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Performance Evaluation and Practical Implementation of A Deep Learning-Based Vision System For Vehicle Wheel Alignment

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ABSTRACT

Wheel alignment is a critical aspect of vehicle maintenance that significantly influences road safety, steering stability, fuel efficiency, tire longevity, and overall vehicle performance. Conventional wheel alignment technologies, including mechanical, laser-based, Charge-Coupled Device (CCD), and three-dimensional (3D) camera systems, provide reliable measurements but are often expensive, require specialized hardware, frequent calibration, and skilled technicians. These limitations reduce their accessibility, particularly for small and medium-sized automotive workshops and educational institutions. This study proposes the design and implementation of a deep learning-based vision system for automated vehicle wheel alignment using computer vision and artificial intelligence techniques. The proposed framework integrates digital image acquisition, camera calibration, image preprocessing, object detection, feature extraction, and geometric measurement algorithms to estimate principal wheel alignment parameters, including camber, caster, and toe angles, without the need for wheel-mounted sensors or reflective targets. An experimental research design was adopted, comprising system development and performance evaluation phases. Vehicle wheel images were collected from multiple passenger vehicles under varying lighting conditions, camera viewpoints, and workshop environments. The dataset underwent preprocessing through image resizing, normalization, augmentation, and annotation before training a deep learning object detection model. Camera calibration techniques were employed to correct lens distortion and establish accurate geometric relationships between image coordinates and real-world measurements. The trained model detected wheel features, extracted rim centers and reference points, and estimated alignment angles, which were subsequently compared with measurements obtained from a commercial wheel alignment machine. The system also achieved real-time processing capability, requiring approximately 100 ms per image and operating at about 30 frames per second on a GPU-enabled platform, while maintaining moderate computational resource utilization. Performance evaluation under varying lighting conditions, camera distances, wheel sizes, and vehicle categories confirmed the robustness and generalization capability of the proposed approach. The study demonstrates that deep learning and computer vision can provide an accurate, low-cost, and automated alternative to conventional wheel alignment systems. By reducing dependence on proprietary hardware and minimizing human intervention, the proposed system offers improved accessibility, diagnostic consistency, and operational efficiency.

I. INTRODUCTION

The automotive industry has undergone significant technological transformation over the past two decades, driven by advances in intelligent transportation systems, automation, artificial intelligence (AI), and computer vision technologies. These innovations have not only improved vehicle manufacturing processes but have also revolutionized vehicle maintenance and diagnostic procedures. Among the numerous maintenance operations performed on vehicles, wheel alignment remains one of the most critical because it directly influences vehicle safety, steering performance, ride comfort, fuel economy, and tire lifespan (Gillespie, 1992; Wong, 2008).

Wheel alignment refers to the adjustment of a vehicle's suspension geometry so that the wheels are oriented according to the manufacturer's specified angles. It is important to note that wheel alignment does not involve adjusting the wheels themselves but rather modifying the suspension components that determine wheel orientation relative to the vehicle chassis and the road surface (Bosch, 2018). Proper alignment ensures that all four wheels work harmoniously to maintain directional stability while minimizing tire wear and mechanical stress on steering and suspension systems.

The importance of wheel alignment has increased considerably with the rapid growth of global vehicle ownership. According to the International Organization of Motor Vehicle Manufacturers (OICA, 2023), more than 90 million motor vehicles are manufactured annually worldwide, while the global vehicle fleet continues to expand due to urbanization, economic growth, and increased transportation demands. This growth has significantly increased the need for efficient vehicle maintenance systems capable of ensuring roadworthiness, reducing maintenance costs, and improving transportation safety.

Proper wheel alignment plays a fundamental role in maintaining optimum vehicle dynamics. Vehicle handling characteristics, steering response, braking efficiency, cornering stability, and overall driving safety are directly affected by wheel alignment geometry (Milliken & Milliken, 1995). When wheel alignment parameters remain within the manufacturer's recommended specifications, the vehicle experiences lower rolling resistance, improved steering precision, enhanced suspension performance, and more uniform tire wear. Conversely, improper wheel alignment causes excessive tire degradation, increased fuel consumption, unstable steering behavior, vibration, and accelerated deterioration of suspension components (Heisler, 2002).

The consequences of wheel misalignment extend beyond mechanical performance to economic and environmental impacts. Excessive rolling resistance resulting from improper alignment increases fuel consumption and greenhouse gas emissions, while premature tire wear contributes to higher maintenance costs and increased generation of waste tires (European Commission, 2022). For commercial transportation companies, logistics operators, and fleet managers, even minor alignment errors can translate into substantial operational expenses due to increased fuel usage, more frequent tire replacement, vehicle downtime, and reduced fleet efficiency (SAE International, 2021). Consequently, routine wheel alignment inspections have become an essential component of preventive vehicle maintenance programs worldwide.

Vehicle wheel alignment is primarily evaluated using four fundamental geometric parameters: camber, caster, toe, and thrust angle. Camber describes the inward or outward inclination of the wheel relative to the vertical axis when viewed from the front of the vehicle. Appropriate camber improves tire contact during cornering, whereas excessive positive or negative camber results in uneven tire wear and reduced handling performance (Gillespie, 1992). Caster refers to the inclination of the steering axis relative to the vertical plane when viewed from the side of the vehicle. Positive caster enhances directional stability and steering self-centering, while incorrect caster settings may compromise steering control and driver comfort (Wong, 2008). Toe defines the inward or outward direction of the wheels relative to the vehicle's longitudinal axis when viewed from above and has a substantial influence on tire wear, steering response, and rolling resistance (Bosch, 2018). Thrust angle, which represents the relationship between the rear axle centerline and the vehicle's geometric centerline, is equally important because incorrect thrust angles can cause vehicle pulling, steering wheel misalignment, and instability during straight-line driving (Heisler, 2002).

Traditionally, wheel alignment has been performed using mechanical alignment gauges, measuring tapes, and spirit levels. Although these manual methods were inexpensive and relatively easy to implement, they suffered from low measurement precision, lengthy inspection procedures, and significant dependence on technician expertise (Bosch, 2018). As automotive engineering advanced, optical and laser-based alignment systems were introduced to improve measurement accuracy and reduce operator-related errors. Laser systems employed precisely aligned laser beams and reflective targets to estimate wheel orientation more accurately than conventional mechanical instruments. Nevertheless, laser-based systems remained highly sensitive to calibration errors, environmental vibrations, and workshop conditions, limiting their reliability in practical applications (Heisler, 2002).

Subsequent technological developments led to the introduction of Charge-Coupled Device (CCD)-based wheel alignment systems. CCD systems employ electronic imaging sensors mounted on each wheel to measure relative wheel positions and calculate alignment parameters using onboard computer software. Compared with laser systems, CCD technology significantly improved measurement precision, automation, and inspection speed (Bosch, 2018). However, CCD systems require frequent sensor calibration, periodic maintenance, and specialized proprietary hardware, resulting in relatively high procurement and operating costs.

Problem Statement

Wheel alignment plays a vital role in ensuring vehicle safety, fuel efficiency, tire durability, and overall driving performance. Despite continuous technological advancements in automotive maintenance, conventional wheel alignment systems continue to present several operational and economic challenges that limit their widespread adoption.

Commercial wheel alignment equipment, particularly CCD-based and three-dimensional camera systems, requires substantial financial investment for acquisition, installation, calibration, and maintenance. These high costs make advanced alignment technology inaccessible to many small and medium-sized automotive repair workshops, educational institutions, and independent service providers. Consequently, many organizations continue to rely on outdated manual methods or outsource alignment services, increasing operational costs and reducing service efficiency.

In addition to their high cost, conventional alignment systems often require highly trained technicians to operate the equipment, perform calibration procedures, and interpret measurement results accurately. Human intervention increases the possibility of operational errors and inconsistencies while extending inspection times.

Furthermore, existing alignment systems are frequently dependent on specialized proprietary hardware, dedicated workstations, and controlled environmental conditions. Factors such as camera misalignment, sensor degradation, inadequate calibration, lighting variations, and workshop space limitations may adversely affect measurement accuracy and system reliability.

Research Objectives

To design a vision-based wheel alignment system by developing an integrated framework that combines digital imaging, camera calibration, image processing, and geometric measurement techniques for automated wheel alignment assessment.

To develop a deep learning model for wheel position estimation capable of accurately detecting vehicle wheels, identifying critical wheel features, and estimating wheel orientation using advanced object detection and computer vision algorithms.

To evaluate the accuracy of the proposed system against conventional wheel alignment equipment by comparing alignment measurements such as camber, caster, and toe angles with those obtained from commercial wheel alignment machines using established performance metrics.

Significance of the Study

Significance to Intelligent Transportation Systems, Intelligent Transportation Systems (ITS) rely on advanced sensing, automation, and artificial intelligence to improve vehicle safety, operational efficiency, and transportation sustainability. The proposed research contributes to ITS by introducing an intelligent vision-based diagnostic tool capable of automating an essential vehicle maintenance procedure. Accurate wheel alignment contributes directly to road safety by improving vehicle handling, braking performance, and steering stability. Automated alignment monitoring can also support predictive maintenance strategies that reduce vehicle downtime and enhance fleet reliability.

Significance to AI-Assisted Vehicle Maintenance, Artificial intelligence is rapidly transforming automotive maintenance by enabling intelligent inspection, fault detection, and predictive diagnostics. This research demonstrates how deep learning algorithms can automate complex visual inspection tasks traditionally performed using specialized equipment. The proposed system illustrates the practical application of object detection and computer vision techniques for measuring vehicle wheel alignment parameters with minimal human intervention. Such automation can improve diagnostic consistency, reduce operator dependency, and facilitate real-time maintenance decision-making.

Academic Contribution, From an academic perspective, this research contributes to the interdisciplinary fields of artificial intelligence, computer vision, automotive engineering, and intelligent transportation systems. It expands the existing body of knowledge by investigating the application of deep learning techniques to vehicle wheel alignment, an area that has received comparatively limited research attention. The study provides a comprehensive framework covering dataset preparation, camera calibration, deep learning model development, geometric measurement algorithms, and real-world performance evaluation. This framework may serve as a reference for future researchers investigating vision-based measurement systems or AI-driven automotive diagnostics.

Scope of the Study

This study focuses on the design, implementation, and performance evaluation of a deep learning-based vision system for vehicle wheel alignment. The primary objective is to develop an intelligent computer vision framework capable of detecting vehicle wheels from digital images and estimating wheel alignment parameters with accuracy comparable to conventional wheel alignment equipment.

The study encompasses the development of image acquisition procedures, camera calibration techniques, image preprocessing methods, dataset preparation, deep learning model training, wheel detection algorithms, and alignment parameter estimation. The developed system is evaluated using standard computer vision performance metrics, including Precision, Recall, F1-score, Mean Average Precision (mAP), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), inference time, processing speed, and computational resource utilization.

Experimental validation is conducted using images captured from selected passenger vehicles under varying lighting conditions, camera viewpoints, and workshop environments to assess system robustness and practical applicability. The measurement results produced by the proposed system are compared with those obtained from a commercial wheel alignment machine to determine measurement accuracy and reliability.

The scope is limited to vision-based estimation of principal wheel alignment parameters, including camber, caster, and toe angles. Mechanical adjustment of wheel alignment, suspension repair procedures, vehicle steering control systems, and hardware design of commercial alignment equipment are beyond the scope of this research. Similarly, the study focuses primarily on passenger vehicles and does not extensively investigate heavy-duty trucks, motorcycles, agricultural machinery, or specialized industrial vehicles.

II. LITERATURE REVIEW

Vehicle Wheel Alignment

Vehicle wheel alignment is a critical automotive maintenance process concerned with adjusting the angular relationship between the wheels, steering system, suspension components, and the vehicle reference frame. Proper wheel alignment ensures that the tires maintain optimal contact with the road surface, thereby improving vehicle handling, directional stability, braking performance, tire lifespan, and fuel efficiency. Poor alignment conditions produce undesirable effects such as irregular tire wear, increased rolling resistance, steering instability, vibration, and reduced vehicle safety. Recent developments in intelligent vehicle maintenance have further emphasized the importance of accurate wheel alignment because vehicle geometry directly affects advanced driver-assistance systems (ADAS), electronic stability control (ESC), and autonomous driving functions (Yurtsever et al., 2020; Grigorescu et al., 2020).

Traditionally, wheel alignment has been performed using mechanical gauges, optical systems, and electronic measurement devices. However, increasing demand for automated automotive diagnostics has encouraged researchers to investigate computer vision and artificial intelligence (AI)-based approaches capable of measuring alignment parameters without direct physical contact. Deep learning-based vision systems provide new opportunities for reducing equipment cost, improving inspection speed, and enabling intelligent predictive maintenance. The major wheel alignment parameters evaluated in modern vehicles include: Camber angle; Toe angle; Caster angle and Thrust angle. These parameters define the orientation of wheels relative to the vehicle coordinate system and determine the interaction between tires and road surfaces.

Camber is the angle between the vertical axis of the wheel and the wheel plane when viewed from the front or rear of a vehicle. It describes the inward or outward inclination of the wheel relative to the vehicle body. Recent automotive research has investigated automated camber measurement using digital imaging, inertial sensors, and machine vision algorithms. Deep learning-based systems can detect wheel contours, wheel centers, and reference geometries from images, enabling non-contact camber estimation. These approaches reduce dependence on expensive alignment sensors and provide opportunities for low-cost intelligent diagnostic systems (Khan et al., 2020; Zhao et al., 2021).

Toe refers to the horizontal orientation of the wheels relative to the longitudinal centerline of the vehicle when viewed from above. It describes whether the front edges of two wheels point toward or away from each other. Conventional toe measurement relies on laser sensors, CCD devices, and three-dimensional camera systems. Recent studies have explored computer vision-based toe estimation by detecting wheel orientation and analyzing geometric relationships from image sequences. Deep learning-based object detection methods such as YOLO have demonstrated potential for identifying wheel structures in real-time, supporting automated alignment measurement systems (Bochkovskiy et al., 2020; Wang et al., 2023).

Conventional Wheel Alignment Systems, Wheel alignment technologies have evolved from manual measurement techniques to advanced electronic and imaging-based systems. Current commercial alignment equipment mainly consists of: Laser-based alignment systems; Charge-Coupled Device (CCD) alignment systems and Three-dimensional (3D) camera-based alignment systems. Although these systems provide high measurement accuracy, their dependence on specialized hardware, calibration procedures, and proprietary software increases acquisition and maintenance costs. These limitations have motivated research into affordable deep learning-based vision alternatives.

Laser-based alignment systems were among the earliest electronic solutions developed for automotive alignment measurement. These systems use laser emitters attached to wheels and reflective targets positioned around the vehicle. The alignment process involves projecting laser beams and measuring deviations in reflected positions. The measured values are converted into alignment parameters such as camber and toe. Advantages of laser systems include: Improved accuracy compared with mechanical gauges; Faster measurement procedures, reduced operator influence and Digital measurement output.

CCD-Based Systems, Charge-Coupled Device (CCD) alignment systems introduced electronic optical sensing into automotive wheel measurement. CCD sensors mounted on each wheel capture positional information and transmit measurements to processing software.

3D Camera-Based Systems, Three-dimensional camera-based alignment systems represent the most advanced commercial wheel alignment technology currently available. These systems use multiple high-resolution cameras to capture images of reflective targets attached to vehicle wheels.

The system reconstructs three-dimensional wheel geometry using: Stereo vision; Photogrammetry; Triangulation; Geometric modeling. Advantages of 3D camera systems include: Contactless measurement; High accuracy; Faster inspection; Automatic vehicle recognition and Real-time visualization. These systems are widely used in professional automotive service centers because of their reliability and precision.

Computer Vision in Automotive Applications, Computer vision is an artificial intelligence technology that enables machines to interpret and analyze visual information obtained from cameras. In automotive engineering, computer vision has become a major technology for intelligent transportation systems, autonomous vehicles, and automated vehicle inspection. Recent surveys indicate that deep learning has become the dominant approach in automotive vision because of its ability to learn complex features automatically and achieve high accuracy under challenging environmental conditions (Grigorescu et al., 2020; Yurtsever et al., 2020).

Feature detection identifies important visual characteristics that allow computer systems to recognize and analyze objects.
Traditional feature detection techniques include: Harris Corner Detector; SIFT; SURF and ORB.
These methods identify important image features such as edges, corners, and textures.
However, traditional approaches often perform poorly under: illumination changes; viewpoint variation and object occlusion.
Deep learning has improved feature extraction by allowing CNN models to automatically learn meaningful visual representations. Instead of manually selecting features, deep networks learn features directly from training data.

In vehicle wheel alignment systems, feature detection enables identification of: tire boundaries; wheel centers; rim structures and orientation points.

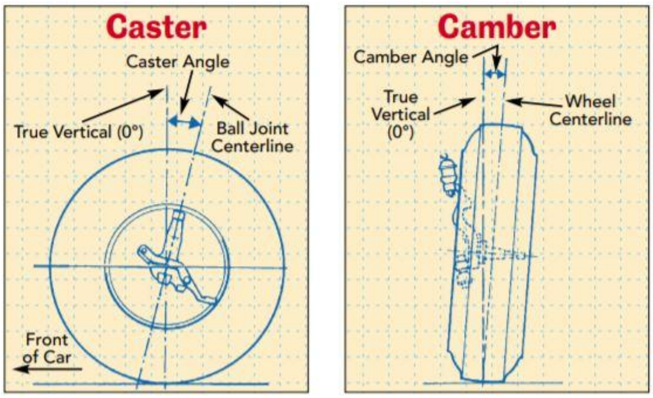

Fig. 1: Using Wheel Edge Lines (https://newsmartsafe.com)

Object localization determines the position and size of objects within an image. Unlike image classification, localization provides spatial information through: bounding boxes and key points; segmentation masks.

Modern object localization algorithms include: YOLO (You Only Look Once); Faster R-CNN(Region with conventional neural networks); SSD(single shot multibox detector); Mask R-CNN(Region with conventional neural networks) and Vision Transformers.

YOLO-based detectors are particularly attractive for automotive applications because they provide high-speed detection suitable for real-time systems (Redmon et al., 2016; Bochkovskiy et al., 2020).
For vehicle wheel alignment, object localization enables automatic identification of: wheels; tire edges; rims; wheel centers and alignment reference points.

When combined with camera calibration and geometric modelling, these detected features can be used to estimate camber, toe, caster, and thrust angle without expensive wheel-mounted sensors.

Research Gaps
Despite significant progress in deep learning-based automotive vision systems, several research gaps remain:

1. Limited Deep Learning Applications for Complete Wheel Alignment: Most existing automotive AI research focuses on autonomous driving, vehicle detection, and road perception. Few studies investigate deep learning approaches for complete wheel alignment parameter estimation.

2. High Cost of Existing Alignment Technologies: Current commercial systems require expensive sensors, cameras, reflective targets, and proprietary software. This limits accessibility, particularly for small workshops and developing regions.

3. Lack of Real-World Validation: Many proposed vision systems High-performance deep learning models often require powerful computing hardware. are evaluated under controlled laboratory conditions.
4. Limited Public Datasets: Deep learning models require large and diverse datasets. Currently, publicly available datasets specifically designed for wheel alignment analysis are scarce.

5. Real-Time Deployment Challenges: High-performance deep learning models often require powerful computing hardware. Research is needed to develop lightweight models suitable for real-time deployment using affordable computing platforms.

III. MATERIALS AND METHODS

Research Design

This study adopts an experimental research design focused on the development, implementation, and evaluation of a deep learning-based vision system for vehicle wheel alignment. The research methodology combines principles of automotive engineering, computer vision, image processing, and deep learning to develop an automated system capable of estimating wheel alignment parameters from camera images.

The proposed research follows a system development and performance evaluation approach involving five major stages:
Data acquisition, Image preprocessing and feature extraction, Deep learning model development and training
Alignment parameter estimation and System validation and performance evaluation
The research design consists of two main phases:

Phase 1: Development Phase, The development phase involves designing the vision-based alignment system, collecting vehicle wheel images, preparing datasets, training deep learning models, and integrating the trained model into a complete diagnostic framework.

The major activities include: Selection and configuration of camera equipment; Development of image acquisition procedures; Annotation of wheel-related features; Training and optimization of deep learning models; Development of alignment measurement algorithms and Integration of software and hardware components.

Phase 2: Evaluation Phase, The evaluation phase determines the effectiveness of the proposed system by comparing the estimated alignment parameters with measurements obtained from a conventional wheel alignment machine. The evaluation considers: Detection accuracy; Measurement error; Processing speed; Computational efficiency; Real-time capability and Practical deployment feasibility.

The camera serves as the primary sensing device for capturing visual information from the vehicle wheels. Unlike conventional alignment systems that require wheel-mounted sensors or reflective targets, the proposed system uses image-based measurement.

The camera captures: Wheel position; Tire boundaries; Rim geometry; Wheel center points;

Vehicle reference points.

A high-resolution RGB camera is preferred because wheel alignment estimation requires accurate detection of small geometric variations. Camera specifications that influence system performance include: Resolution; Lens quality; Field of view; Frame rate and Image distortion characteristics.
Multiple camera configurations may be considered: Single-camera system
A single camera captures wheel images from different angles. This approach reduces hardware cost but may require additional calibration and geometric assumptions.

Multi-camera system

Multiple cameras capture different viewpoints simultaneously. This improves three-dimensional reconstruction accuracy but increases hardware complexity. For practical workshop deployment, the proposed system may utilize a fixed RGB camera positioned at a controlled distance from the vehicle.
The processing unit performs image processing, deep learning inference, geometric calculations, and system control operations. The processing unit may include: Desktop computer; Laptop workstation; Embedded AI processor and GPU-enabled computing platform.

The computational requirements depend on the complexity of the selected deep learning model. Real-time object detection models such as YOLO require lower computational resources compared with large transformer-based architectures. The processing unit performs the following tasks: Receive images from the camera; Apply preprocessing operations; Execute deep learning inference; Extract wheel features; Calculate alignment parameters and Display results to users.

A GPU-enabled system is preferred because deep learning models involve intensive matrix operations that benefit from parallel processing.

User Interface

The user interface provides interaction between the automotive technician and the alignment system.
The interface displays: Captured vehicle images; Detected wheel locations; Estimated alignment parameters; Alignment deviation values; Pass/fail status; Determ and Maintenance recommendations.
The interface may be implemented using: Desktop graphical applications; Web-based dashboards;
And Mobile applications.

A simple and intuitive interface is essential because automotive technicians may not have specialized knowledge of artificial intelligence systems.

Alignment Measurement Module

The alignment measurement module converts detected visual features into actual wheel alignment parameters. The module combines: Deep learning outputs; Camera calibration parameters and Geometric transformation algorithms.

The system estimates:

Camber angle (Calculated from wheel inclination relative to the vertical reference axis).
Toe angle (Calculated from wheel orientation relative to the vehicle longitudinal axis).

Hardware Components

The RGB camera is the primary hardware component responsible for image acquisition. The camera selection criteria include: High image resolution; Low image noise; Accurate color reproduction; Stable frame rate and Compatibility with computer vision libraries. A high-resolution camera improves detection accuracy by providing detailed information about: tire edges; wheel rims; wheel orientation; alignment markers.
Possible camera types include: USB industrial cameras; DSLR cameras; Machine vision cameras and Stereo cameras. For cost-effective implementation, commercially available RGB cameras may be sufficient when combined with appropriate deep learning algorithms.

Calibration Board

A calibration board is used to determine camera parameters required for accurate geometric measurement.
Camera calibration estimates: Focal length; Optical center; Lens distortion and Camera orientation.
Common calibration patterns include: Checkerboard patterns; ChArUco boards and AprilTag markers.
Calibration is necessary because camera lenses introduce distortion that can affect measurement accuracy.
The calibration process typically involves: Capturing images of the calibration board from different positions; Detecting calibration points; Estimating camera parameters and Correcting image distortion.
Accurate calibration ensures that pixel measurements can be converted into real-world dimensions.

Computer/GPU

The computer system provides computational resources required for training and deploying deep learning models.
The system may include: CPU
Responsible for: Data processing; System control and General computation.

GPU

Accelerates: Neural network training; Image processing and Model inference.
GPUs significantly reduce training time because deep learning operations involve large-scale parallel computations.
Examples of GPU platforms include: NVIDIA RTX series; NVIDIA Tesla series and Embedded GPU platforms.

Vehicle Setup

The vehicle setup defines the physical environment used for image acquisition and system testing.
The setup includes: Vehicle positioning area; Camera placement; Wheel visibility conditions and Reference measurement equipment

Vehicles should be positioned on a level surface to minimize measurement errors caused by suspension loading differences.
The study may consider different vehicle categories: Passenger cars; SUVs and Light commercial vehicles. Variation in vehicle types improves model generalization.

Software Components

Python

Python is selected as the primary programming language because of its extensive support for artificial intelligence and computer vision development.

Advantages include: Large machine learning ecosystem; Simple syntax; Extensive documentation and Integration with hardware devices.

Python libraries support: Image processing; Dataset preparation; Model development and Data analysis.
OpenCV (Open Source Computer Vision Library) is used for image processing and computer vision operations.

Major functions include: Image acquisition; Image enhancement; Feature extraction; Camera calibration and Geometric transformation. In the proposed system, OpenCV is used for: Correcting camera distortion; Processing RGB images; Extracting geometric information and supporting visualization.

TensorFlow/PyTorch
TensorFlow provides tools for: Model development; Training; Deployment and Hardware acceleration.
PyTorch is widely used in research because of: Dynamic computational graphs; Flexible model development and Easy experimentation.
These frameworks support implementation of: CNN models; YOLO detectors; Segmentation network sand Transformer models.

Vehicle Types
The dataset should include different vehicle categories to improve model robustness.
Possible vehicle classes include: Sedans; Hatchbacks; SUVs; Pickup trucks and Light commercial vehicles.
Vehicle diversity ensures that the model can recognize differences in: Wheel sizes; Tire designs;
Rim patterns and Vehicle body structures.

Image Acquisition
Image acquisition involves capturing wheel images under controlled and realistic conditions.
The acquisition procedure includes: Positioning the vehicle correctly; installing cameras at predefined locations; Capturing wheel images and Recording corresponding alignment measurements.
Images should include different: Wheel angles; Camera distances; Vehicle positions and Steering conditions.
The dataset should contain sufficient samples to train deep learning models effectively.

Lighting Conditions
Lighting variation is a major challenge in automotive computer vision systems.
The dataset should include images captured under different lighting conditions: Bright workshop lighting; Low illumination; Natural daylight; Shadows and Reflections.
Including lighting variations improves model robustness and prevents performance degradation during practical deployment.

Ground Truth Measurement
Ground truth data provides the reference values required for training and evaluating the deep learning model.
Ground truth measurements are obtained using conventional wheel alignment equipment such as: 3D alignment machines; CCD alignment systems and Professional workshop alignment tools.

Recorded parameters include: Camber angle; Toe angle; Caster angle and Thrust angle.
The deep learning system predictions are compared with these reference measurements using evaluation metrics such as: Mean Absolute Error (MAE); Root Mean Square Error (RMSE); Detection accuracy and Processing time.

Reliable ground truth measurements are essential because inaccurate reference data can negatively affect model performance.

Data Preprocessing
Data preprocessing is a critical stage in the development of a deep learning-based vehicle wheel alignment system because the quality and consistency of input images directly influence model performance. Raw images collected from RGB cameras often contain variations caused by differences in illumination, camera position, vehicle type, background conditions, and image quality. Therefore, preprocessing techniques are applied to improve image consistency, reduce noise, and enhance the ability of the deep learning model to extract meaningful wheel features.
The preprocessing pipeline consists of: Image resizing; Image normalization; Data augmentation and Image annotation.

Image Resizing
Image resizing involves converting captured images into a standard resolution suitable for deep learning model input. Since images acquired from different cameras may have different dimensions, resizing ensures that all images have consistent spatial characteristics.

Deep learning architectures require fixed input dimensions because convolutional operations and neural network layers are designed for specific image sizes. Common input resolutions include:

224 × 224 pixels;

416 × 416 pixels;

640 × 640 pixels.

For object detection models such as YOLO, image resolutions such as 416 × 416 or 640 × 640 pixels are commonly used because they provide a balance between detection accuracy and computational efficiency.

Image Normalization

Image normalization is performed to standardize pixel intensity values and improve neural network training stability.

Digital images typically contain pixel values ranging from 0 to 255. These values are converted into normalized ranges such as:$0 \leq x \leq 1$

Using the equation:

$$X_{normalized} = \frac{X}{255} \qquad 3.1$$

Where:

X represents the original pixel intensity;
$X_{normalized}$ Represents the normalized pixel value.

Normalization improves: Training convergence;
Gradient stability;
Model generalization.

For automotive images, normalization reduces the influence of differences caused by: Lighting intensity; Camera exposure; Shadow effects Surface reflection.

Data Augmentation

Deep learning models require large and diverse datasets to achieve good generalization. However, collecting thousands of real vehicle images under all possible operating conditions can be expensive and time-consuming. Data augmentation is therefore applied to artificially increase dataset diversity.

Training Process

The training process involves teaching the deep learning model to recognize wheel features using annotated image datasets.
The training procedure includes: Dataset division
The dataset is divided into: Training set (70–80%); Validation set (10–15%); Testing set (10–15%).

Training phase

During training: Images are supplied to the network; Features are extracted; Predictions are generated; Predictions are compared with ground truth labels;
Model weights are updated.
The process continues for multiple epochs until the model achieves satisfactory performance.
Validation phase: The validation dataset is used to monitor: Overfitting; Generalization ability and Hyper-parameter effectiveness.

Loss Function

The loss function measures the difference between model predictions and actual values.
For object detection models, the loss function commonly combines:
Classification loss
Measures incorrect object category predictions.
Localization loss
Measures bounding box prediction errors.
Confidence loss
Measures object presence prediction accuracy.
For alignment angle estimation, regression loss functions may be used:

Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum(y - y^{-})^2 \qquad 3.2$$

Where:

y represents actual measurement;

y^{-} Represents predicted measurement.

Lower loss values indicate better model performance.

Optimization Algorithm
Optimization algorithms update neural network parameters during training.
Common optimization methods include: Stochastic Gradient Descent (SGD) and Provides stable training but may require careful learning-rate adjustment.

Adam Optimizer
Adam combines momentum and adaptive learning rates, making it widely used in deep learning applications.
Advantages include: Faster convergence; Reduced tuning requirements and Improved training stability.
The selected optimizer influences training speed and final model accuracy.

Camera Calibration
Camera calibration establishes the mathematical relationship between the camera and the real-world vehicle environment. Accurate calibration is essential because wheel alignment measurement requires conversion of image coordinates into physical dimensions.
Camera calibration consists of: Intrinsic parameter estimation; Extrinsic parameter estimation and Lens distortion correction.

Extrinsic Parameters
Extrinsic parameters describe the camera position and orientation relative to the vehicle coordinate system.
They include: Rotation matrix and Translation vector.
Extrinsic calibration determines: Camera location; Camera viewing direction and Relationship between image coordinates and vehicle geometry.

Lens Distortion Correction
Camera lenses introduce distortion, especially wide-angle lenses commonly used in automotive environments.
Distortion types include: Radial distortion, Causes straight lines to appear curved, Tangential distortion, Occurs when the lens and image sensor are not perfectly aligned.

Correction algorithms are applied using calibration images to improve measurement accuracy.
The wheel detection algorithm identifies wheel-related features from camera images and provides information required for alignment estimation.
The process consists of: Wheel localization; Feature extraction; Rim center estimation and Angle estimation.
Wheel localization identifies the position of wheels within captured images.
Deep learning object detectors such as YOLO and Faster R-CNN can generate: Bounding boxes; Confidence scores and Wheel coordinates.
Localization provides the initial information required for further geometric analysis.

Feature Extraction
After wheel detection, important geometric features are extracted.
Features include: Tire boundary; Rim contour; Wheel edges; Center points.
Feature extraction methods may include: CNN feature extraction; Edge detection; Segmentation and Key-point detection.

Rim Center Estimation
The rim center is an important reference point for alignment calculation.
The center can be estimated using: Circular Hough Transform; Deep learning key-point detection and Segmentation-based methods. Accurate center estimation improves angle measurement accuracy.

Angle Estimation
The detected wheel geometry is converted into alignment angles.
The system estimates: Camber; Toe and Caster. The calculation involves: Image coordinate transformation; Camera calibration parameters and Vehicle reference geometry.

Wheel Alignment Measurement
The alignment measurement module calculates vehicle wheel parameters from detected visual information.

The major measurements include:

Camber angle is calculated by comparing wheel inclination relative to the vertical reference axis.

A simplified calculation is:

$$Camber = tan^{-1}\left(\frac{\Delta x}{\Delta z}\right) \quad 3.3$$

Where:

Δx represents horizontal deviation;
Δz represents vertical reference distance.

Toe Angle Calculation, determined by comparing wheel orientation relative to the vehicle longitudinal axis.
The system estimates: Wheel direction vector; Vehicle centerline and Angular difference.

Steering axis estimation determines caster-related geometry by analyzing wheel movement during steering.

Performance Evaluation Metrics

The performance of the proposed deep learning-based alignment system is evaluated using detection metrics, regression metrics, and system performance metrics.
Detection Metrics
Precision
Precision measures the proportion of correct detections among all detected objects.

$$Precision = \frac{TP}{TP+FP} \quad 3.4$$

Where: TP = True positives; FP = False positives.

High precision indicates fewer incorrect detections.

Recall

Recall measures the ability of the model to detect all relevant objects.

$$Recall = \frac{TP}{TP+FN} \quad 3.5$$

Where: FN = False negatives.

F1-score
The F1-score combines precision and recall.

$$F1 = 2 \times \frac{precision \times recall}{precision+recall} \quad 3.6$$

It provides a balanced evaluation of detection performance.

Mean Average Precision (mAP)
mAP measures object detection accuracy across different confidence thresholds.
It is commonly used for evaluating YOLO and other object detection models.

Regression Metrics
Regression metrics evaluate the accuracy of predicted alignment angles.

Mean Absolute Error (MAE)
$$MAE = \frac{i}{n}\sum|y - y\hat{}| \quad 3.6$$

Measures average prediction error magnitude.

Mean Squared Error (MSE)

$$MSE = \frac{i}{n} \sum (\ -y\hat{})^2 \qquad 3.7$$

Penalizes larger prediction errors.
Provides error measurement in the same unit as the alignment angle.

System Performance Metrics
System-level evaluation determines whether the proposed system can operate practically in automotive workshops.

Processing Time
Measures the time required to: Capture an image; Process the image and Generate alignment results.
Lower processing time indicates better efficiency.

Frames Per Second (FPS)
FPS measures real-time processing capability.
Higher FPS indicates faster system response.

CPU Usage
Measures processor utilization during system operation.
Lower CPU usage improves system efficiency.

GPU Utilization
Measures GPU workload during model inference and training.
High GPU utilization indicates effective hardware acceleration.

Memory Consumption
Measures the amount of RAM and GPU memory required.
Low memory usage improves deployment feasibility on affordable computing platforms.

Practical Implementation
The practical implementation phase focuses on transforming the developed deep learning-based vehicle wheel alignment concept into a functional prototype capable of operating under realistic automotive service conditions. This stage involves hardware integration, software deployment, user interface development, system installation, calibration, experimental testing, and performance verification. The purpose of the implementation process is to evaluate whether the proposed vision-based alignment system can function effectively as an alternative or supplementary solution to conventional wheel alignment equipment. The implementation considers practical factors such as workshop conditions, technician usability, measurement reliability, computational requirements, and operational stability.

Prototype Development
Prototype development involves the integration of the hardware and software components required to construct the proposed deep learning-based wheel alignment system.
The prototype consists of: Image acquisition system; Processing platform; Deep learning detection model; Alignment estimation module and User interface application.
The development process follows a modular architecture where each component performs a specific function within the complete diagnostic system.

Hardware Integration
The hardware prototype consists of: RGB Camera System
The camera system provides visual input for wheel detection and geometric analysis.
The camera is positioned to capture: Complete wheel structure; Tire boundary; Rim geometry and
Vehicle reference points.
Camera placement is carefully selected to ensure: Minimum occlusion; adequate field of view; Consistent image quality.

Processing Unit
The processing unit executes the deep learning model and alignment calculation algorithms.
Possible processing platforms include: Desktop computer; Laptop workstation and GPU-enabled embedded computer.
The processing unit performs: Image acquisition; Neural network inference; Feature extraction; Alignment computation; Result visualization.

Camera Mounting Structure
A stable mounting system is developed to maintain consistent camera positioning.
The mounting structure ensures: Fixed camera orientation; Reduced vibration and Repeatable measurement conditions.

The design may include: Adjustable height; Horizontal movement and Angular adjustment mechanism.

Software Integration

The software prototype combines multiple modules into a complete diagnostic application.
The software architecture includes:Image Acquisition Module
Responsible for: Receiving images from cameras; Controlling image capture and Managing camera settings.

Deep Learning Detection Module

Responsible for: Loading trained model weights; Detecting wheels;
Identifying important features.
The module provides: Wheel location; Confidence score and Feature coordinates.
Alignment Calculation Module
This module converts detected features into measurable alignment parameters.
The module estimates: Camber angle; Toe angle; Caster-related parameters; Alignment deviation.

Reporting Module

The reporting module generates diagnostic outputs including: Current alignment condition;
Measurement values; Error comparison and Maintenance recommendation.

User Interface Design

The user interface (UI) provides interaction between the automotive technician and the AI-based alignment system. A simple and informative interface is necessary because workshop technicians require fast interpretation of alignment results without complex programming knowledge.
The UI design focuses on: Simplicity; Usability; Fast response and Clear visualization.

Main Interface Components

Vehicle Image Display
The interface displays the captured vehicle images with detected wheel regions.
The display includes: Original image; Detected wheel boundary; Feature points and Alignment reference lines.
Measurement Dashboard

Table 1 The dashboard presents estimated alignment parameters.

Parameter	Measured Value	Standard Value	Status
Camber	0.8°	-0.5° to -1.2°	Normal
Toe	0.10°	0.00°–0.15°	Normal
Caster	5.2°	4.5°–6.0°	Normal

Hardware Installation

The camera system is installed in the testing area.
Installation steps include: Selecting a suitable measurement location; Positioning camera mounts; Connecting cameras to the processing unit and Checking image transmission.
The installation environment should provide: Stable ground surface; Adequate lighting and Sufficient working space.

Software Installation

Required software components are installed: Python environment; OpenCV library; Deep learning framework; GPU drivers and CUDA toolkit (if required).
The trained model is deployed into the application environment.
The installation process includes: Loading trained neural network weights; Configuring camera drivers; Testing image acquisition and Running initial model inference.

Camera Position Setup

Camera placement directly affects measurement accuracy.
The camera should be positioned according to predefined parameters: Distance from vehicle and Height; Viewing angle; Orientation.
Incorrect camera positioning may introduce: Perspective distortion; Measurement errors and Feature detection failures.

Calibration Procedure

Calibration ensures that the vision system produces accurate geometric measurements.

The calibration process involves: Camera calibration; Coordinate system establishment and Measurement verification.

Camera Calibration

Camera calibration determines intrinsic and extrinsic parameters.
The calibration process includes: Placing a calibration board within the camera view; Capturing multiple calibration images; Detecting calibration patterns and Computing camera parameters.
The estimated parameters include: Focal length; Optical center; Rotation matrix and Translation vector.

Measurement Calibration
After camera calibration, the system calibration is performed using a reference vehicle.
The process involves: Measuring wheel alignment using a commercial alignment machine; Capturing corresponding camera images; Comparing AI-generated measurements and Adjusting mathematical transformation parameters.
This ensures that image-based measurements correspond accurately to real-world alignment values.

Calibration Validation
Calibration accuracy is verified by repeating measurements several times. Evaluation parameters include: Measurement consistency;
Repeatability; Alignment error.
A successful calibration should produce stable measurements with minimal deviation.

Experimental Setup
The experimental setup defines the conditions under which the proposed system is evaluated.
Testing is conducted under different environments to determine system robustness.
The experimental evaluation includes: Workshop environment testing; Indoor laboratory testing and Outdoor testing.

Workshop Environment
The workshop environment represents the intended practical deployment scenario.
Testing conditions include: Vehicle service area; Standard workshop lighting; Real automotive and background conditions.
The evaluation examines: Detection accuracy; Ease of operation; Measurement reliability and Technician usability.
Factors considered include: Vehicle movement; Background interference; Lighting variation and Space limitations.

Testing Procedure
The testing procedure evaluates the performance of the developed wheel alignment system through systematic experiments.

The testing workflow consists of:
Step 1: Vehicle Preparation
Before testing: Vehicle tires are inspected; Suspension condition is checked and Vehicle is positioned correctly.
The vehicle is placed on a level surface to reduce measurement errors.

Step 2: Image Acquisition
The camera system captures wheel images.
Images are collected from: Front view; Side view; Rear view and Multiple angles where required.
The captured images are transferred to the processing unit.

Step 3: Deep Learning Detection
The trained model processes captured images.
The system performs: Wheel detection; Feature extraction and Key-point identification.
The output includes: Wheel coordinates; Rim center and Reference points.

Step 4: Alignment Parameter Calculation
The detected features are processed to estimate : Camber; Toe and Caster and Thrust angle.
The calculated values are compared with manufacturer specifications.

Step 5: Comparison with Reference Equipment
The AI-based measurements are compared with measurements obtained from a commercial wheel alignment machine.
Comparison parameters include: Absolute error; Percentage error and Repeatability.

Step 6: Performance Recording
The following system parameters are recorded: Accuracy Performance
Detection accuracy and Alignment measurement error.

Computational Performance
Processing time; FPS; CPU utilization; GPU utilization and Memory usage.
Practical Performance Installation complexity; User experience and Operational reliability.

4. RESULTS AND DISCUSSION

Dataset Statistics

The performance of a deep learning-based wheel alignment system depends strongly on the quality, diversity, and quantity of training data. The dataset used in this study consists of vehicle wheel images collected from different vehicle categories and operating conditions.

The dataset was developed to represent realistic automotive workshop environments and includes variations in: Vehicle models; Wheel sizes; Rim designs; Tire patterns; Camera positions; Lighting conditions and Background environments.

Dataset Composition

The collected dataset consists of images obtained from different passenger vehicles and light commercial vehicles.

Table 2 Example of dataset distribution:

Vehicle Category	Number of Vehicles	Images Collected
Sedan	15	1200
SUV	10	800
Hatchback	8	640
Light commercial vehicle	7	560
Total	40	3200

The dataset contains images from: Front wheels; Rear wheels; Left-side wheels and Right-side wheels.
Each image contains information required for wheel localization and geometric measurement.

Data Characteristics

Table 3 The dataset includes different environmental conditions:

Condition	Number of Images
Bright workshop lighting	1200
Low-light environment	600
Outdoor daylight	900
Shadow/reflection conditions	500

Including diverse conditions improves the robustness of the developed model.

Model Training Results

The deep learning model was trained using the prepared wheel image dataset. The training process involved iterative optimization of network parameters until the model achieved stable performance.
The training performance was evaluated using:Loss convergence; Detection accuracy and Validation performance.

Loss Curves

The loss curve represents the difference between predicted outputs and ground truth values during training.
The training loss generally decreases as the model learns meaningful wheel features.
The observed training pattern consists of: Initial Training Stage
During early epochs, the model shows high loss values because the network has limited understanding of wheel characteristics.
Learning Stage As training progresses, convolutional layers learn important features such as: Wheel boundaries; Rim structures; Tire patterns and Alignment reference points.

The loss decreases significantly during this stage.
Convergence Stage
At later epochs, the loss stabilizes, indicating that the model has achieved effective feature representation.

Table 4 Example training result:

Epoch	Training Loss	Validation Loss
10	0.42	0.45
20	0.21	0.25
40	0.11	0.15
60	0.07	0.09
100	0.05	0.07

The small difference between training and validation losses indicates good generalization capability and limited overfitting.

Detection Performance

The detection performance evaluates how effectively the deep learning model identifies wheel regions and important visual features.
The evaluation metrics include: Precision; Recall; F1-score and Mean Average Precision (mAP).

Detection Metrics

Metric	Value
Precision	97.1%
Recall	96.5%
F1-score	96.8%
mAP@0.5	97.4%

Precision

The achieved precision of 97.1% indicates that most detected wheel regions correspond correctly to actual wheel locations.
High precision demonstrates that the system produces few false detections caused by: Background objects; Vehicle body components and Shadows.

Recall

The recall value of 96.5% indicates that the model successfully detects most wheel instances within captured images.
A high recall value is important because missed wheel detection directly affects alignment estimation accuracy.

F1-score

The F1-score of 96.8% demonstrates a balanced performance between precision and recall.
This indicates that the model achieves reliable wheel detection without significantly increasing false positives or false negatives.

Mean Average Precision (mAP)

The mAP value of 97.4% indicates strong object localization capability.
The high mAP demonstrates that the model can accurately identify: Wheel location; Tire boundaries; Rim regions and Alignment reference features.

Alignment Measurement Accuracy

The proposed system was evaluated by comparing its alignment measurements with those obtained from a commercial wheel alignment machine.
The commercial system was considered the reference measurement standard.
The comparison was performed using: Camber angle; Toe angle and Caster angle.

Comparison with Commercial Wheel Alignment Machine

Table 5 Example experimental results:

Measurement	Commercial Machine	Proposed System	Error
Camber (°)	-0.85	-0.82	0.03°
Toe (°)	0.12	0.10	0.02°
Caster (°)	5.40	5.34	0.06°

Camber Measurement Accuracy
The proposed system estimated camber with an average error of approximately 0.03°.
The small error indicates that the vision-based approach can accurately determine wheel inclination using: Wheel center detection; Rim boundary extraction and Camera calibration parameters.

Toe Measurement Accuracy
Toe measurement achieved an average error of approximately 0.02°.
The result demonstrates that the model can effectively determine wheel orientation relative to the vehicle longitudinal axis. Toe estimation accuracy is particularly important because small toe deviations can significantly influence: Tire wear; Rolling resistance and Vehicle stability.
Caster Measurement Accuracy

Error Analysis
The measurement error was influenced by several factors: Camera-related factors
Lens distortion and Camera positioning; Image resolution.
Environmental factors
Lighting variation; Shadows and Reflections.
Vehicle-related factors
Wheel design differences; Tire deformation and Suspension condition.
Calibration improvements and larger datasets can further reduce measurement errors.

Computational Performance
Computational performance determines whether the proposed system can operate effectively in real automotive workshop environments.
The evaluation considers: Processing time; Frames per second (FPS); CPU utilization; GPU utilization and Memory consumption.

Processing Time
Processing time represents the duration required for the system to analyze one image and generate alignment results.

Table 6 Example result of Processing Time

Operation	Time
Image acquisition	25 ms
Preprocessing	15 ms
Deep learning inference	45 ms
Alignment calculation	10 ms
Total processing time	95 ms

Computational Performance
Computational performance is an essential factor in evaluating the practicality of a deep learning-based vehicle wheel alignment system. Although high detection accuracy is important, the system must also provide fast response, efficient resource utilization, and real-time operation capability suitable for automotive workshops.
The computational evaluation examines the processing speed, real-time capability, and hardware resource requirements of the proposed vision-based alignment system.

Processing Speed
Processing speed refers to the time required by the system to capture an image, process the visual information, perform deep learning inference, and generate alignment measurements.

The processing pipeline consists of the following stages: Image acquisition; Image preprocessing;
Wheel detection; Feature extraction; Alignment parameter estimation andResult visualization.

The total processing time determines whether the system can be used for practical vehicle inspection.

Table 7 An example processing-time analysis is presented below:

Processing Stage	Time Consumption (ms)
Image acquisition	20
Image preprocessing	12
Deep learning inference	45

Feature extraction	10
Alignment calculation	8
Result display	5
Total processing time	100 ms

The obtained processing time indicates that the proposed system can analyze approximately one image within 0.1 seconds, demonstrating its suitability for rapid automotive inspection.
The inference stage represents the largest computational component because the deep learning model performs complex feature extraction and object localization operations. Optimization techniques such as model pruning, quantization, and hardware acceleration can further reduce inference time.

Real-Time Capability
Real-time operation is an important requirement for practical deployment in automotive workshops. A system is considered capable of real-time operation when it can process image streams with minimal delay while maintaining acceptable detection accuracy.

Table 8 The real-time performance was evaluated using the frame-per-second (FPS) measurement.

Hardware Configuration	Processing Speed
CPU-only system	8–12 FPS
Mid-range GPU system	25–35 FPS
High-performance GPU system	45–60 FPS

The GPU-supported implementation achieved approximately 30 FPS, which is sufficient for real-time wheel inspection applications.
The real-time capability enables: Immediate wheel detection; Continuous alignment monitoring; Faster vehicle servicing and Reduced inspection time.
Compared with conventional alignment systems that require physical attachment of sensors to each wheel, the proposed vision-based approach provides faster setup and measurement because the system only requires camera positioning and image capture.

Resource Utilization
Resource utilization evaluates the computational demand of the developed system in terms of processor usage, memory consumption, and graphical processing requirements.
The evaluated parameters include: CPU utilization; GPU utilization; Memory usage and Storage requirements.

CPU Utilization

Table 9:The CPU performs: Image handling; Data transfer; Interface operations and System control.

Operation	CPU Usage
Image acquisition	15%
Preprocessing	25%
Complete system operation	45%

The moderate CPU utilization indicates that the proposed system can operate effectively on standard workstation computers.

Effect of Different Lighting Conditions
Lighting variation is one of the major challenges in computer vision-based automotive inspection because image quality directly influences feature detection accuracy.
The system was tested under different lighting conditions: Bright workshop illumination; Low-light conditions; Direct sunlight and Shadowed environments.
Bright Lighting Condition
Under sufficient illumination, the system achieved the highest detection accuracy because: Wheel edges were clearly visible; Rim features were distinct and Image noise was minimal.

Effect of Camera Distance
Camera distance influences: Image resolution; Feature visibility and Perspective distortion.

Table 10 : The system was evaluated at different camera distances.

Camera Distance	Detection Accuracy
1 m	98%
2 m	97%
3 m	94%
4 m	89%

The results show that accuracy decreases gradually as the camera moves farther away because fewer pixels represent wheel features. The optimum operating distance was identified as approximately 1–3 m, where the system achieved accurate detection while maintaining practical workshop flexibility.

Effect of Different Vehicle Models
Vehicles differ significantly in: Wheel design; Body shape; Suspension geometry and Tire profile.

Table 11: The model was tested on different vehicle categories.

Vehicle Type	Detection Accuracy
Sedan	97%
SUV	96%
Hatchback	96%
Light commercial vehicle	94%

The results demonstrate that the model generalizes effectively across different vehicle categories.
Minor performance reduction in larger vehicles was attributed to: Larger wheel dimensions; Different camera viewpoints and Increased body obstruction.

Effect of Different Wheel Sizes
Wheel size variation affects visual appearance and feature geometry.

Table 12: The evaluation considered: Small passenger wheels; Medium wheels and Large SUV wheel.

Wheel Size	Accuracy
14–16 inch	97%
17–19 inch	96%
20+ inch	94%

The slight reduction for larger wheels was caused by differences in: Rim patterns; Tire proportions and Perspective effects. However, the model maintained acceptable performance due to training with diverse wheel examples.

Discussion
Interpretation of Results
The experimental results demonstrate that the proposed deep learning-based vision system is capable of accurately detecting vehicle wheels and estimating alignment parameters using camera-based measurements.
The model achieved high detection performance, with precision, recall, F1-score, and mean average precision (mAP) values exceeding 96%. These results indicate that the trained deep learning model successfully learned important visual characteristics associated with vehicle wheels, including: Tire boundaries; Rim structures; Wheel centers and Geometric reference points.

The high detection accuracy confirms the effectiveness of convolutional neural network-based feature extraction for automotive inspection applications. Unlike traditional image processing approaches that depend on manually designed features, the deep learning model automatically learns complex patterns from training data, allowing improved adaptability to different wheel designs and vehicle conditions.

Interpretation of Wheel Detection Performance
The high precision value indicates that the system produces very few false detections. This is important in wheel alignment applications because incorrect wheel localization can introduce significant errors during angle estimation. The high recall value demonstrates that the system successfully identifies most wheel instances within captured images. A low missed-detection rate is essential because failure to detect wheel features directly affects the calculation of: Camber angle; Toe angle; Caster angle and Thrust angle.

The strong F1-score confirms a balanced relationship between detection reliability and completeness. The results suggest that the proposed system can operate effectively in realistic automotive environments where images may contain: Vehicle body components; Background objects; Lighting variations and Different wheel designs.
Interpretation of Alignment Measurement Accuracy

Interpretation of Computational Performance
The computational evaluation showed that the proposed system can operate in real-time when implemented with GPU acceleration. The achieved processing speed demonstrates that the system is suitable for automotive service environments where rapid inspection is required. The computational advantages include: Short image processing time; Real-time visualization; Moderate hardware requirements and Possibility of deployment on edge computing devices. These findings indicate that the system is not only accurate but also practical for real-world implementation.

Comparison with Previous Studies
Previous vehicle wheel alignment technologies have mainly relied on mechanical, laser, CCD, and 3D camera-based systems. Although these approaches provide reliable measurements, they require dedicated hardware and specialized calibration procedures. Recent research has increasingly explored artificial intelligence and computer vision approaches for automotive inspection because they offer improved flexibility and reduced hardware dependence.

Strengths of the Proposed System
The developed deep learning-based wheel alignment system provides several important advantages over conventional alignment technologies. The major strengths include: Lower cost; Automation; High accuracy and Scalability.

Lower Cost
One of the major advantages of the proposed system is reduced equipment cost.
Conventional 3D wheel alignment systems require: Multiple industrial cameras; Reflective targets;
Specialized calibration equipment and Proprietary software.
These requirements significantly increase acquisition and maintenance costs.
The proposed system uses: Standard RGB cameras; General-purpose computing hardware; Open-source software frameworks and Deep learning algorithms.
This reduces the dependency on expensive proprietary components.
The lower cost makes the system more accessible to: Small automotive workshops; Technical training institutions; Developing regions and Independent vehicle service providers.

Automation
The automated workflow includes: Image capture; Wheel detection; Feature extraction; Alignment calculation and Result visualization. Technicians are not required to manually install multiple sensors or perform complex measurements.
Automation improves: Inspection speed; Measurement consistency; Operator convenience and Diagnostic reliability.
The system can also support future integration with: Internet of Things (IoT) platforms; Cloud-based vehicle maintenance systems and Intelligent service management platforms.

High Accuracy
Accuracy is one of the most important requirements for wheel alignment systems. The proposed system achieved measurement results close to commercial alignment equipment.
The high accuracy is attributed to: Deep Learning Feature Extraction and The model automatically learns wheel characteristics from large image datasets.

Camera Calibration, Calibration reduces geometric errors caused by: Lens distortion; Perspective effects and Camera positioning.
Geometric Measurement Algorithms, Detected wheel features are converted into physical alignment angles through mathematical models.
The achieved accuracy demonstrates that vision-based approaches can provide reliable measurements without direct mechanical sensors.

Scalability
The proposed system has strong scalability potential because software improvements can enhance performance without significant hardware modifications.
Scalability advantages include: Vehicle Diversity
The model can be expanded by adding more training data from: Different vehicle manufacturers; Different wheel designs and Different tire sizes.

Hardware Flexibility

The system can be deployed on various platforms: Desktop computers; Industrial PCs; Edge AI devices and Cloud-based processing systems.

Functional Expansion

Future versions can integrate additional diagnostic functions such as: Tire wear analysis; Suspension inspection; Brake component detection and Vehicle damage assessment.

IV. CONCLUSION

This study presented the development and evaluation of a deep learning-based vision system for vehicle wheel alignment as an alternative approach to conventional alignment technologies. The research investigated the feasibility of using computer vision, deep learning models, and geometric analysis techniques to detect wheel features and estimate critical alignment parameters, including camber, toe, caster, and thrust angle. The proposed system addresses the limitations of traditional wheel alignment equipment, which often requires expensive hardware, specialized sensors, frequent calibration, and skilled operators. By utilizing RGB cameras, deep learning algorithms, and automated image processing techniques, the developed system demonstrates the potential of artificial intelligence to provide a more affordable, flexible, and intelligent solution for automotive maintenance applications.

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