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Stereo Camera-Based Motor Vehicle Dimension Measurement with Luxmeter-Based Light Intensity Detection

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Abstract−Over Dimension and Over Loading (ODOL) vehicles require accurate and efficient dimension inspection systems to support transportation safety and regulatory compliance. This study proposes an automatic motor vehicle dimension measurement system based on stereo vision integrated with YOLOv8 object detection and luxmeter-based illumination monitoring. The system was developed using a Research and Development (R&D) approach involving stereo camera calibration, hardware-software integration, experimental testing, and validation against manual measurements. Two Logitech C270 USB cameras with a fixed 50 cm baseline were calibrated using a 9 × 6 checkerboard pattern and processed using OpenCV and Python. Vehicle and wheel objects were detected using YOLOv8 models with stereo disparity estimation performed using Semi-Global Block Matching (SGBM) and triangulation methods to calculate Overall Length (OAL), Front Overhang (FOH), Wheelbase (WB), Rear Overhang (ROH), and Overall Height (OAH). Environmental lighting conditions were monitored using a luxmeter under illumination ranges of 5,000-100,000 lux. Experimental results showed a stereo calibration success rate of 96% from 100 stereo image pairs. The developed system achieved average measurement accuracies of 98.58%, 98.92%, and 98.89% at testing distances of 7 m, 8 m, and 9 m, respectively, while the highest accuracy of 99.44% was obtained at the T_8M_LC configuration under stable illumination conditions. Operational efficiency analysis showed that the automatic measurement process, including image acquisition and computational processing, reduced total measurement time from 187 seconds in manual measurements to 5 seconds in the automated system, corresponding to an efficiency improvement of 97.32%. The results show that the proposed stereo vision system provides accurate, efficient, and lighting-robust vehicle dimension measurements suitable for automated motor vehicle inspection applications.

Keywords: Stereo Vision; Vehicle Dimension Measurement; YOLOv8

1. INTRODUCTION

Motor vehicle freight transportation supports the distribution of goods and contributes to the continuity of economic activities in society. Freight transport vehicles are specifically designed to carry various types of commodities and function as the main connector between producers and consumers within the supply chain system. These transportation modes are capable of delivering raw materials, semi-finished products, and finished goods efficiently across different regions. The existence of freight transportation significantly influences macroeconomic stability because distribution effectiveness determines the continuity of industrial and commercial activities [1]. In addition, freight transportation offers high operational flexibility through road-based vehicle distribution systems that support the continuity of land transportation networks [2]. The ability of freight vehicles to operate in diverse road conditions and transportation routes further strengthens their role as an essential component of national logistics infrastructure.

The delivery process in logistics activities consistently depends on freight transportation vehicles with varying specifications, capacities, and operational purposes [3]. These freight vehicles are generally utilized on different road terrains according to the designated road classifications and transportation regulations. Such flexibility allows freight vehicles to function effectively as last-mile transportation systems that connect logistics terminals with final destination points. Consequently, freight transportation not only serves the purpose of moving goods but also becomes an integral element within national distribution systems focused on efficiency, punctuality, and economic sustainability [4].

However, the increasing demand for higher transportation capacity often encourages operators to maximize cargo loads beyond the recommended standards. This situation is frequently considered more economically beneficial despite the potential technical and safety consequences involved. Therefore, improving the monitoring and measurement process of freight vehicle specifications becomes increasingly important to maintain transportation safety and operational compliance.

In efforts to improve delivery effectiveness, practices that violate transportation regulations are frequently encountered in freight operations. One of the most common violations involves Over Dimension and Over Loading (ODOL) vehicles, which create serious impacts on safety, vehicle performance, and road infrastructure conditions. Statistical data indicate that 27.78% of ODOL violations are related to overloading, while 84% are associated with over-dimension modifications, and ODOL trucks contributed to approximately 41% of road traffic accidents in Indonesia during 2020 [5].

These findings show that the enforcement of vehicle dimension and load regulations has not yet been fully effective in practical implementation. From a technical perspective, operating vehicles beyond their designed capacity can significantly increase braking distance and reduce driving safety. Excessive loading conditions may also decrease

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vehicle stability and driver controllability, particularly during emergency situations on highways. Furthermore, dimensional modifications that exceed regulatory standards can result in uneven load distribution, increasing the risk of vehicle rollover and accelerating the deterioration of critical components such as braking systems, suspension systems, and tires [6].

Vehicle dimensions are considered one of the primary factors contributing to overload conditions because enlarging the vehicle structure directly increases cargo capacity. Modifications involving additional length, width, or height in cargo compartments automatically create larger loading spaces that encourage operators to transport heavier goods. In many cases, vehicle owners intentionally modify vehicle dimensions to maximize transportation efficiency without considering technical limitations and regulatory compliance requirements [7]. These unauthorized modifications often result in vehicles that no longer conform to manufacturer specifications or road transportation standards. Such practices not only violate legal transportation regulations but also increase the risk of structural failure and traffic accidents involving other road users. Consequently, many vehicles currently operating on public roads exhibit dimensions that differ significantly from their original specifications [8].

In the process of motor vehicle inspection, measurement accuracy becomes a crucial aspect that cannot be neglected. Vehicle dimensions such as length, width, height, Front Overhang (FOH), Rear Overhang (ROH), and Wheelbase play essential roles in vehicle classification, technical evaluation, and safety regulation compliance. However, current inspection practices still predominantly rely on manual measurement methods that require direct human involvement [8]. Manual measurement techniques are generally time-consuming, highly dependent on operator precision, and vulnerable to inconsistencies caused by environmental conditions or subjective interpretation. As a result, the obtained measurements frequently lack consistency and operational efficiency compared with modern automated systems that offer higher precision and reliability [9]. Along with technological advancement, computer vision and digital image processing technologies provide more advanced solutions capable of improving measurement accuracy and automation efficiency [10].

One promising approach involves the implementation of stereo camera technology, which utilizes two cameras with different viewing angles to produce depth information from captured images. Through stereo vision and triangulation methods, object dimensions can be calculated digitally without direct physical contact with the measured vehicle [11]. However, conventional stereo vision methods still face significant technical limitations in outdoor environments, particularly when applied to vehicle measurements under natural lighting conditions. Variations in illumination intensity, shadows, occlusion, and specular reflections on shiny vehicle surfaces can reduce stereo correspondence accuracy and generate unstable disparity maps, ultimately affecting depth estimation precision. In addition, inaccurate object boundary detection and wheel localization may introduce dimensional estimation errors, especially for rear vehicle regions and upper body contours. These challenges show that robust object detection and environmental illumination monitoring are necessary to improve stereo vision measurement reliability in practical outdoor applications.

Therefore, several previous studies have explored vision-based approaches for object dimension and distance estimation, however, important limitations remain for practical vehicle inspection applications. Study [2] developed a binocular stereo vision system mounted on an unmanned aerial vehicle (UAV) for truck contour dimension measurement. Although the method showed promising dimensional estimation capabilities, the study focused primarily on contour extraction and did not incorporate deep learning-based vehicle and wheel localization under varying outdoor illumination conditions. Then, study [4] proposed a stereo camera-based distance measurement algorithm using triangulation principles and achieved high measurement accuracy. Nevertheless, the research was conducted under relatively controlled experimental conditions and did not evaluate vehicle dimension measurement performance in real inspection environments. Study [9] introduced Dist-YOLO, which combines object detection and distance estimation for real-time applications.

However, the system was designed mainly for object distance estimation and did not perform comprehensive vehicle dimensional measurements such as Overall Length (OAL), Front Overhang (FOH), Rear Overhang (ROH), Wheelbase (WB), and Overall Height (OAH). Furthermore, study [10] investigated stereo vision-based depth and object size estimation integrated with SLAM, while study [11] and. [12] reviewed various depth estimation approaches based on stereo vision and deep learning techniques. Although these studies showed the potential of computer vision for depth estimation, they did not specifically address automatic vehicle dimension inspection systems equipped with environmental illumination monitoring to ensure measurement stability under real-world outdoor conditions.

Therefore, a significant research gap remains in the development of an integrated vehicle dimension measurement system that simultaneously combines stereo vision, deep learning-based vehicle and wheel detection, and real-time illumination monitoring for reliable operation under varying outdoor lighting conditions encountered in motor vehicle inspection facilities. To address this gap, this study develops a stereo camera-based measurement system integrated with YOLOv8 object detection and luxmeter-based light intensity monitoring. The system is capable of automatically measuring Overall Length (OAL), Front Overhang (FOH), Wheelbase (WB), Rear Overhang (ROH), and Overall Height (OAH), while evaluating calibration performance, measurement accuracy, lighting robustness, and operational efficiency relative to conventional manual measurements.

The main contributions of this study are threefold. First, it proposes an integrated framework that combines stereo vision, YOLOv8-based object detection, and luxmeter-based illumination monitoring for vehicle dimension measurement. Second, it provides an experimental evaluation of measurement accuracy under outdoor lighting

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conditions ranging from 5,000 to 100,000 lux and testing distances of 7-9 m. Third, it shows the practical feasibility of automated vehicle inspection by achieving high measurement accuracy and significantly reducing inspection time compared with manual measurement procedures. These contributions support the modernization and digitalization of motor vehicle inspection processes.

2. RESEARCH METHODOLOGY

2.1 Reseach Location

This research was conducted at the Motor Vehicle Inspection Workshop, Campus 2 of the Politeknik Keselamatan Transportasi Jalan located on Jl. Abdul Syukur No.17, Margadana District, Tegal City, Central Java, Indonesia. The research activity was carried out during the 2025-2026 academic period, covering literature studies, proposal preparation, system assembly, calibration, experimental testing, and evaluation stages. The selected research location was considered appropriate because it provides a controlled environment for motor vehicle testing and dimensional inspection activities.

In this study, a stereo camera-based measurement system was developed to automatically estimate vehicle dimensions under different environmental lighting conditions. The developed system integrated stereo vision technology, digital image processing, and YOLOv8 object detection algorithms to improve the efficiency and accuracy of dimensional measurements. In addition, environmental light intensity was monitored using a luxmeter to evaluate the influence of illumination conditions on the measurement results.

2.2 Research Object

The primary research object in this study was a Mitsubishi L300 pickup vehicle used as the representative freight vehicle for dimensional measurement experiments. The vehicle was selected because it represents light commercial vehicles frequently used in logistics transportation and commonly subjected to dimensional modification practices associated with ODOL violations. The measured dimensional parameters included Overall Length (OAL), Overall Height (OAH), Front Overhang (FOH), Rear Overhang (ROH), and Wheelbase (WB). Experimental observations were conducted under outdoor environmental conditions with varying illumination intensities ranging from 5,000 lux to 100,000 lux to evaluate system robustness under real operational scenarios.

The research employed the Research and Development (R&D) method to design, develop, and experimentally evaluate the proposed measurement system [13]. The initial stage involved identifying field problems related to the absence of an automatic system capable of measuring vehicle dimensions rapidly and accurately. After problem identification, the research continued with data collection through direct observation, manual measurement, documentation, and environmental monitoring processes. Observations were performed on a Mitsubishi L300 pickup vehicle used as the testing object under real operational conditions. Manual measurements were conducted using measuring tapes, poles, water passes, chalk markers, and pendulum tools to obtain ground truth data for validation purposes.

Documentation activities were carried out by recording photographs of the measurement process and system outputs to provide empirical evidence of system functionality. Environmental data collection focused on measuring natural light intensity using a digital luxmeter during the testing period between 08.00 and 11.00 WIB to represent morning illumination variations.

2.3 Research Procedure

The system development stage consisted of hardware assembly, programming, calibration, and experimental validation processes. During hardware assembly, the stereo camera baseline was carefully determined and fixed because baseline variation directly affects calibration accuracy and depth estimation performance. A fixed stereo baseline of 50 cm was selected as a compromise between disparity sensitivity and practical installation constraints within the vehicle inspection environment. Considering the testing distances of 7-9 m, the baseline configuration was designed to maintain sufficient disparity resolution while minimizing stereo occlusion and geometric instability. Depth estimation uncertainty theoretically increases as object distance becomes larger; therefore, disparity refinement and sub-pixel optimization were implemented to reduce depth uncertainty during long-range measurements. The software development stage was performed using Python programming language in the Visual Studio Code (VS Code) environment integrated with the OpenCV library for image processing operations. Stereo camera calibration was conducted using a checkerboard pattern to determine intrinsic and extrinsic camera parameters based on pixel alignment and stereo correspondence techniques [14].

After calibration, the developed system was tested using both printed object images and real vehicle objects to evaluate system consistency under different testing scenarios. The obtained measurement outputs were subsequently compared with actual vehicle dimensions measured manually to determine system accuracy and operational feasibility. If the measurement outputs corresponded closely to actual dimensions, the developed system was considered capable of functioning according to its intended objectives. The flowchart research procedure shown in Figure 1.

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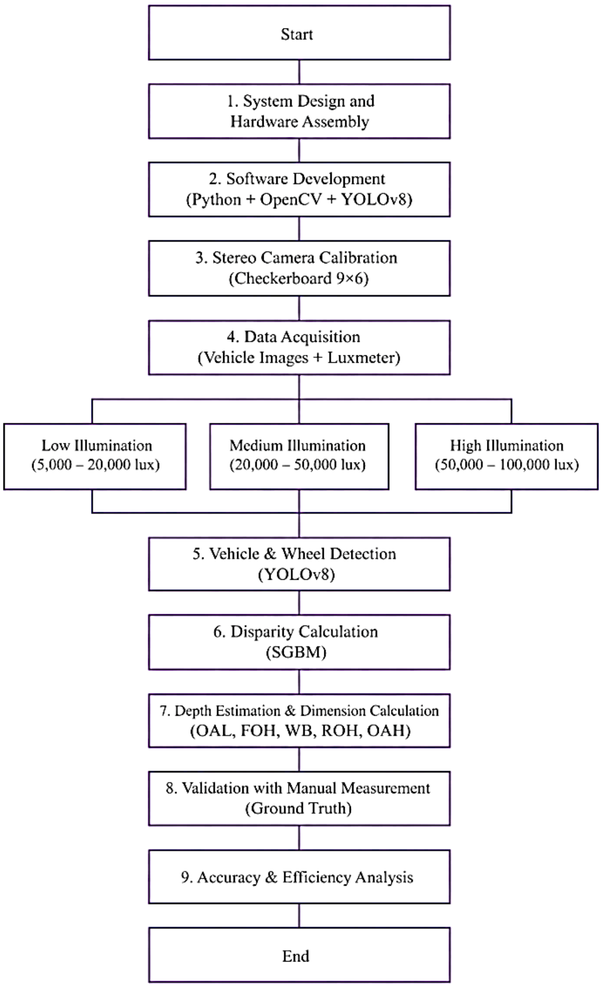

Figure 1. Research Procedure

The measurement process began by positioning the Mitsubishi L300 pickup vehicle on a flat and level surface to ensure consistent acquisition geometry, as shown in Figure 2.

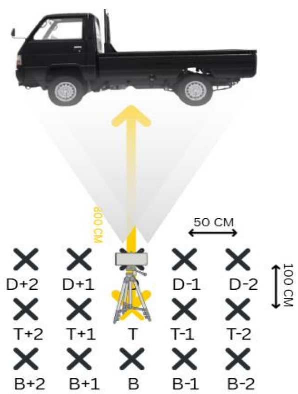

Figure 2. Stereo Image Acquisition Scheme and Camera Positioning Configuration

The stereo cameras were placed perpendicular to the vehicle object with a camera angle of 90° and camera height of 120 cm. The distance between the stereo camera and the midpoint of the vehicle object was set to 800 cm, while horizontal and vertical positional shifts were arranged at 50 cm and 100 cm, respectively. After positioning, the stereo camera system was connected to the programming interface for image acquisition and processing activities. Measurements were conducted under different environmental illumination conditions using a luxmeter as a light intensity monitoring device. Three illumination ranges were defined in this study, namely 5,000-20,000 lux, 20,000-50,000 lux, and 50,000-100,000 lux, representing low, medium, and high natural lighting conditions. The luxmeter sensor was positioned facing the vehicle object and camera acquisition direction to measure reflected environmental illumination received by the camera sensor during image acquisition sessions. This configuration was selected to

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better represent the effective lighting conditions influencing image quality, object detection performance, and stereo disparity estimation.

The developed system workflow consisted of several integrated computational stages beginning with stereo image acquisition from two synchronized cameras. The captured images were initially represented in RGB color format and subsequently converted into grayscale images to simplify image processing operations. Vehicle object detection was then performed using the YOLOv8 algorithm to identify vehicle regions and generate bounding boxes containing pixel coordinate information. The developed system utilized the YOLOv8s (Small) architecture due to its balance between computational efficiency and detection accuracy for real-time processing applications. The detection model employed transfer learning from pre-trained COCO weights and was further adapted using a custom vehicle-wheel dataset collected during the experimental process. The custom dataset consisted of manually annotated stereo vehicle images captured under varying outdoor illumination conditions and measurement distances. Following object detection, the Semi-Global Block Matching (SGBM) algorithm was applied to calculate disparity values between corresponding stereo image points. The disparity map generated from this process served as the basis for depth estimation and three-dimensional distance calculation.

In addition to the automated system, manual measurements were also conducted to provide reference data for validation and comparison purposes. The manual procedure involved three personnel using measuring tapes, poles, pendulum tools, chalk markers, and supporting instruments to determine vehicle dimensions conventionally. Vehicle positioning was standardized by placing the vehicle on a flat surface with the parking brake activated to prevent movement during measurement. Chalk markers were used to indicate reference points such as the front bumper, rear bumper, and wheel center positions. The overall vehicle length, height, wheelbase, Front Overhang (FOH), and Rear Overhang (ROH) were then measured manually using measuring tapes and poles. All obtained results were recorded systematically along with measurement duration and personnel involvement. This manual process served as the ground truth dataset against which the automatic stereo vision measurements were evaluated.

Data collection in this study applied triangulation techniques to improve the comprehensiveness and validity of the obtained results [15]. Three primary data sources were combined, including automatic system measurements, manual measurements as ground truth references, and environmental lighting conditions as control variables. Primary data consisted of stereo camera measurement outputs, manual dimensional measurements, environmental lighting conditions, image acquisition records, and processing time observations. Secondary data included scientific journals, technical books, articles, and previous studies related to stereo vision systems, image processing, and vehicle inspection technologies. The image acquisition process employed a static snapshot method in which images were captured at specific moments after environmental light conditions were considered stable. Testing was conducted during three observation periods, namely 08.00-09.00 WIB, 09.00-10.00 WIB, and 10.00-11.00 WIB, with three measurement sessions in each interval, resulting in a total of nine experimental datasets. This procedure allowed the evaluation of system performance under varying natural illumination conditions.

The research utilized several hardware and software components to support system development and experimentation. The primary processing device was an ASUS TUF Gaming F15 laptop equipped with a 12th Generation Intel Core i5 processor for programming and image processing operations. Stereo image acquisition utilized two Logitech C270 cameras with a maximum resolution of 720p at 30 fps, 3 MP image resolution, 4.0 mm focal length, and a 60° field of view. The stereo cameras were mounted on an Inbex IB-2R tripod with a maximum height of 170 cm and integrated water pass functionality to maintain camera stability during measurement. A custom stereo camera cover was also implemented to maintain fixed baseline distance and protect the cameras from physical disturbances. Furthermore, a 9×6 checkerboard pattern was employed for stereo calibration procedures to determine intrinsic and extrinsic camera parameters accurately [14]. Manual validation measurements were performed using conventional measuring tapes as reference instruments.

2.4 Research Evaluation

To evaluate environmental lighting stability during image acquisition, light intensity fluctuation analysis was performed using the equation (1).

$$\frac{\mathrm{Lux}_{\mathrm{max}}-\mathrm{Lux}_{\mathrm{min}}}{\mathrm{Lux}_{\ \mathrm{median}}} \times 100\ \% \tag{1}$$

where $\mathrm{Lux}_{\mathrm{max}}$ represents the maximum recorded light intensity, $\mathrm{Lux}_{\mathrm{min}}$ represents the minimum light intensity, and $\mathrm{Lux}_{\ \mathrm{median}}$ denotes the median lux value measured during the observation interval. Data were categorized as valid when the fluctuation percentage was less than or equal to 15%, while fluctuations above 15% required repeated measurement procedures. In addition, measurement efficiency analysis was conducted by comparing the time required for manual and automatic measurement methods. The efficiency percentage was calculated using the equation (2).

$$E(\%) = \frac{wm-ws}{wm} \times 100\% \tag{2}$$

where $E(\%)$ represents efficiency percentage, wm is manual measurement time, and ws denotes automatic system measurement time. Descriptive statistical analyses including average values, standard deviations, and measurement ranges were also applied to evaluate system consistency and accuracy comprehensively [16].

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Table 1. Comparison Between Manual and Automatic Measurement Methods

Parameter	Manual Measurement	Stereo Camera System
Instruments	Measuring tape, pole, pendulum, water pass, chalk, ladder	Stereo cameras, laptop, tripod
Measurement Time	08.00 WIB	08.00-11.00 WIB
Measured Parameters	Height, length, FOH, ROH, wheelbase	Height, length, FOH, ROH, wheelbase

The final stage of this research involved validating and analyzing the obtained measurement data. Automatic system outputs generated through stereo depth estimation and YOLOv8 object detection were compared directly with manual measurements to determine system accuracy. Statistical comparisons focused on dimensional parameters including vehicle length, height, wheelbase, Front Overhang (FOH), and Rear Overhang (ROH). Measurement consistency, environmental lighting influence, and processing efficiency were also evaluated comprehensively. If the resulting measurement errors remained within acceptable tolerances and no significant differences were observed between automatic and manual methods, the developed system could be considered valid and reliable for practical implementation. The proposed stereo camera-based measurement system showed potential advantages in reducing human error, improving operational efficiency, and supporting future digitalization of motor vehicle inspection systems.

3. RESULT AND DISUSSION

The implementation stage of the developed system was conducted after the completion of hardware assembly and software programming processes. At this stage, the stereo camera-based vehicle dimension measurement system was integrated through several procedures including software installation, hardware installation, camera calibration, application programming, and vehicle measurement testing. The developed system utilized two USB cameras configured as a stereo camera system, OpenCV libraries for image processing, YOLOv8 algorithms for vehicle and wheel detection, and Python programming language as the primary software environment. The implementation process showed that the integration between stereo vision technology and object detection algorithms was capable of supporting automatic vehicle dimension measurements in real-time conditions. In addition, the system was equipped with graphical user interface (GUI) functionality to simplify user interaction during measurement operations.

3.1 System Development and Implementation

Three primary program files were developed in this research, namely capture.py, calibrate.py, and main.py. The capture.py program was designed to acquire synchronized checkerboard images from the left and right stereo cameras for calibration purposes. The calibrate.py program was developed to process stereo calibration using checkerboard image pairs and determine intrinsic and extrinsic camera parameters. Meanwhile, the main.py program functioned as the primary operational system responsible for vehicle detection, wheel detection, depth calculation, vehicle dimension estimation, and automatic data storage into Excel files.

3.1.1 Software and Library Development

The developed application integrated several software libraries including OpenCV, NumPy, Pillow, CustomTkinter, Ultralytics YOLOv8, Torch DirectML, and OpenPyXL. Each library contributed to specific computational tasks such as image processing, graphical interface rendering, neural network inference, and data recording operations, as shown in Table 2.

Table 2. Software and Libraries Used in System Development

No	Software	Function
1	Visual Studio Code	Used for writing, editing, and executing Python source code
2	Python	Main programming language for system operation
3	FFmpeg	Used to access USB cameras through DirectShow
4	OpenCV	Used for image processing, checkerboard detection, camera calibration, and frame processing
5	NumPy	Used for numerical computation and matrix processing
6	Pillow	Used for image conversion within GUI display
7	CustomTkinter / Tkinter	Used for graphical user interface development
8	Ultralytics	Used to execute YOLOv8 object detection models
9	Torch DirectML	Used for model inference acceleration through DirectML
10	OpenPyXL	Used for saving measurement results into Excel files

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3.1.2 Stereo Image Acquisition

The stereo image acquisition system was developed to capture synchronized image pairs from two cameras simultaneously. This process supported stereo calibration activities by collecting checkerboard image pairs under different positions and orientations. Real-time image visualization from the left and right cameras was displayed during acquisition to ensure proper alignment and image quality. Captured image pairs were automatically stored within the images folder using sequential naming formats such as chessboard-L[n].png and chessboard-R[n].png. The implemented acquisition algorithm also evaluated checkerboard visibility, image sharpness, and frame stability before saving images into the dataset. Several coding components were responsible for camera initialization, frame acquisition, checkerboard detection, blur analysis, and synchronized image storage, as shown in Table 3.

Table 3. Main Functions of Stereo Image Capture Program

No	Coding Component	Description
1	CAPTURE_WIDTH, CAPTURE_HEIGHT, CAPTURE_FPS	Configures image resolution at 1280 × 720 pixels and 30 FPS
2	OUTPUT_DIR = "images"	Defines storage folder for stereo image pairs
3	CHECKERBOARD = (9, 6)	Defines checkerboard pattern size
4	run_ffmpeg_list_dshow_devices()	Reads available USB camera devices
5	FFmpegCamera	Handles camera initialization and frame acquisition
6	_detect_chessboard_fast()	Detects checkerboard corners using OpenCV
7	_blur_score()	Measures image sharpness to avoid blurry captures
8	_capture_loop()	Executes synchronized stereo acquisition process
9	_freeze_with_pending()	Freezes frame before image saving
10	save_pair()	Saves synchronized stereo image pairs
11	cancel_save()	Cancels image saving process

Stereo camera calibration was performed using checkerboard image pairs captured from both cameras. The calibration process aimed to determine intrinsic camera matrices, distortion coefficients, stereo rotation matrices, translation vectors, and stereo rectification parameters. The system successfully detected checkerboard corners in both left and right images, indicated by the status values “L: True” and “R: True.” Detected checkerboard corners were visualized using colored markers and lines to confirm successful corner localization. The calibration process utilized 96 valid stereo image pairs from a total of 100 acquisition attempts, while four image pairs were rejected due to detection errors or poor image quality. The successful stereo calibration process provided accurate camera geometry parameters required for disparity computation and depth estimation in Table 4. Consequently, the calibrated stereo camera system became capable of supporting accurate vehicle dimension measurements under real testing conditions, as shown ini Figure 3.

Figure 3. Stereo checkerboard detection results during calibration process

Table 4. Stereo Camera Calibration Results

No	Calibration Parameter	Physical Value	System Result	Description
1	Checkerboard Pattern	9 × 6	9 × 6	Valid
2	Checkerboard Square Size	0.04 m	0.04 m	Valid
3	Stereo Camera Baseline	50 cm	50 cm	Fixed
4	Image Acquisition	100 images	96 valid	4 errors

3.1.3 Stereo Camera Calibration

The developed calibration program implemented several computational stages including grayscale conversion, checkerboard corner detection, stereo calibration, stereo rectification, and reprojection error analysis. Checkerboard corner refinement was performed using sub-pixel corner optimization to improve calibration accuracy. Stereo rectification aligned stereo image pairs such that corresponding points appeared along identical epipolar lines, simplifying disparity calculations. Reprojection error values generated during calibration indicated that the stereo calibration quality remained within acceptable limits for measurement purposes. In addition, calibration parameters

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were stored into stereo_calib_result.npz files for subsequent use in the measurement system. The calibration workflow showed that the stereo camera system maintained geometric consistency throughout the experimental process, as shown in Table 5.

Table 5. Main Functions of Stereo Calibration Program

No	Coding Component	Description
1	CHECKERBOARD = (9,6)	Defines checkerboard corner configuration
2	SQUARE_SIZE = 0.04	Defines checkerboard square size
3	cv2.findChessboardCorners()	Detects checkerboard corners
4	cv2.cornerSubPix()	Refines corner coordinates
5	cv2.calibrateCamera()	Calculates intrinsic camera parameters
6	cv2.stereoCalibrate()	Calculates stereo geometry
7	cv2.stereoRectify()	Aligns stereo image pairs
8	np.savez()	Saves calibration parameters
9	cv2.projectPoints()	Calculates reprojection points
10	cv2.norm()	Calculates reprojection error

3.1.4 Vehicle Measurement System Development

The primary measurement system integrated stereo camera processing with YOLOv8-based object detection to estimate vehicle dimensions automatically in real-time. The system detected vehicles and wheel positions simultaneously from left and right stereo images using dedicated YOLOv8 detection models. After object detection, stereo matching and disparity calculations were performed to estimate object depth using stereo triangulation principles as shown in Figure 4. The calculated disparity values were refined through sub-pixel disparity optimization to improve distance estimation accuracy. Based on the estimated depth and detected wheel positions, the system automatically calculated Overall Length (OAL), Front Overhang (FOH), Wheelbase (WB), Rear Overhang (ROH), and Overall Height (OAH) as in Table 6. Measurement results were displayed directly within the graphical interface and automatically saved into image snapshots and Excel files for further analysis. The implementation showed that stereo vision combined with YOLOv8 algorithms could support automated vehicle dimension measurements efficiently under different environmental conditions.

Figure 4. Real-time vehicle and wheel detection using YOLOv8 stereo vision system

Table 6. Main Functions of Vehicle Measurement Program

No	Coding Component	Description
1	VEHICLE_CONF dan WHEEL_CONF	Confidence thresholds for YOLO detection
2	initialize_cameras()	Connects left and right cameras
3	apply_camera_tuning()	Adjusts exposure, gain, and gamma
4	vehicle_model = YOLO(...)	Loads vehicle detection model
5	wheel_model = YOLO(...)	Loads wheel detection model
6	detect_vehicles_scaled()	Detects vehicles within image frames
7	detect_wheels_in_vehicle_rois()	Detects wheels within vehicle regions
8	pair_vehicles_rectified()	Matches stereo vehicle detections
9	refine_disparity_subpixel()	Calculates refined disparity values
10	depth_cm_from_disparity()	Calculates depth estimation
11	foh = ...	Calculates Front Overhang
12	wb = ...	Calculates Wheelbase
13	roh = ...	Calculates Rear Overhang
14	oal = foh + wb + roh	Calculates Overall Length
15	oah = ...	Calculates Overall Height

3.1.5 Hardware installation

The hardware installation process involved integrating stereo cameras, luxmeter sensors, checkerboard calibration boards, and supporting structural components as shown in Figure 5 and Figure 6. Two USB cameras were mounted

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rigidly onto a fixed frame to maintain a constant stereo baseline of 50 cm throughout the experiments. The stereo camera assembly was subsequently mounted on a tripod to maintain camera stability and perpendicular alignment relative to the test vehicle. A luxmeter sensor was positioned above the stereo camera baseline facing upward at a 90° angle to monitor ambient lighting conditions continuously. During checkerboard calibration, the checkerboard board was positioned at multiple orientations and distances relative to the stereo cameras to improve calibration robustness. The Mitsubishi L300 pickup vehicle used as the testing object was positioned on a flat surface to minimize geometric distortions during measurements. In addition, important vehicle reference points such as wheel centers, vehicle front, and rear positions were marked using chalk to support manual measurement validation.

Figure 5. Stereo camera and luxmeter installation configuration

Figure 6. Vehicle positioning and image acquisition mapping scheme

The stereo camera calibration test showed that the developed system successfully detected checkerboard corners automatically within both stereo images. The stereo images chessboard-L40.png and chessboard-R40.png clearly illustrated geometric differences between left and right camera perspectives, representing the fundamental principle of stereo vision systems. These geometric differences enabled the system to calculate disparity values necessary for depth estimation calculations. The calibration results indicated that the stereo camera baseline remained stable at 50 cm throughout the testing process. Furthermore, 96 out of 100 checkerboard image pairs were successfully processed, indicating reliable image acquisition performance. The low number of rejected image pairs suggested that the acquisition system effectively maintained image quality and checkerboard visibility during calibration procedures. Therefore, the calibration process confirmed that the stereo vision system was sufficiently accurate for subsequent vehicle measurement operations.

3.2 System Performance Evaluation

Vehicle and wheel detection experiments were conducted under three different lighting conditions, 5,000-20,000 lux, 20,000-50,000 lux, and 50,000-100,000 lux. Experimental results showed that both vehicle bodies and wheel axle positions were successfully detected under all lighting conditions at distances of 7 m, 8 m, and 9 m.

3.2.1 Vehicle Detection and Lighting Condition

The YOLOv8 object detection model successfully identified vehicle boundaries and wheel positions consistently within stereo images as shown in Table 7. Even under high illumination conditions exceeding 50,000 lux, the system maintained stable detection performance without significant object loss. Similarly, under relatively low illumination conditions of 5,000-20,000 lux, the stereo vision system still produced reliable detection results despite slightly higher measurement variations. These findings showed that the proposed stereo vision system possessed strong robustness against natural environmental lighting variations. Consequently, the developed system showed strong potential for practical outdoor vehicle inspection applications.

Table 7. Vehicle and Wheel Detection Results Under Different Lighting Conditions

No	Lighting Condition	Vehicle Detected	Wheel Detected	Description
1	5,000-20,000 lux	Yes	Yes	Wheel axle positions clearly detected at 7 m, 8 m, and 9 m
2	20,000-50,000 lux	Yes	Yes	Wheel axle positions clearly detected at 7 m, 8 m, and 9 m
3	50,000-100,000 lux	Yes	Yes	Wheel axle positions clearly detected at 7 m, 8 m, and 9 m

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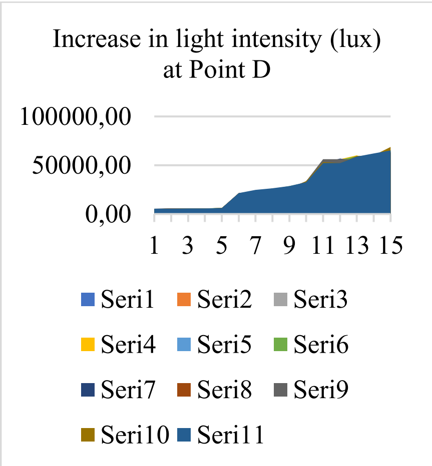
The influence of environmental lighting conditions was evaluated by analyzing luxmeter readings obtained during testing at distances of 7 m, 8 m, and 9 m. At the 7 m testing distance, the recorded light intensity values showed fluctuation percentages ranging from approximately 3% to 14%. These variations indicate that although changes in illumination occurred at different measurement points, the fluctuations remained within the acceptable threshold of 15% established in this study. The observed variations were primarily caused by changes in natural sunlight intensity, temporary shadows, and differences in the angle of incident light. Despite these fluctuations, the stereo camera system maintained stable vehicle and wheel detection performance, and the resulting dimensional measurements remained highly accurate.

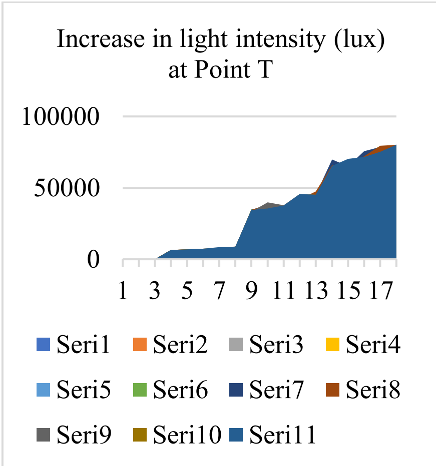
At the 8 m testing distance, the fluctuation percentages ranged from approximately 4% to 14%. Several measurement points, including T-1, T, T+1, and T-2, exhibited fluctuation values exceeding 10% during certain observation periods. These results indicate moderate changes in illumination during image acquisition. Nevertheless, all fluctuation values remained below the maximum allowable limit, confirming that the environmental conditions were still suitable for valid measurement. Under these lighting conditions, the system achieved the highest overall measurement accuracy, with the optimal configuration (T_8M_LC) producing an average accuracy of 99.44%.

At the 9 m testing distance, the measured lux values generally increased from point B+2 toward point B-2. The lowest illumination levels were consistently recorded at point B+2, while the highest values were observed at point B-2. The maximum snapshot value reached approximately 94,895 lux during the session conducted at 10:58 WIB. The fluctuation percentages ranged from 4.89% to 14.98%, with the highest fluctuation occurring at point B-1 during the 10:56 WIB session. These relatively high fluctuation values indicate more substantial changes in sunlight intensity during the measurement period. However, because all values remained within the predefined acceptance range, the collected data were considered valid.

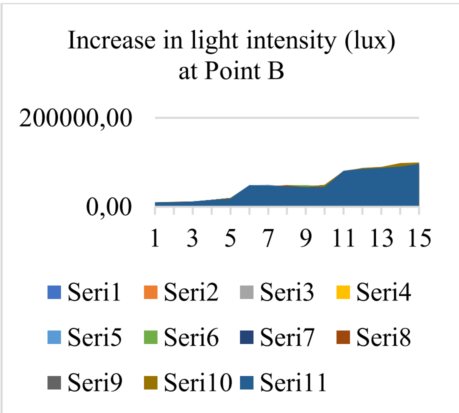
The results show that the developed stereo camera-based measurement system remained robust under varying natural lighting conditions ranging from 5,000 to 100,000 lux. Although fluctuations in illumination were observed at all testing distances, the luxmeter-based monitoring system ensured that environmental changes remained within acceptable limits. This capability contributed to the stability of object detection, depth estimation, and dimensional measurement processes, confirming that the proposed system is suitable for practical outdoor motor vehicle inspection applications. Figure 7 shows the increase in light intensity (lux) at Point; (a) D; (b) T; and (B).



(a)



(b)



(c)

Figure 7. Increase in light intensity (lux) at Point; (a) D; (b) T; and (B)

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3.2.2 Distance Measurement and Time Efficiency Evaluation

Vehicle distance measurement experiments were conducted at distances of 7 m, 8 m, and 9 m to evaluate system accuracy under different illumination conditions. At a measurement distance of 7 m, all lighting conditions produced results closely matching the actual reference distance of 700 cm. The average error remained below 0.3% for all lighting categories, indicating highly accurate depth estimation performance. Under low illumination conditions (LA), the average measured distance was 698.26 cm, while medium and high illumination conditions produced slightly higher measurements. Medium illumination conditions (LB) generated the lowest measurement error of approximately 0.15%, indicating the most stable performance at 7 m. At 8 m distance, the system maintained excellent accuracy with the best result obtained under LB conditions, where the average measured distance reached 800.46 cm with only 0.06% error. At 9 m distance, low illumination conditions unexpectedly produced the most accurate result with an average distance of 900.23 cm and an error of approximately 0.03%, demonstrating the stability of stereo depth estimation even at larger distances.

Environmental lighting analysis showed that natural light intensity varied significantly throughout the morning testing sessions. At 7 m distance, average illumination increased from 5,708.20 lux during early morning sessions to 57,447.25 lux approaching midday, representing an overall increase of approximately 906.40%. Similar trends were observed at 8 m and 9 m distances, where illumination intensity increased continuously as testing progressed toward midday. Despite substantial illumination variations, measured lux fluctuation percentages remained within approximately 3%-15%, indicating relatively stable environmental conditions during image acquisition. The highest lux fluctuation was recorded at 14.98% during the 9 m testing session, likely caused by changes in sunlight intensity and shadow movement. Nevertheless, all fluctuation values remained within acceptable limits for valid measurement conditions according to the predefined research criteria. These results indicated that the luxmeter-based monitoring system successfully controlled environmental lighting variations throughout the experiments.

Time efficiency analysis showed a substantial improvement in measurement speed when using the stereo vision system compared with manual methods. Manual measurements involving three operators required approximately 187 seconds or 3 minutes and 7 seconds to complete the entire vehicle dimension measurement process. In contrast, the stereo camera system completed the same measurement tasks within only 5 seconds. The efficiency percentage was calculated using the following equation (3)-(5).

$$E(\%) = \frac{(187-5)}{187} \times 100\% \tag{3}$$

$$E(\%) = \frac{182}{187} \times 100\% \tag{4}$$

$$E(\%) = 0{,}9732 \times 100\% \tag{5}$$

$$E \quad = 97{,}32\%$$

The calculated efficiency value indicated that the stereo camera measurement system improved operational efficiency by approximately 97.32% compared with conventional manual measurements. This substantial efficiency improvement showed the strong potential of automated stereo vision systems for supporting practical vehicle inspection processes. Comparison between manual and automatic measurement time shows in Table 8.

Table 8. Comparison Between Manual and Automatic Measurement Time

No	Measurement Method	Measurement Duration	Difference
1	Manual Measurement	187 seconds (3 minutes 7 seconds)	
2	Stereo Vision System	5 seconds	182 seconds

3.2.3 Vehicle Dimension Measurement Accuracy

Accuracy analysis showed that the developed system achieved excellent overall measurement performance. Average measurement accuracy exceeded 98% across all experimental distances. The highest average accuracy was obtained at 8 m distance with 98.92%, followed by 9 m with 98.89%, and 7 m with 98.58%. Among all dimensional parameters, Wheelbase (WB) achieved the highest accuracy with values exceeding 99.7% across all measurement distances. Front Overhang (FOH) also showed excellent performance, particularly at 8 m where accuracy reached 99.97%. However, Rear Overhang (ROH) and Overall Height (OAH) exhibited relatively lower accuracy values, particularly at 7 m and 9 m distances. These findings suggested that rear vehicle boundaries and upper vehicle edges remained more difficult to estimate accurately due to limitations in object boundary detection and depth estimation algorithms. Although the obtained accuracy values were relatively high, the experiments were conducted under controlled testing conditions involving a single vehicle type, fixed stereo camera baseline, stable camera positioning, and relatively uniform environmental conditions. Therefore, the reported performance should be interpreted as system performance within controlled experimental scenarios rather than as generalized performance for all real-world vehicle inspection conditions. The possibility of reduced accuracy under more complex operational environments, different vehicle geometries, dynamic backgrounds, or varying object textures remains an important consideration for future studies.

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Tables 9 - Table 11 present the measurement accuracy comparison at testing distances of 7 m, 8 m, and 9 m. The results show that the developed stereo camera-based measurement system produced high accuracy for all vehicle dimensional parameters, with most values exceeding 96%. The highest and most consistent accuracy was obtained for the FOH and WB parameters, where the accuracy values reached up to 99.97% and 99.88%, respectively. This indicates that the system was able to detect wheel positions and front vehicle boundaries reliably.

Table 9. Measurement Accuracy at 7 m Testing Distance

Parameter	Reference (cm)	Measured Result (cm)	Difference	Error (%)	Accuracy (%)
OAL	420	415.743	+4.26	1.01%	98.99%
FOH	95	94.596	+0.41	0.43%	99.57%
WB	220	219.636	+0.64	0.29%	99.71%
ROH	105	101.509	+3.49	3.32%	96.68%
OAH	180	176.292	+3.71	2.06%	97.94%

Table 10. Measurement Accuracy at 8 m Testing Distance

Parameter	Reference (cm)	Measured Result (cm)	Difference	Error (%)	Accuracy (%)
OAL	420	417.74	+2.26	0.54%	99.46%
FOH	95	95.03	-0.03	0.03%	99.97%
WB	220	219.74	+0.26	0.12%	99.88%
ROH	105	102.18	+2.82	2.69%	97.31%
OAH	180	176.33	+3.67	2.04%	97.96%

Table 11. Measurement Accuracy at 9 m Testing Distance

Parameter	Reference (cm)	Measured Result (cm)	Difference	Error (%)	Accuracy (%)
OAL	420	418.41	+1.59	0.380%	99.62%
FOH	95	95.41	-0.41	0.430%	99.57%
WB	220	219.53	+0.47	0.210%	99.79%
ROH	105	103.45	+1.55	1.480%	98.52%
OAH	180	174.51	+5.49	3.050%	96.95%

Based on Figure 8, the 8 m testing distance provided the most stable overall performance compared with the 7 m and 9 m distances. At this distance, OAL, FOH, WB, ROH, and OAH achieved accuracy values of 99.46%, 99.97%, 99.88%, 97.31%, and 97.96%, respectively. Although ROH and OAH showed slightly lower accuracy than the other parameters, the obtained values remained acceptable for vehicle dimension measurement purposes. The lower accuracy observed in the OAH parameter may have been influenced by several technical factors, including perspective distortion, imperfect ground plane alignment, slight camera tilt deviations, and reduced disparity consistency near the upper vehicle boundary. In stereo vision systems, vertical object measurements are generally more sensitive to calibration inaccuracies and camera orientation errors because small angular deviations can significantly affect depth estimation along the vertical axis. In addition, the upper contour of the vehicle tended to produce less stable feature correspondence during SGBM disparity computation, particularly under varying illumination conditions. These factors likely contributed to the consistently larger errors observed in OAH measurements compared with FOH and WB parameters.

The current study was conducted using a Mitsubishi L300 vehicle with relatively bright surface characteristics. The performance of the SGBM algorithm on dark-colored vehicles was not comprehensively evaluated in this research. Dark vehicle surfaces generally absorb more light and produce lower texture contrast, which can reduce stereo correspondence quality and increase disparity estimation uncertainty. As a result, object boundary detection and depth estimation accuracy may decrease when processing vehicles with darker colors or reflective surfaces under low illumination conditions. Therefore, additional experiments involving multiple vehicle colors, materials, and surface textures are necessary to evaluate the robustness and generalizability of the proposed stereo vision system under more diverse real-world operating conditions.

3.2.4 Optimal Measurement Configuration

The measurement results show that the proposed stereo vision system is capable of producing accurate and consistent vehicle dimension measurements at different testing distances. The 8 m distance can be considered the most optimal configuration because it produced balanced accuracy across all measured parameters. Nevertheless, the current findings should be interpreted within the limitations of the experimental setup, particularly the controlled environment, limited vehicle variation, and constrained lighting scenarios used during testing. Future work should include broader validation involving multiple vehicle types, vehicle colors, outdoor environmental variations, and dynamic operational conditions to further evaluate system robustness and minimize the risk of overfitting to controlled measurement scenarios.

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Based on results in the Table 12, the developed system showed excellent measurement performance, with all average accuracy values exceeding 98%. The 8 m measurement distance produced the highest average accuracy of 98.92%, followed by 9 m with 98.89% and 7 m with 98.58%. Among all measured parameters, Wheelbase (WB) showed the highest consistency, achieving accuracy values above 99.7% at all testing distances. Front Overhang (FOH) also exhibited very high accuracy, particularly at the 8 m distance where the accuracy reached 99.97%. In contrast, Rear Overhang (ROH) at the 7 m distance and Overall Height (OAH) at the 9 m distance produced the lowest accuracy values, namely 96.68% and 96.95%, respectively. These findings show that the rear section and upper boundary of the vehicle remain more challenging to estimate accurately than other dimensional parameters.

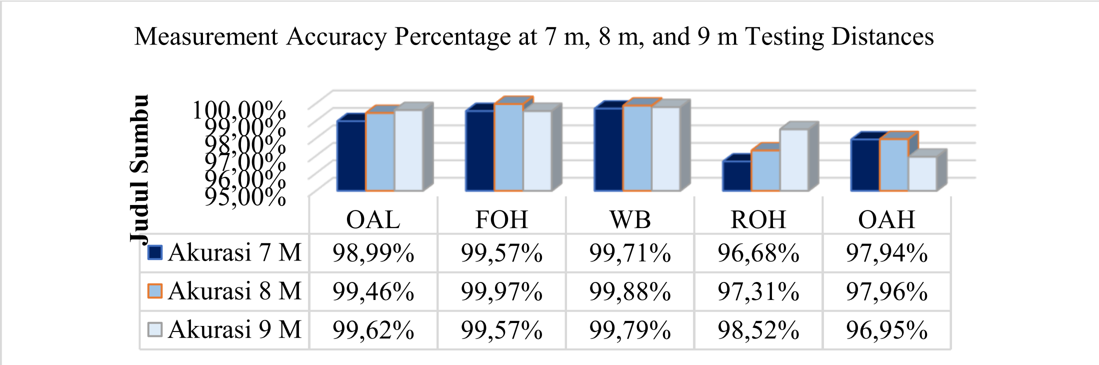

Figure 8. Percentage of Measurement Accuracy

Table 12. Most Accurate Measurement Result at T_8M_LC Position

Parameter	Reference (cm)	T_8M_LC Result (cm)	Difference	Error (%)	Accuracy (%)
OAL	420	422.75	+2.75	0.65%	99.35%
FOH	95	95.07	+0.07	0.07%	99.93%
WB	220	219.50	-0.50	0.23%	99.77%
ROH	105	105.10	+0.10	0.10%	99.90%
OAH	180	176.88	-3.12	1.73%	98.27%

To further identify the optimal measurement configuration, the most accurate result was obtained at the T_8M_LC testing point, which produced an overall average accuracy of approximately 99.44% when compared with manual measurements using a measuring tape as the reference. In this configuration, the Overall Length (OAL) was measured at 422.75 cm compared with the reference value of 420 cm, resulting in an accuracy of 99.35%. The Front Overhang (FOH) measurement reached 95.07 cm compared with the reference value of 95 cm, corresponding to an accuracy of 99.93%. Wheelbase (WB) was measured at 219.50 cm compared with the reference value of 220 cm, yielding an accuracy of 99.77%. Rear Overhang (ROH) was measured at 105.10 cm compared with the reference value of 105 cm, resulting in an accuracy of 99.90%. Meanwhile, Overall Height (OAH) was measured at 176.88 cm compared with the reference value of 180 cm, corresponding to an accuracy of 98.27%. These results confirm that the T_8M_LC configuration produced measurements that were highly consistent with the actual vehicle dimensions and represented the most accurate testing condition in this study [17]-[20]. Figure 9 shows most precise point in this research.

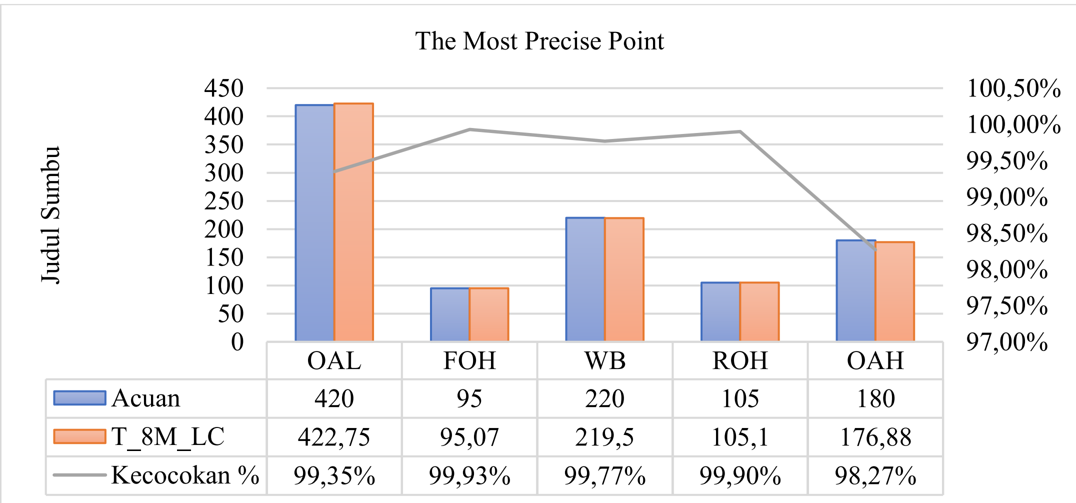

Figure 9. The Most Precise Point

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3.3 Discussion

The proposed stereo vision-based vehicle measurement system achieved high measurement accuracy under different testing distances and illumination conditions. The integration of stereo cameras, YOLOv8-based object detection, and disparity-based depth estimation enabled automatic measurement of vehicle dimensions, including Overall Length (OAL), Front Overhang (FOH), Wheelbase (WB), Rear Overhang (ROH), and Overall Height (OAH). The overall accuracy exceeded 98% across all experimental configurations, showing that the developed system was capable of providing reliable dimensional measurements for vehicle inspection applications. These findings are consistent with previous studies that reported the effectiveness of binocular stereo vision for object dimension measurement and distance estimation through triangulation-based approaches, the suitability of stereo vision technology for transportation and vehicle-related measurement tasks [2], [4], [10].

The experimental showed that the 8 m testing distance produced the highest overall accuracy compared with the 7 m and 9 m configurations. This finding can be explained by the relationship between camera geometry, object scale, and disparity resolution in stereo vision systems. At shorter distances, perspective distortion and image scale variations may affect dimensional estimation, while at longer distances the reduction in disparity values can increase depth estimation uncertainty. Therefore, the 8 m configuration appears to provide a more favorable balance between object visibility and disparity stability, resulting in the highest average measurement accuracy. Similar observations have been reported in stereo vision studies, where measurement performance is strongly influenced by the stereo baseline, camera-object distance, and the quality of disparity reconstruction [4], [17].

Among all measured parameters, Wheelbase (WB) and Front Overhang (FOH) consistently achieved the highest accuracy values. This performance is likely related to the ability of the YOLOv8 model to detect wheel locations and vehicle boundaries reliably in both stereo images. Wheel regions generally contain distinctive geometric features that facilitate object localization and stereo correspondence matching, thereby reducing positional uncertainty during dimension calculation. Previous research has shown that integrating object detection with distance estimation improves localization accuracy and enables more precise measurement of real-world object dimensions, particularly in computer vision systems operating in real time [9], [10].

Rear Overhang (ROH) and Overall Height (OAH) exhibited slightly lower accuracy than the other dimensional parameters. The lower accuracy of OAH measurements may be associated with the sensitivity of vertical measurements to calibration errors, camera orientation deviations, and imperfect feature correspondence near the upper boundary of the vehicle. In stereo vision systems, depth estimation quality depends heavily on accurate disparity matching, and regions with limited texture or weaker visual features often produce less stable depth information. Previous studies on stereo-based depth estimation have similarly identified disparity quality, feature correspondence, and calibration accuracy as important factors affecting measurement performance and three-dimensional reconstruction accuracy [17].

The robustness of the proposed system under illumination levels ranging from 5,000 lux to 100,000 lux. Despite fluctuations in natural lighting during testing, vehicle bodies and wheel positions were successfully detected under all illumination categories. The luxmeter monitoring system also confirmed that illumination variations remained within the predefined acceptance threshold, allowing measurement activities to be conducted under controlled environmental conditions. These results indicate that combining stereo vision with deep learning-based object detection can maintain stable measurement performance under changing outdoor lighting environments. Similar studies have highlighted the importance of robust object detection and depth estimation methods for ensuring reliable measurement performance under varying environmental conditions [9], [17].

The developed system also showed substantial practical benefits in terms of operational efficiency. Compared with conventional manual measurements requiring approximately 187 seconds and multiple operators, the proposed system completed the measurement process in only 5 seconds, corresponding to an efficiency improvement of approximately 97.32%. This result shows the potential of automated stereo vision systems to support faster and more efficient vehicle inspection procedures without compromising measurement accuracy. Consistent with previous studies on stereo vision-based measurement systems, the integration of object detection, depth estimation, and dimensional analysis can significantly improve inspection efficiency while maintaining reliable measurement performance [2], [9], [10]. The excellent performance obtained at the T_8M_LC configuration, which achieved an average accuracy of approximately 99.44%, further confirms the feasibility of implementing the proposed system in practical vehicle inspection applications.

4. CONCLUSION

The stereo camera-based motor vehicle dimension measurement system integrated with luxmeter light intensity detection was successfully developed and showed strong performance for automatic vehicle dimension measurements under controlled experimental conditions. The system utilized two Logitech C270 USB cameras configured with a fixed 50 cm stereo baseline and integrated Python-based processing using OpenCV, YOLOv8, and CustomTkinter to estimate Overall Length (OAL), Front Overhang (FOH), Wheelbase (WB), Rear Overhang (ROH), and Overall Height (OAH). Stereo calibration testing achieved a 96% success rate, with 96 out of 100 checkerboard image pairs processed successfully using a 9 × 6 checkerboard pattern. The developed system produced average accuracies of 98.58% at 7

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m, 98.92% at 8 m, and 98.89% at 9 m testing distances, while the optimal configuration (T_8M_LC) achieved an overall accuracy of approximately 99.44%. Environmental illumination significantly influenced measurement stability, where the 20,000-50,000 lux range produced the most stable depth estimation performance and the 50,000-100,000 lux range generated the highest dimensional measurement accuracy. However, the study also identified several limitations of the developed system. The experiments were conducted only under static vehicle conditions; therefore, the influence of vehicle motion, vibration, and motion blur on stereo matching and YOLOv8 object detection performance was not evaluated. In practical implementation, moving vehicles may introduce image blur and disparity instability that could reduce dimensional measurement accuracy, particularly at higher vehicle speeds. In addition, although the system remained operational within the tested illumination range of 5,000-100,000 lux, the breakdown point of the system under extremely low-light or excessively high-glare conditions was not experimentally determined. The stereo vision and SGBM disparity algorithms may experience performance degradation under illumination levels below 5,000 lux due to insufficient texture information and reduced contrast, while excessive sunlight reflections above the tested range may also affect stereo correspondence consistency. The experiments were limited to a single vehicle type under relatively controlled environmental conditions, which may restrict the generalizability of the obtained results to broader real-world scenarios involving multiple vehicle geometries, colors, and dynamic operational environments. Nevertheless, the proposed system demonstrated substantial operational efficiency improvements by reducing measurement duration from 187 seconds using manual procedures to only 5 seconds using the automated system, corresponding to an efficiency improvement of 97.32%.

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