mean Average Precision (mAP) indicators.

Precision and recall can measure the model’s performance in binary classification by calculating each indicator. This can be done using the confusion matrix, which shows the relationship between predictions and actual values in a matrix format. Precision and recall for each class can be derived from the confusion matrix. Precision and recall are defined as Eqs. (1) and (2), respectively.

$$Precision = \frac{TP}{TP+FP} \tag{1}$$

$$Recall = \frac{TP}{TP+FN} \tag{2}$$

where, True Positive (TP) refers to a scenario in which the model predicted a positive outcome and it actually turned out to be positive, False Negative (FN) refers to a situation in which the model predicted a negative outcome but it actually turned out to be positive. False Positive (FP) refers to a case where the model predicts a positive outcome, but it is actually negative. True Negative (TN) refers to a case where the model predicts a negative outcome, and it is indeed negative. TP, TN, FP, and FN of each class can be obtained from the confusion matrices of Figs. 5 and 6.

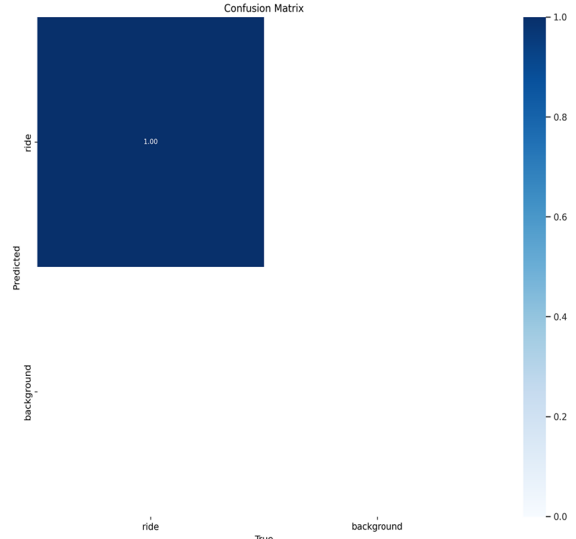


Fig. 5. Confusion matrix of RIDE model.

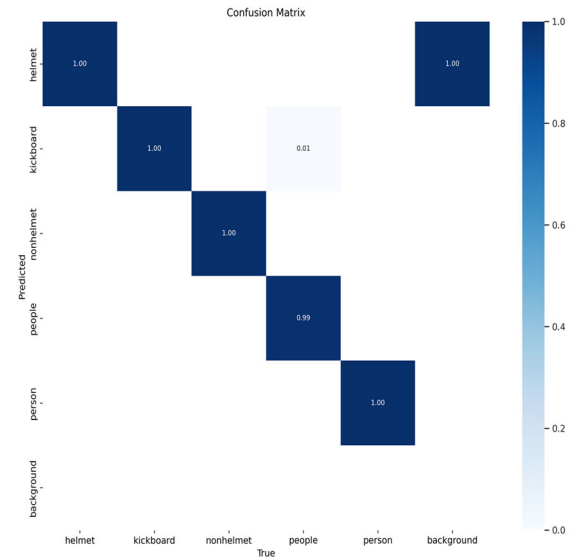


Fig. 6. Confusion matrix of Violation model.

The results of the figure are summarized in Table I. The F1-Score is the geometric mean value of precision and recall. It is an evaluation index that considers both precision and recall of the model. The higher the F1-Score, the better the model’s performance. The F1-Score is defined as follows Eq. (3).

$$F1 - Score = 2 \times \frac{Precision+Recall}{Precision \times Recall} \tag{3}$$

TABLE I. PRECISION OF EACH MODEL CLASS

Name of model	Class	Precision
RIDE	Ride	1.0
Violation	Helmet	1.0
Violation	Non-helmet	1.0
Violation	Kickboard	1.0
Violation	Person	1.0
Violation	People	0.99

The F1-Scores of the two models obtained from the confusion matrix are as follows. The “RIDE” model scored 1, and the “Violation” model also scored 1. The PR curve is a graph that displays recall on the x-axis and precision on the y-axis for all potential classification thresholds. The recall rate represents the proportion of actual positive samples that the model correctly classifies as positive. A model located in the upper right corner indicates better performance. The precision-recall curve values of both models are shown in Table II.

TABLE II. PR-CURVE VALUES OF EACH MODEL

Name of model	Precision-Recall Curve Value	
	Class	mAP50
RIDE	ride	0.995
	Helmet	0.995
	Kickboard	0.994
Violation	Non-helmet	0.993
	People	0.995
	Person	0.995

As depicted in the figure, the PR curve of Ride, a class in the “Ride” model, was measured at 0.995. For the classes “helmet”, “kickboard”, “non-helmet”, “people”, and “person” under the “violation” category, the PR curves were 0.995, 0.994, 0.993, 0.995, and 0.995, respectively. Table III summarizes the learning performance, including mAP performance.

The proposed YOLOv5s model was evaluated using F1-Score, PR curve, and mAP. The “RIDE” model showed the best performance with an F1-Score of 1, while the “Violation” model exhibited high precision for each class. The PR curve analysis indicated that, both models performed exceptionally well, located at the top right, achieving high precision and recall simultaneously. Furthermore, both models achieved high mAP values, confirming their excellent detection accuracy. Considering a comprehensive evaluation of various performance indicators, the proposed YOLOv5 model is expected to accurately detect legal violations. The experimental results of the implemented model will be discussed in the following section.

TABLE III. TRAINING PERFORMANCE OF EACH MODEL

Name of model	mAP50-95	mAP50	Precision	Recall
RIDE	99.457	99.5	0.99969	1
Violation	86.521	99.433	0.99755	0.99885

IV. EXPERIMENT AND RESULTS

In this section, we present the results of testing using the learned model. First, we present the parameters used

during model training. The YOLOv5s model was trained in a Windows environment, and the weight file “Best.pt” was loaded onto the Raspberry Pi. At this time, the learning settings have the batch size set to 32 and the epoch set to 250. The first model was trained using 226 Train sets, 66 Validation sets, and 35 Test sets, out of the total 327 datasets, divided in a ratio of approximately 7:2:1. The second model was trained with 1,454 Train sets, 410 Validation sets, and 210 Test sets out of the total 2,074 datasets, divided in a ratio of approximately 7:2:1.

The results of detection using the learned model are shown in Fig. 9. Fig. 9(a) shows the detection result of the first RIDE model. As depicted in the figure, when a person is riding the kickboard, the system detects the action as “RIDE” and captures a screenshot, which is then stored in the MCU. Fig. 9(b) detects the violation class in the saved image using the RIDE model. In the figure, it is evident that 2 person classes, 1 People class, 1 kickboard class, and 2 non-helmet classes were detected.

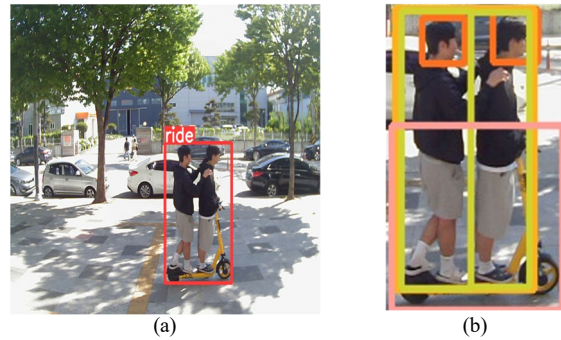


Fig. 9. Detect result: (a) RIDE model, (b) Violation model.

Once violation detection is completed, the information is automatically saved in text format for the purpose of imposing a fine based on the relevant content. The results saved in text format can be seen in Fig. 10. The stored data is transferred to the DB and implemented so that it can be accessed through a web page. The User Interface (UI) of the implemented web page can be seen in Fig. 11. As depicted in the figure, a penalty has been imposed for the violation that was previously documented in text format. Through this, it can be confirmed that a system that automatically collects fines for violations is in operation.

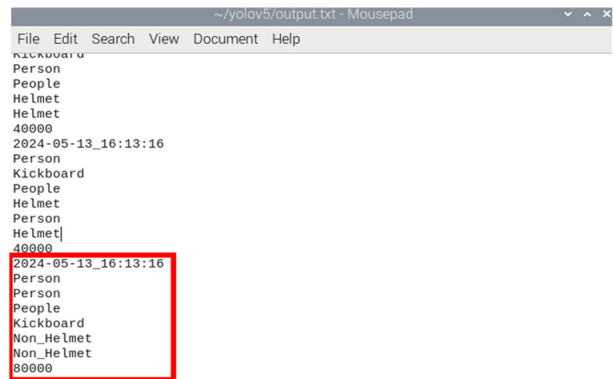


Fig. 10. Result of saving violation text.

Home > Case inquiry > Inquiry and payment for violations of shared E-scooter laws

Inquiry and payment for violations of shared E-Scooter laws

This is the details of Lim**'s violations of the law.

Time	Date	Illegal	Place	Penalty
16:13	2024-05-13	Not wearing a helmet Not wearing a helmet Multi-person boarding	Tech University of Korea	80,000

Fig. 11. Implemented webpage screen.

Afterwards, the proposed model was compared with existing models to evaluate its performance. In the case of existing models, a system that only detects helmet wearing was proposed, and detect accuracy was derived according to the data set size. Therefore, for validity when comparing with the proposed method, the performance of the existing model with a dataset size of 2600 was compared with that of the existing model. The performance of each model is presented in Table IV.

TABLE IV. PERFORMANCE COMPARISON OF EACH MODEL

Parameter	Proposed	Ref. [11]
No. data	2,074	2,600
Accuracy	99%	82.6%

As can be seen in the table, the proposed model achieved detection accuracy about 16% higher, because the proposed model detects violations secondarily after performing primary detection using the RIDE model. This means that when YOLO detects boarding through the RIDE model, an image of a certain size is CROP. When using a cropped image as training data for a secondary model, the data has relatively uniform characteristics, so more accurate detection performance can be obtained.

V. CONCLUSION

This study aims to efficiently detect illegal electric scooter driving, as well as to verify and process payments for legal violations. To promote compliance with traffic rules and enhance road safety, an AI-based electric scooter enforcement platform has been implemented. AWS was utilized to construct a webpage that detects illegal activities in real-time and automatically issues fines using the YOLOv5 model. As a result of the performance evaluation, the implemented system demonstrated high

overall accuracy. However, the recognition rate was low in specific situations where locations distant from the camera were identified. This confirms that when a location far from the camera is recognized and cropped in the RIDE model, the recognition rate decreases in the A violation of law model due to the poor image quality of the cropped photo. To address this issue, additional data labeling and model optimization tailored to specific situations are necessary, along with a camera that offers optimized FPS performance.

In the future, we plan to compare the performance of image processing using MCUs of NVIDIA. Moreover, we intend to integrate GPS into the electric scooter to distinguish between users. Our goal is to develop a system that classifies users, automatically alerts them of illegal activities, and enables real-time payment of fines.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

S. H. Oh and J. G. Kim conducted the research; S. H. Oh and S. H. Lee analyzed the data; S. H. Oh and S. H. Lee implemented the experiment; J. G. Kim validated the result; S. H. Oh wrote the original draft; J. G. Kim supervised the overall process; all authors had approved the final version.

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