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Tactile Paving Detection and Classification Method Based on Cyclist-Participatory Road Image Sensing

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Abstract

This study proposes a method for collecting tactile paving location information by acquiring road surface images and GPS data using a bicycle equipped with a compact camera and a GPS module. As a preliminary experiment, road surface images were captured under different camera positions and angles to identify optimal installation conditions. An object detection model based on YOLO11 achieved tactile paving detection with a mAP_{50} of 0.777. Subsequently, a Convolutional Neural Network (CNN) based on ResNet18 classified tactile paving types (guiding or warning) with a macro-F1 score of 0.898. These results demonstrate the feasibility of the approach while highlighting challenges such as model optimization for camera placement and expanding training data.

CCS Concepts

• **Information systems** → **Mobile information processing systems**; **Location based services**; • **Computer vision** → **Object detection**; • **Networks** → *Sensor networks*; • **Applied computing** → Digital government.

Keywords

Participatory Sensing, Bicycle, Tactile Paving, Image Recognition, Object Detection, Smart City

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1 Introduction

The population of visually impaired individuals in Japan was reported to be approximately 273,000 as of fiscal year 2022 [5]. Tactile paving plays a crucial role as a barrier-free facility supporting the safe and smooth mobility of visually impaired individuals. However, many installed tactile paving systems have deteriorated over time due to wear, fading, and other factors. Such deteriorated blocks are difficult for visually impaired individuals to recognize and can pose serious safety hazards. The report of the Administrative Counseling Center, Ministry of Internal Affairs and Communications, titled “Appropriate Installation and Maintenance of Tactile Paving and Related Facilities for the Visually Impaired” [7], pointed out as many as 341 deficiencies in certain sections of Okinawa Prefecture, highlighting the challenges of on-site maintenance. Therefore, regular inspection and maintenance are indispensable to ensure both the safety and usability of tactile paving.

The inspections of tactile paving are primarily conducted through foot patrols, bicycle patrols, or vehicle patrols. This approach incurs high human and time costs, making it difficult to achieve sufficient inspection frequency and coverage. According to the report published by Kanto Regional Administrative Evaluation Bureau, Ministry of Internal Affairs and Communications, “Survey on the Maintenance and Management of Tactile Paving for the Visually Impaired” [6], the national highway offices in Omiya, Tokyo, and Yokohama conduct walking inspections once every one to two days, but the surveyed sections are limited to only 1 km for each day. Furthermore, some local governments conduct inspections only once a year or on an irregular basis, indicating persistent challenges in establishing a nationwide maintenance system for tactile paving. From these backgrounds, the automatic and periodic acquisition of information on the placement and deterioration of tactile paving could streamline inspection work and substantially reduce labor costs.

In this study, we aim to realize a system that collects road surface images while riding a bicycle through participatory sensing and visualizes the placement and deterioration of tactile paving on a map. In the future, we envision expanding this system to support a wide range of mobility aids, such as wheelchairs, strollers, and white canes, thereby realizing a more efficient information collection framework.

Specifically, this paper investigates a method for acquiring road surface images and location information while riding a bicycle equipped with a compact camera and a GPS module, followed by detecting tactile paving using an object detection model and classifying block types using a CNN. The overview of the proposed research is shown in Figure 1.

2 Related Works

This section reviews prior studies on user-participatory sensing in urban environments, open data initiatives for tactile paving, and tactile paving detection using image recognition. We then position the present study within this context.

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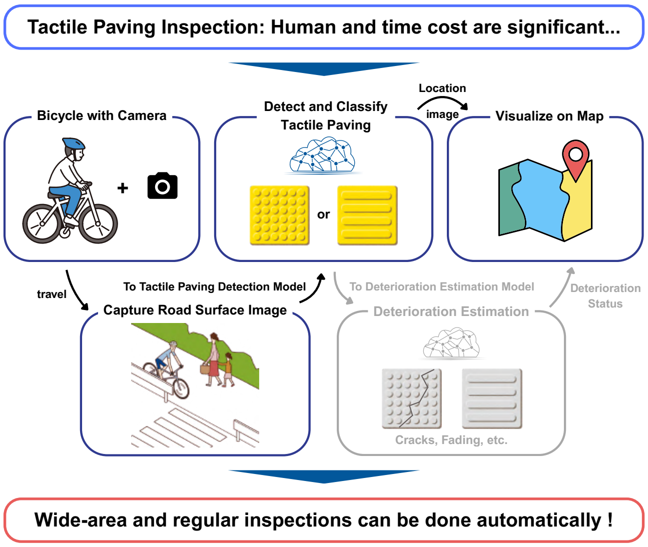


Figure 1: Contents of this paper

Research on using participatory sensing to understand urban conditions spans various domains. Examples include collecting streetlight information to evaluate nighttime road safety [3], gathering litter data [10], and developing platforms to enable such sensing [4]. Additionally, participatory sensing has been applied to detect road surface irregularities and quality using the GPS and inertial sensors of smartphones mounted on bicycles or cars. Attaching sensors to highly mobile carriers allows for more efficient, large-scale collection of urban environmental data [8, 11, 16, 17].

Moreover, Tanaka [13] developed a web system using participatory GIS to centrally manage information on the installation status, condition, and managing organizations of tactile paving. However, data collection still relies on manual pedestrian surveys and registration. Consequently, the limited survey scope and frequency hinder large-scale and regular information updates.

Various studies focus on detecting tactile paving using image recognition [9, 12, 14, 15]. Chengyi et al. [9] improved the detection accuracy of the YOLOv7 object detection model by approximately 4.1% by integrating the CBAM (Convolutional Block Attention Module) attention mechanism. Takano et al. [12] proposed a detection method using the multi-objective genetic optimization algorithm NSGA-Ⅱ (Non-dominated Sorting Genetic Algorithm Ⅱ), which focuses on the linearity and yellow color of tactile paving. This successfully maintained high detection accuracy even with obstacles or significant illumination changes. Wakamatsu et al. [14] proposed extracting the regions of guiding and warning blocks from head-mounted wearable camera images using an FCN (Fully Convolutional Network). This method achieved a recall rate exceeding 84% and demonstrated stable detection from a walking viewpoint. Wang et al. [15] proposed a real-time inspection method using UAVs equipped with fisheye cameras. By introducing the Lightweight Shared Detail Enhanced Oriented Bounding Box (LSDE-OBB) head into YOLOv8, they reduced parameters by approximately 25% without significantly compromising recognition accuracy.

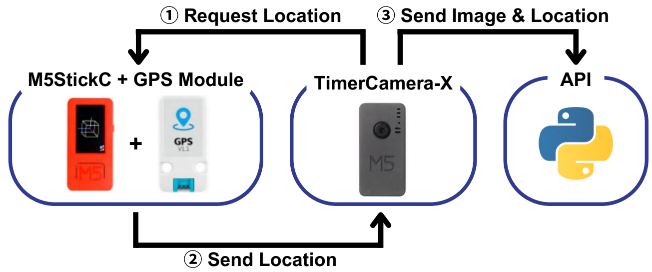


Figure 2: Overview of the Sensing System

While various image recognition methods exist for tactile paving detection, the training images used in references [9, 12] are ideal, featuring minimal blur and clear blocks. Conversely, images captured during cycling often suffer from motion blur and distortion due to higher speeds, raising concerns about reduced detection accuracy with existing methods. Furthermore, although [15] enables real-time, wide-area inspection, it requires specialized UAV operation skills. Therefore, this research aims to construct a system that can stably detect tactile paving even under low image quality conditions, utilizing easily accessible bicycles.

3 Proposed Method

We propose a participatory sensing system for acquiring the placement of tactile paving while cycling. In the following sections, we describe each step in detail.

Step 1: Constructing the Sensing System

First, we build a sensing system to collect tactile paving location data. An overview of the system is shown in Figure 2. The system operates by capturing an image, acquiring the corresponding position data from a GPS module, and sending both to an API. The next image capture is initiated immediately upon receiving a response from the API. The API is implemented using Flask[1], a lightweight Python web application framework.

The prototype uses M5Stack-manufactured devices. The camera is a TimerCamera-X[2], and the GPS module is the M5Stack GPS Unit v1.1[3], connected via Grove to an M5StickC[4]. As illustrated in Figure 2, for device coordination, the TimerCamera-X sends location requests to the M5StickC. The M5StickC retrieves data from the GPS module and returns it to the TimerCamera-X for integration.

Step 2: Capturing Road Surface Images via Bicycle

To capture road surface images along with location data, a compact camera and a GPS module are mounted on a bicycle. Because bicycles come in various frame types, such as cross bikes or utility bikes, it is preferable to choose a mounting location that is common to all frame types and does not interfere with riding. Furthermore, since bicycles generally travel on the left side of the road in Japan, the camera is intended to be mounted on the left side of the bicycle.

[1]https://flask.palletsprojects.com/
[2]https://docs.m5stack.com/en/unit/timercam_x
[3]https://docs.m5stack.com/en/unit/unit-gps%20v1.1
[4]https://docs.m5stack.com/en/core/m5stickc

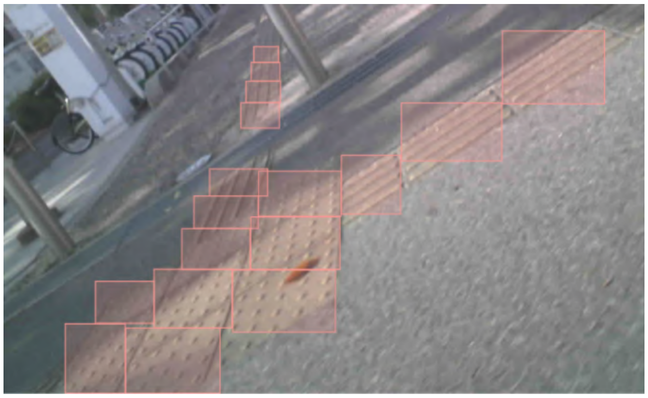


Figure 3: Example of annotation

Once powered on, the system automatically acquires road surface images and corresponding location data while the user rides normally.

Step 3: Detecting Tactile Paving Using YOLO11

Next, an object detection model is trained using the road surface images collected in **Step 2**. This paper employs YOLO11 [1] as the object detection model.

For training, images containing tactile paving are selected, and bounding boxes are annotated around each block. This annotation task performed by author (1 person). Images captured during cycling may exhibit motion blur or distortion. In such cases, enclosing the entire tactile paving within a bounding box may include excessive background, which can degrade detection accuracy by causing the model to learn irrelevant features. Therefore, bounding boxes are positioned to include the tactile paving area as centrally as possible. Additionally, images with severe motion blur where tactile paving boundaries are unclear are excluded from the training dataset. For tactile paving inspection, detected blocks should be sufficiently contained within the image. Since regular photography allows multiple recordings of the same location, it is unnecessary to force detection of blocks that are not fully visible. Therefore, we annotated tactile paving that is visible at least 70% of the total. For example, in Figure 3, tactile paving is annotated with red rectangles. However, the paving at the far right edge of the image is only partially visible and is therefore not annotated.

Moreover, this study uses images captured from multiple camera positions for training, aiming to develop a general-purpose model that is independent of camera installation position.

Step 4: Classifying Block Types Using a ResNet18

Finally, a model is constructed to classify the type of tactile paving detected in **Step 3**. This paper employs ResNet18 as the CNN.

The training and test datasets are constructed by cropping annotated regions from the images used for the object detection model. Furthermore, to improve classification performance with a small dataset and to reduce training time, transfer learning is applied using a pre-trained model.

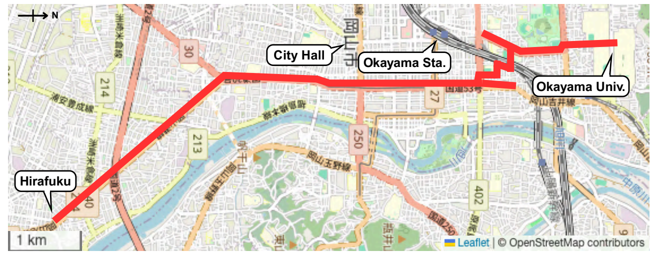
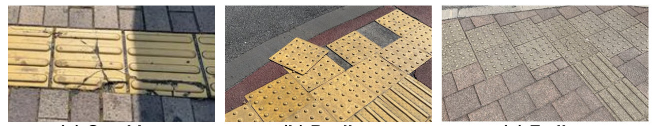


Figure 4: Survey area (shown as red lines)



(a) Cracking (b) Peeling (c) Fading

Figure 5: Degraded tactile paving

4 Experiments and Evaluation

This section describes four preliminary experiments based on the proposed method presented in Section 3.

4.1 Preliminary Survey of Tactile Paving Installation Conditions

This section describes a survey conducted in Okayama City to investigate the installation and deterioration status of tactile paving, as well as the feasibility of capturing images of tactile paving from a bicycle.

4.1.1 Survey Overview. This survey targeted an approximately 11.8 km route from Minami Ward in Okayama City to Okayama University, as shown in Figure 4. It was conducted on foot, the mainstream method for such field surveys. The installation and deterioration status of tactile paving were recorded using the participatory location-based photo collection platform,"Repot" [2]. For assessing the feasibility of photographing tactile paving from a bicycle, the survey assumed cycling on the roadway-adjacent side of sidewalks where bicycle passage is currently permitted. This assumption accounts for the amendment to the Road Traffic Act of Japan scheduled for April 2026, which will restrict bicycle access to sidewalks.

4.1.2 Survey Results. Of the approximately 11.7 km surveyed route, tactile paving was installed along about 8.0 km. Of this installed length, approximately 6.9 km was accessible for image capture while cycling. Furthermore, numerous instances of deterioration, such as damage and fading, were observed. Examples are shown in Figure 5.

The pedestrian survey required approximately six hours to complete. Considering that actual maintenance and inspection tasks necessitate recording detailed information on installation and damage, these results highlight the considerable time and human costs associated with tactile paving upkeep.

4.2 Data Collection

This section describes a road surface photography experiment using a bicycle equipped with a compact camera.

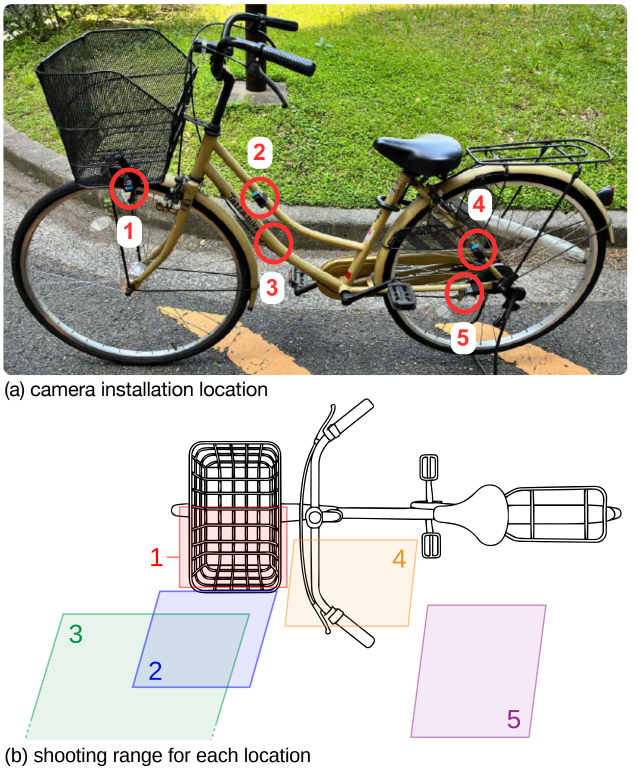


Figure 6: (a) Camera installation locations (1: Under front basket, 2: Under handle bar/top tube, 3: Under handle bar/down tube, 4: Rear wheel/seat stay, 5: Rear wheel/chain stay), and (b) their shooting ranges

Table 1: Camera angle settings by camera installation

Installation Location	Camera Angle
1: Under front basket	Directly below
2: Under handle bar/top tube	Diagonally forward
3: Under handle bar/down tube	Diagonally sideways
4: Rear wheel/seat stay	Front
5: Rear wheel/chain stay	Side

4.2.1 *Camera Settings Using Arduino.*

The TimerCamera-X[2] used in this experiment can be configured for resolution and image quality via Arduino. Resolution options include XGA, SXGA, and QXGA, while image quality can be specified as an integer from 0 to 63, with lower values corresponding to higher quality. These settings were investigated under outdoor conditions simulating actual operation to determine a combination that allows stable image capture and transmission.

The investigation revealed that when the image file size exceeded approximately 300 kB, the camera's memory could potentially overflow. Therefore, the most suitable settings for clear and stable imaging were found to be: resolution SXGA (1280×1024) and image quality 30.

4.2.2 *Adjusting Camera Placement and Angle.*

To investigate optimal device placement and camera angles for detecting tactile paving, cameras were installed at five locations shown in Figure 6 (a) to capture road surface images. For this experiment, a standard utility bicycle was used, and camera angles were adjusted for locations 2 to 5 as shown in Figure 6 (b). A shallow camera angle (close to horizontal) allows for a wider field of view, but tends to produce unclear images of tactile paving and raises privacy concerns due to the inclusion of pedestrians, houses, and other objects. In contrast, a steep camera angle (close to vertical) limits the area captured but is expected to capture each tactile paving more clearly.

Table 2: Breakdown of dataset capture locations

Installation Location	Number of Training Data	Number of Test Data
1	54	77
2	123	83
3	0	87
4	174	87
5	50	0

Table 1 summarizes the camera angle settings for each installation location, and Figure 7 shows examples of road surface images captured under those settings. For installation location 1, image capture was only possible when the bicycle had a basket and was sufficiently close to tactile paving. Nevertheless, compared to other locations, this setting produced the clearest images of tactile paving. At installation location 4, depending on the timing of capture, the user's feet occasionally appeared in the image, potentially hindering image collection. At installation location 5, the proximity of the camera to the ground tended to cause significant motion blur. From these observations, it was determined that installation locations 1, 2, and 3 provided camera settings with minimal motion blur and fewer obstructions in the images.

4.3 Tactile Paving Detection Using YOLO11

This section describes the detection method for tactile paving using the object detection model YOLO11 and its evaluation, utilizing the images collected in Section 4.2.

4.3.1 *Model Training and Evaluation.*

First, following the method proposed in Section 3, we annotated the training data. A training dataset consisting of 320 images for training and 81 images for validation (a total of 401 images) was created. Using this dataset, we trained the lightest YOLO11 model, `yolo11n.pt`, for 50 epochs. After training, to evaluate the model's performance, we collected and annotated 334 new road surface images to create a test dataset. Since the dataset was created in chronological order of capture dates, the number of images per camera location is uneven. The breakdown is shown in Table 2.

We evaluated the model using the entire test dataset as well as for each camera installation location. The results are summarized in Table 3. The evaluation metrics used were Precision, Recall, and Mean Average Precision (mAP_{50}). Looking at the results, the average mAP_{50} across the entire test dataset was 0.777, while some individual installation locations achieved higher values. This suggests that constructing separate models for each installation location could simplify the detection task and potentially improve performance. Further investigation is required to validate this hypothesis.

Figure 7: Road surface images during bicycle travel

Table 3: Evaluation of tactile paving detection

Evaluation Metrics	Overall	Installation Location			
		1	2	3	4
Precision	0.856	0.713	0.776	0.940	0.879
Recall	0.668	0.742	0.789	0.595	0.729
mAP_{50}	0.777	0.780	0.824	0.711	0.806

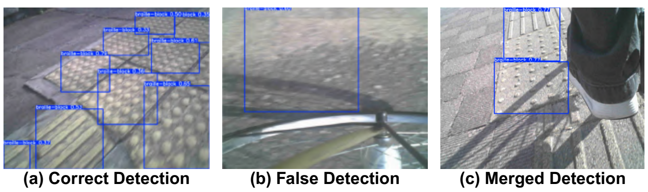


Figure 8: Example detection results

4.3.2 *Discussion.* Figure 8 shows examples of detection results obtained using the aforementioned model on the test dataset.

In the example of Figure 8 (a), even in images with some motion blur, each tactile paving was detected individually. In contrast, in the example in Figure 8 (b), the asphalt pavement was misdetected. This is thought to be because shadows and patterns on the pavement formed features similar to those of the guiding blocks. To suppress such misdetections, adding background images without tactile paving to the training data is considered effective.

Finally, in the example of Figure 8 (c), two different types of tactile paving are being detected as identical. This is likely due to either a small amount of training data for warning blocks or insufficient training data for situations where different types of tactile paving appear side by side. As an improvement, increasing the amount of training data that includes warning blocks in diverse situations could be considered.

4.4 Block Types Classification Using ResNet18

This section describes and evaluates a ResNet18-based classification method for tactile paving types, using the blocks detected in Section 4.3 as input.

4.4.1 *Model Training and Evaluation.* First, following the methodology proposed in Section 3, we constructed the training and test datasets by cropping the annotated regions from 735 images. The breakdown of guiding and warning blocks within each dataset is shown in Table 4.

Next, we performed transfer learning on a pre-trained ResNet18 model using the training dataset, setting the parameters to 10

Table 4: Breakdown of block types in the dataset

Block Type	Training Data	Test Data
Guiding Block	453	1019
Warning Block	74	240

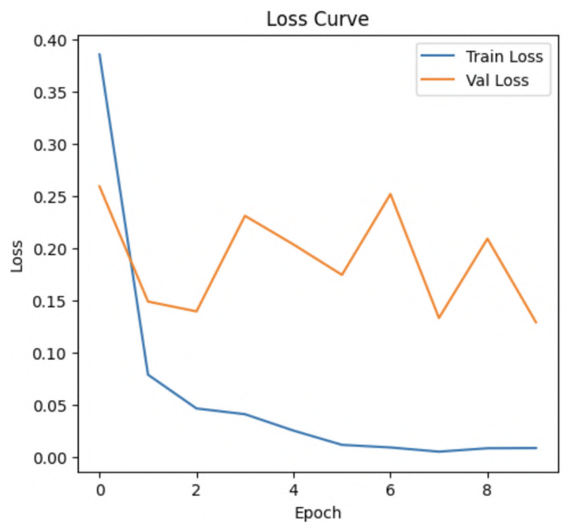


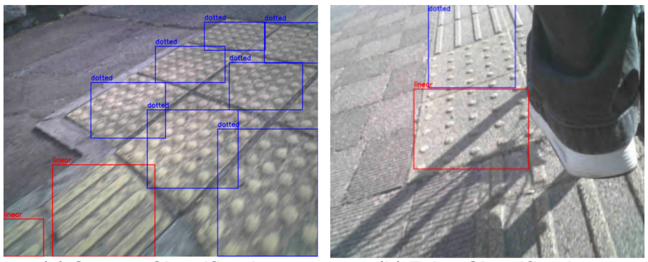
Figure 9: Loss curve

epochs and a batch size of 32. We used Cross-entropy loss as the loss function and Adam as the optimizer. The loss curve obtained during training is shown in Figure 9. The persistent gap between the train loss and the validation loss suggests signs of overfitting.

Finally, we evaluated the model. Since the test data exhibits significant class imbalance, we balanced the number of test cases per class by randomly selecting 74 guiding block test cases (equal to the number of warning blocks). Evaluation metrics included Precision, Recall, and F1-Score. Considering the training data bias, we also used macro-averaged-Recall and macro-F1, prioritizing the latter due to its balanced consideration of Precision, Recall, and dataset imbalance. The evaluation results are presented in Table 5, with classification examples shown in Figure 10. The results show a macro-F1 of 0.892, with high scores also recorded for other metrics. Despite the signs of overfitting, the improved classification performance likely stems from the input data being small, cropped sections of tactile paving rather than the entire image, resulting in minimal feature differences between the training and test sets. Examining the classification examples in Figure 10: (a) shows successful classification even when guiding and warning

Table 5: Evaluation of tactile paving classification

Evaluation Metrics	Score
Precision	0.824
Recall	0.975
F1	0.881
macro-averaged-Recall	0.872
macro-F1	0.871



(a) Correct Classification **(b) False Classification**

Figure 10: Example classification results

Table 6: Evaluation results by dropout rate

Evaluation Metrics	Dropout Rate			
	0.3	0.4	0.5	0.6
Precision	0.779	0.777	**0.847**	0.802
Recall	**1.000**	0.987	0.973	0.987
F1	0.876	0.869	**0.906**	0.885
macro-averaged-Recall	0.858	0.851	**0.899**	0.872
macro-F1	0.855	0.849	**0.898**	0.870

blocks are mixed. Conversely, (b) shows the misclassification of warning blocks as guiding blocks, which we attribute to the limited amount of training data for warning blocks. Furthermore, detection errors that cause blocks from different classes to be input together prevent classification. Therefore, improving the performance of the detection model is necessary.

4.4.2 Discussion. The model constructed in Section 4.4.1 demonstrated high classification performance but showed signs of overfitting. Therefore, this section aims to mitigate overfitting using dropout and further improve classification accuracy. Training parameters such as the number of epochs were set identically to Section 4.4.1, and model training and evaluation were performed with dropout rates of 0.3, 0.4, 0.5, and 0.6. The evaluation results for model performance at each dropout rate are shown in Table 6. When the dropout rate was 0.5, the macro-F1 score reached its maximum, achieving a slight improvement in classification performance compared to before applying dropout.

5 Conclusion

This paper proposes a method for acquiring tactile paving location information and classifying block types using a bicycle equipped with a compact camera and a GPS module. The proposed approach successfully demonstrated that even images captured while cycling, which are prone to motion blur and distortion, can achieve tactile paving detection with mAP_{50} of 0.777 using the object detection model YOLOv11, and classification with a macro-F1 score of 0.898 using the CNN ResNet18.

However, we identified challenges, including the false detection of asphalt surfaces and the inability to classify when multiple blocks are erroneously detected as a single object. Moving forward, we plan to address these issues by expanding the training data and developing and verifying object detection models optimized for specific camera installation locations.

Acknowledgments

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