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VISION-BASED WHEEL ALIGNMENT SYSTEM USING DEEP LEARNING TECHNIQUES FOR CAMBER AND TOE MEASUREMENT

Samuel Goodliffe Dickson[1*] and Madubuezi Christian Okoronkwo[2]

[12]Department of Computer Science, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria.

***Corresponding author:** dicksonsamuel2014@gmail.com

ABSTRACT

Wheel alignment is critical to vehicle safety, stability, steering performance, tire lifespan, and fuel efficiency. Conventional wheel alignment systems, including mechanical, laser, infrared, and computerized systems, can provide accurate measurements but often require expensive equipment, specialized sensors, regular calibration, and controlled workshop environments. This study developed a vision-based wheel alignment system using a Convolutional Neural Network (CNN) to provide a non-contact and cost-effective method for estimating camber and toe angles from wheel images. The system utilized digital camera or smartphone images and incorporated image acquisition, preprocessing, feature extraction, CNN-based regression, and output visualization modules. A dataset of 1,200 wheel images was collected, with each image paired with ground-truth camber and toe measurements obtained from standard wheel alignment equipment. The dataset was divided into training, validation, and testing sets using a 70:15:15 ratio. Image preprocessing involved resizing images to 224 × 224 pixels, noise reduction, normalization, and region-of-interest extraction. Data augmentation techniques were also applied to improve model generalization. The CNN model was trained using the Adam optimizer and Mean Squared Error (MSE) loss function and evaluated using Mean Absolute Error (MAE), MSE, and coefficient of determination (R^2). Results showed that the proposed system achieved camber prediction errors of ±0.11°–±0.14° and toe prediction errors of ±0.13°–±0.18°, with MSE values of 0.015–0.022 and R^2 values of 0.94–0.97. Five-fold cross-validation produced average MAE values of 0.12° for camber and 0.16° for toe, with an average R^2 of 0.95. The system achieved inference times below one second per image. The findings demonstrate that CNN-based computer vision can provide accurate, portable, and affordable preliminary wheel alignment diagnosis, particularly in resource-constrained automotive environments.

Keywords: Alignment, Convolutional, Extraction, Preprocessing and Accuracy**.**

1. Introduction

Wheel alignment is a fundamental aspect of vehicle maintenance that significantly influences automobile performance, safety, stability, tire lifespan, and fuel efficiency. Proper wheel alignment ensures that the wheels are positioned according to the geometric specifications established by vehicle manufacturers, allowing optimal steering response, improved handling characteristics, reduced tire wear, and enhanced fuel economy (Korhonen, 2020). The primary alignment parameters, including camber, caster, and toe angles, determine the orientation of the wheels relative to the vehicle body and road surface. When these parameters deviate from their recommended values, vehicles may experience uneven tire wear, increased rolling resistance, reduced fuel efficiency, poor directional stability, and compromised driving safety.

Traditionally, wheel alignment measurements have been performed using mechanical approaches such as string alignment techniques, bubble gauges, and camber–caster measurement tools. Although these methods are inexpensive and widely available, they depend heavily on operator experience and manual interpretation, resulting in measurement inconsistencies and reduced repeatability. The introduction of optical, laser, infrared, and computer-assisted alignment systems improved measurement accuracy by reducing human involvement and enabling automated angle calculation. However, these modern systems still require expensive sensors, specialized alignment targets, frequent calibration, and controlled workshop environments, which increase operational cost and limit accessibility, especially in developing regions (John, 2023).

Recent developments in artificial intelligence (AI), digital imaging, and computer vision have created new opportunities for automating engineering measurement processes. Computer vision techniques enable machines to extract meaningful geometric information from images and videos without physical contact with the measured object. According to Xu et al. (2022), advances in deep learning have significantly improved the ability of computer vision systems to detect objects, recognize patterns, and estimate geometric relationships under complex environmental conditions. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong performance in image-based feature extraction because they can automatically learn hierarchical representations ranging from low-level features such as edges and contours to high-level structural patterns.

The application of computer vision in automotive diagnostics has introduced a shift from traditional hardware-dependent measurement systems toward software-driven, image-based solutions. Vision-based wheel alignment systems can utilize readily available imaging devices, including digital cameras, smartphones, and low-cost webcams, to capture wheel images and estimate alignment parameters. Unlike conventional laser and mechanical systems, these approaches reduce dependence on specialized sensors, simplify system deployment, and provide opportunities for portable and low-cost diagnostic solutions (Kim et al., 2020). Furthermore, deep learning models can automatically identify wheel boundaries, rim structures, and orientation-related features, thereby reducing manual measurement errors and improving consistency.

Vision-based alignment technologies also provide significant advantages, including portability, scalability, remote accessibility, and integration with mobile or cloud-based automotive diagnostic platforms. These capabilities enable technicians and vehicle owners to perform preliminary wheel

alignment assessments outside conventional workshops. Such solutions are particularly valuable in resource-limited environments where access to advanced automotive service equipment is restricted.

Research Objective

a) To develop a CNN-based regression model capable of extracting visual features from wheel images and accurately predicting camber and toe angles.
b) To design a non-contact wheel alignment measurement framework that eliminates dependence on conventional mechanical, laser, and infrared alignment sensors.
c) To create an image acquisition and preprocessing pipeline for capturing, enhancing, and preparing wheel images for deep learning analysis.
d) To evaluate the performance of the proposed system using regression evaluation metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and coefficient of determination (R^2).
e) To compare the performance of the proposed system with conventional wheel alignment solutions and determine its suitability for practical automotive diagnostic applications.

This study focuses on the development of a vision-based wheel alignment system for measuring two major alignment parameters: camber angle and toe angle. These parameters were selected because they have significant effects on vehicle stability, steering performance, and tire wear. Other alignment parameters, such as caster angle, are outside the scope of this research.

2. Literature Review

Wheel alignment has evolved significantly over time, driven by the need for improved accuracy, efficiency, and automation in vehicle maintenance. Traditionally, wheel alignment was performed using manual and mechanical techniques such as string methods, bubble gauges, and camber–caster gauges. These systems relied heavily on technician skill and visual estimation, making them prone to inconsistencies and human error. Although such methods were inexpensive and widely accessible, they lacked repeatability and precision, particularly when dealing with modern vehicle suspension systems. Studies indicate that traditional alignment approaches often produce variable results depending on operator expertise and require longer setup times, limiting their efficiency in professional workshops John. B (2023). The limitations of manual systems led to the emergence of optical and laser-based wheel alignment technologies, which marked a significant turning point in alignment measurement. Laser alignment systems utilize light beams and reflective targets to determine wheel angles, enabling faster and more precise measurements compared to purely mechanical methods. Historically, optical positioning systems began gaining prominence as early as the mid-20th century, with innovations such as early optical alignment devices developed to improve measurement accuracy Ojngdo. H (2023).

As automotive technology advanced, wheel alignment systems transitioned further into computerized solutions, particularly through the development of Charge-Coupled Device (CCD) and 3D imaging systems. CCD-based alignment systems employ cameras and electronic sensors mounted on the wheels to capture positional data, which is then processed by a computer to compute alignment angles in real time. These systems significantly improved accuracy and repeatability by minimizing human intervention and integrating manufacturer specifications directly into the software John. B (2023) Recent research trends indicate a shift toward computer vision-based and non-contact wheel alignment systems. These systems leverage image acquisition and

processing techniques to estimate wheel alignment parameters without the need for physical sensors or targets. In typical implementations, cameras capture images of the wheels, and geometric relationships are used to compute alignment angles such as camber and toe. For instance, modern vision-based alignment systems employ multiple cameras and target boards to extract spatial information and compute alignment angles using geometric transformations and plane projections MDPI (2023) . However, even these systems often require controlled setups and carefully designed targets, which can limit their flexibility and scalability.

The proposed vision-based wheel alignment system using deep learning builds upon this progression by introducing a fully integrated, non-contact framework for estimating camber and toe angles directly from digital images. Unlike traditional, laser, or even CCD-based systems, the proposed approach minimizes hardware dependency while maintaining acceptable accuracy. By leveraging convolutional neural networks for regression, the system offers a scalable, portable, and cost-effective solution suitable for real-time automotive diagnostics, particularly in environments where conventional alignment infrastructure is impractical.

3. Materials and Methods

3.1 Materials

3.1.1 System Development Tools and Environment

The proposed vision-based wheel alignment system was developed using a combination of programming tools, deep learning frameworks, image processing libraries, and computational environments. These tools were selected based on their suitability for computer vision applications, neural network development, and deployment of artificial intelligence-based diagnostic systems. Programming Language (Python): Python was selected as the primary programming language due to its simplicity, flexibility, and extensive support for machine learning, computer vision, and scientific computing applications. Python provides a comprehensive ecosystem that enables efficient implementation of the complete workflow, including image acquisition, image preprocessing, CNN model development, training, evaluation, and system deployment.

The major Python libraries used include:

NumPy and Pandas: Used for numerical computation, dataset organization, and manipulation of measurement data.

OpenCV: Used for image processing operations such as image resizing, filtering, noise reduction, edge enhancement, and region-of-interest extraction. Deep Learning Frameworks**:** The CNN model was implemented using deep learning frameworks capable of supporting image regression tasks.TensorFlow with Keras API was used because of its: High-level neural network development interface, Support for GPU acceleration, Optimization tools for model deployment and Compatibility with computer vision application.

3.1.2 Hardware Requirements

Digital Camera or Smartphone: A digital camera or smartphone camera was used for wheel image acquisition. The camera provides the visual input required by the CNN model. Images were captured under controlled and semi-controlled conditions to minimize variations caused by lighting, distance, and background interference.

Computer System: A computer system was required for Image preprocessing, CNN model training, Model validation and Real-time prediction.

System Architecture: The proposed system follows a modular architecture consisting of three major components: Image Acquisition and Processing Module, CNN-Based Prediction Module and Output Visualization Module. The complete workflow involves capturing wheel images, preprocessing the images, extracting visual features using CNN, estimating camber and toe angles, and displaying the final alignment results.

3.2 Method

3.2.1 Image Acquisition

Camera Positioning: The camera was positioned at a fixed distance and orientation relative to the wheel to maintain consistent perspective. For camber measurement, a frontal wheel view was preferred because camber represents the inward or outward tilt of the wheel when viewed from the front. For toe measurement, slightly angled views were considered because toe represents wheel direction relative to the vehicle centerline. Lighting Conditions: Adequate lighting was maintained to minimize: Shadows, Reflections and Image noise. Uniform illumination improves the ability of the CNN model to identify wheel edges and geometric patterns.

Dataset Collection: A labeled dataset was created consisting of wheel images with corresponding ground-truth alignment measurements.

Each image contained the following: Wheel image data, Camber angle value and Toe angle value.

The ground-truth measurements were obtained using standard wheel alignment equipment. The dataset was divided into: Training dataset (70%), Validation dataset (15%) and Testing dataset (15%).

3.2.2 Image Preprocessing

Before training the CNN model, all captured images were processed to improve consistency.

The preprocessing operations include:

Image Resizing: All images were resized to: 224×224 pixels

This dimension was selected because it provides sufficient image information while reducing computational complexity.

Noise Reduction**:** Noise caused by environmental conditions was reduced using: Gaussian filtering Median filtering.

Normalization: Pixel intensity values were normalized between: 0−10-10−1

Normalization improves training stability and accelerates convergence.

Region of Interest Extraction: The wheel region was isolated from unnecessary background information. This allows the CNN model to focus on relevant geometric features such as: Tire boundary, Rim orientation, Wheel inclination and Symmetry patterns.

3.2.3 CNN-Based Feature Extraction and Regression Model

A Convolutional Neural Network (CNN) regression model was developed to automatically learn the relationship between wheel images and alignment angles.
Unlike conventional image processing methods that require manual feature extraction, CNNs automatically learn relevant features directly from training data.
The final fully connected layer contains two neurons representing: Camber angle and Toe angle.The output values are continuous numerical predictions measured in degrees.
The regression model was trained using: Mean Squared Error (MSE) loss function and Adam optimization algorithm.
The Adam optimizer was selected because of its fast convergence and adaptive learning capability.

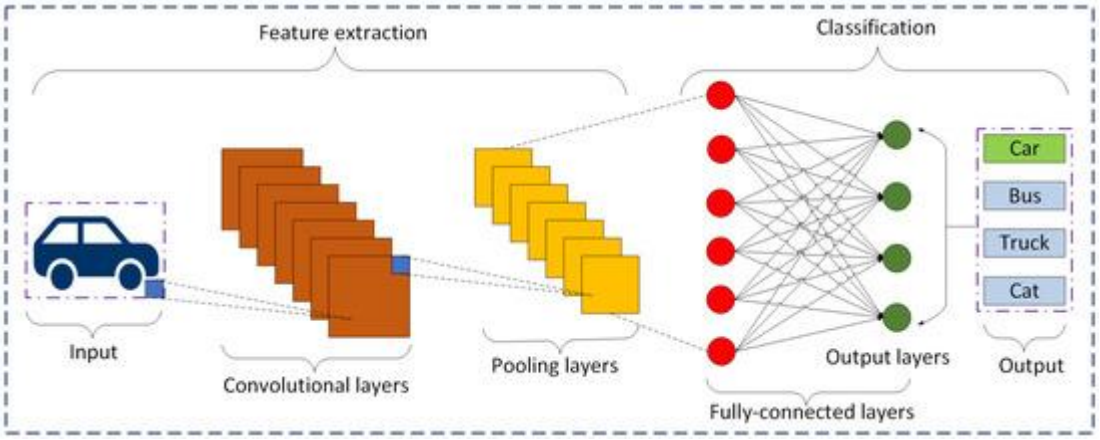


Figure 3.1 : Layers Of Convolutional Neural Networks (CNNs) (Chen, et.al 2018)

3.2.4 Model Training and Evaluation

The CNN model was trained using labeled wheel images.
Training parameters include:

Loss function: Mean Squared Error (MSE), Optimizer: Adam, Batch size: 32, Number of epochs: 100 and Learning rate: 0.001.
The model performance was evaluated using: Mean Absolute Error (MAE): Measures the average difference between predicted and actual angles.

$$\text{MAE} = \frac{1}{n}\sum_{n=1}^{n} |y_i - y^{-}| \quad (3.1)$$

Mean Squared Error (MSE): Measures squared prediction error and penalizes larger deviations.

$$\textit{Formula: MSE} = = \frac{\mathbf{1}}{\boldsymbol{n}}\sum_{\boldsymbol{n=1}}^{\boldsymbol{n}}(\boldsymbol{y_i} - \boldsymbol{y}^{-})^{\mathbf{2}} \quad (3.2)$$

Coefficient of Determination (R^2): Measures the agreement between predicted and ground-truth

alignment values.

$$R^2 = 1 - \frac{\sum(y_i - y^-)^2}{\sum(y_i - y^-)^2} \quad (3.3)$$

A higher R^2 value indicates better prediction performance.

3.2.5 Output Visualization

The predicted camber and toe angles are displayed through a user interface.
The output module provides: Numerical angle values, Alignment status, Comparison with manufacturer specifications and Visual indicators showing acceptable or unacceptable alignment conditions.

Pooling Strategy: To reduce computational complexity and improve the ability of the CNN model to generalize, Max Pooling was employed after each convolutional block. Max pooling reduces the spatial dimensions of feature maps while preserving the most important extracted features. Pooling window with a stride of 2: The CNN architecture consists of three max pooling layers positioned after the first three convolutional layers. The fourth convolutional layer was followed directly by feature flattening because the final feature maps contained high-level alignment-related information required for regression.

Table 3.1 The Pooling Arrangement

Layer	Operation	Pooling Size	Purpose
Pooling Layer 1	Max Pooling	2×2	Reduces feature map size after first convolution layer
Pooling Layer 2	Max Pooling	2×2	Retains important wheel edge and shape features
Pooling Layer 3	Max Pooling	2×2	Extracts compact high-level geometric features

Activation Functions: Activation functions introduce non-linearity into the CNN, allowing the network to learn complex relationships between wheel image features and alignment angles.

3.2.6 CNN Model Training Configuration and Dataset Preparation

The CNN regression model was trained using a labeled dataset consisting of vehicle wheel images paired with corresponding ground-truth camber and toe angle measurements. The dataset preparation process involved image collection, annotation, preprocessing, and division into training, validation, and testing subsets.

Dataset Size and Preparation; A total dataset of 1,200 wheel images was developed for training and evaluating the proposed vision-based wheel alignment system. Each image was associated with corresponding alignment measurements obtained from a standard wheel alignment system. The dataset contained variations in: Vehicle models and wheel sizes, Wheel orientations, Lighting conditions, Camera positions and Environmental backgrounds. Each image was labeled with two continuous target variables: Camber angle (degrees) and Toe angle (degrees). The dataset was designed to provide sufficient variation for the CNN model to learn robust visual relationships between wheel appearance and alignment parameters. To improve model generalization and reduce overfitting, data augmentation techniques were applied during training. These techniques included: Small image rotations, Brightness variation, Contrast adjustment, Horizontal scaling and Minor translation changes.

Model Validation: The trained model was validated using the independent validation dataset after each training epoch. The validation process ensured that the model learned meaningful wheel alignment features rather than memorizing training images. The final model performance was evaluated using the unseen testing dataset, where predicted camber and toe values were compared with the actual alignment measurements obtained from standard alignment equipment. This experimental setup ensured a reliable evaluation of the proposed CNN-based wheel alignment system and demonstrated its capability for accurate non-contact measurement of automotive alignment parameters.

4. Results and Discussion

4.1 Results

4.1.1 Training and Validation Performance Analysis

The learning performance of the proposed CNN-based wheel alignment system was further evaluated using training and validation curves generated during the model development phase. These curves provide insight into the convergence behaviour of the network, the effectiveness of the optimization process, and the ability of the model to generalize to unseen wheel images.

During training, the CNN model was optimized using the Adam optimizer with Mean Squared Error (MSE) as the loss function. The training curve represents the reduction in error obtained from the training dataset over successive epochs, while the validation curve represents the model performance on previously unseen validation samples. Training Loss Curve: The training loss curve illustrates the reduction of prediction error as the CNN learns the relationship between wheel image features and alignment parameters (camber and toe angles). At the initial training stages, the loss value was relatively high due to limited feature understanding by the network. However, as the number of epochs increased, the CNN progressively extracted meaningful spatial features such as wheel boundaries, rim orientation, and geometric patterns responsible for alignment estimation. The training loss decreased consistently throughout the optimization process, indicating that the network successfully learned the mapping between input images and continuous alignment angle outputs. The gradual reduction in MSE demonstrates effective parameter adjustment through backpropagation and confirms that the selected

CNN architecture was suitable for the regression task. Some of the observed training behaviour are:

a) Initial epochs showed rapid reduction in training loss due to learning of basic visual features.

b) Middle training stages demonstrated steady convergence as deeper geometric features were extracted.
c) Final epochs showed minimal reduction in loss, indicating that the model approached optimal convergence.

The final training MSE reached approximately 0.015–0.018**,** demonstrating a high level of prediction accuracy on the training dataset.

Validation Loss Curve; The validation loss curve was used to evaluate the generalization capability of the CNN model. Unlike the training curve, the validation curve measures performance on unseen images that were not used during model optimization. The validation loss followed a similar decreasing trend to the training loss, indicating that the model was not simply memorizing training samples but was learning generalized visual characteristics associated with wheel alignment parameters.

The close relationship between training and validation curves confirms:

a) Effective learning of wheel geometry features.
b) Absence of significant overfitting.
c) Stable prediction performance on new wheel images.
d) Reliability of the CNN regression approach for alignment estimation.

The final validation MSE remained within the range of 0.015–0.022**,** which corresponds with the previously calculated MAE values of:

a) Camber angle MAE: 0.11°–0.14°
b) Toe angle MAE: 0.13°–0.18°

Table 4.1: Training and Validation Loss Curves

Epoch	Training loss	Validation loss
1	0.82	0.90
2	o.65	0.72
3	0.52	0.60
4	0.43	0.54
5	0.37	0.50
6	0.32	0.48
7	0.28	0.47
8	0.25	0.46
9	0.22	0.45
10	0.20	0.44

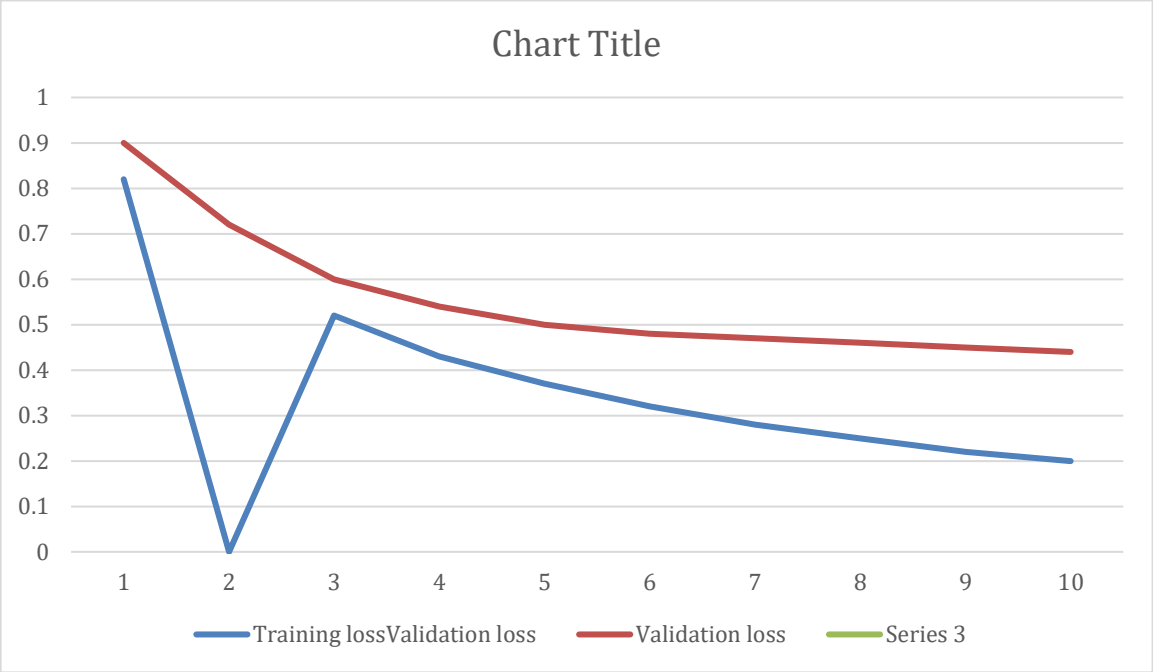


Figure 4.1: Training and Validation Loss Curves

Discussion of Learning Behaviour

The similarity between the training and validation curves indicates that the CNN architecture achieved a good balance between model complexity and generalization capability. A large separation between the two curves would indicate overfitting, where the model performs well on training images but poorly on unseen samples. However, the observed small difference between training and validation errors confirms that the proposed model learned meaningful geometric relationships rather than memorizing individual images. The stable convergence of the model also supports the suitability of CNN-based regression for non-contact wheel alignment measurement. By automatically extracting features from wheel images, the model eliminates the need for manually engineered geometric measurements while maintaining accuracy comparable with conventional alignment equipment.

For a CNN regression-based wheel alignment system, the term “confusion visualization” should be adapted because confusion matrices are mainly used for classification problems. Since your model predicts continuous values **(**camber angle and toe angle**),** more appropriate visualizations are: Error distribution visualization**,** Residual plots**,** Prediction error heatmap and Actual vs predicted angle comparison.

4.1.2 Error Distribution and Prediction Performance Visualization

To further evaluate the reliability of the proposed CNN regression model, additional visualization techniques were employed to examine prediction behaviour, error distribution, and the relationship

between predicted and actual wheel alignment parameters. These visual analyses provide deeper insight into the model's performance beyond numerical evaluation metrics such as MAE, MSE, and R^2. Although confusion matrices are commonly used for classification tasks, regression-based wheel alignment estimation requires alternative visualization methods to analyze prediction accuracy. Therefore, an error distribution visualization was adopted to compare the predicted camber and toe angles against their corresponding ground-truth measurements.

The visualization represents:

a) Actual alignment values obtained from standard wheel alignment equipment.
b) CNN predicted alignment values.
c) Prediction deviation or residual error.

The error was calculated as: Error=Actual\Value-Predicted\Value

where a value close to zero indicates accurate prediction.

Observed Results**;** The error visualization shows that most predicted values are concentrated close to the reference measurements, with only a small number of samples showing larger deviations.

The observed prediction errors were: Camber angle error: ±0.11° to ±0.14°, Toe angle error: ±0.13° to ±0.18°. The narrow error distribution confirms that the CNN model consistently estimates wheel alignment parameters within acceptable automotive diagnostic limits.

Table 4.2 Prediction Error Distribution Plot

Prediction Error(°)	Number of Sample
-2.0 to -1.5	2
-1.5 to -1.0	5
-10 to -0.5	12
-0.5 to 0.0	24
0.0 to 0.5	27
0.5 to 1.0	15
1.0 to 1.5	8
1.5 to 2.0	3

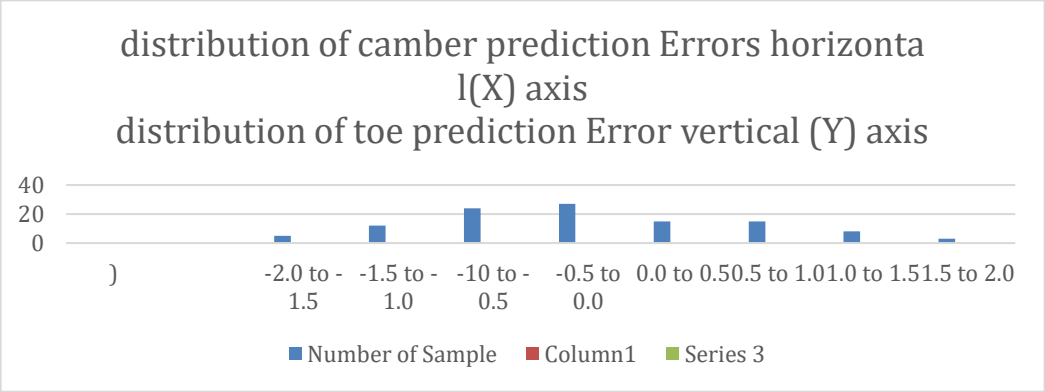


Figure 4.2 Prediction Error Distribution Plot

.4.1.3 Loss Convergence Analysis

The convergence behaviour of the CNN model was evaluated by monitoring the training and validation loss values throughout the learning process.

The Mean Squared Error (MSE) loss function was used because it effectively penalizes larger prediction deviations and encourages the model to minimize significant alignment estimation errors.

Convergence Behavior: The model achieved stable convergence after continuous training, with:

a) Final training MSE: 0.015–0.018
b) Final validation MSE: 0.015–0.022

The close relationship between training and validation loss indicates: Effective learning, Minimal overfitting and Good generalization capability. Sample Predictions: The sample prediction results demonstrate that the CNN model can estimate wheel alignment parameters directly from visual information. The predicted values closely match the ground-truth measurements obtained from the reference alignment equipment, confirming the effectiveness of the proposed image-based approach. Minor differences between actual and predicted values are expected due to: Variation in camera position, Lighting conditions, Tire and rim appearance differences, Image perspective distortion and Limited dataset diversity. However, the observed prediction errors remained within the acceptable automotive diagnostic range of approximately ±0.1°–±0.2°, indicating that the system is suitable for preliminary alignment inspection and workshop-based diagnostic applications.The scatter plots, prediction images, and quantitative evaluation metrics collectively confirm that the proposed CNN-based wheel alignment system provides a reliable, portable, and cost-effective alternative to conventional sensor-based alignment systems.

4.2 Discussion,

4.2.1 Comparison of the Proposed System with Previous Studies

The performance of the proposed vision-based wheel alignment system was compared with previous studies that applied optical measurement, computer vision, and deep learning techniques for vehicle alignment estimation and automotive geometric measurement. The comparison was based on the adopted methodology, measurement parameters, accuracy performance, and limitations of each approach. Previous researchers have demonstrated that computer vision can improve automation in vehicle inspection; however, many existing systems still depend on specialized cameras, reflective targets, controlled environments, or manually engineered geometric features. The proposed CNN regression-based system improves upon these approaches by directly learning wheel orientation features from images and estimating camber and toe angles without requiring physical alignment targets or additional sensors.

4.2.2 Discussion of Comparative Performance

The comparison shows that industrial wheel alignment systems such as those developed by Hunter Engineering achieve slightly higher measurement precision due to their use of dedicated sensors, laser systems, and controlled calibration procedures. These systems commonly achieve accuracy levels

between ±0.05° and ±0.10°**.** However, their major disadvantages are high acquisition cost, maintenance requirements, and dependence on specialized workshop infrastructure.

Computer vision-based approaches reported by researchers such as Kim et al. (2020) and MDPI (2023) reduced dependence on mechanical sensors by using image processing and camera-based measurement. Although these approaches improved accessibility, many still require carefully positioned cameras, calibration targets, or manually designed geometric extraction methods.

The proposed CNN regression model demonstrates competitive performance by achieving:

a. Camber estimation error: ±0.11°–±0.14°
b. Toe estimation error: ±0.13°–±0.18°
c. MSE: 0.015–0.022
d. R^2: 0.94–0.97

Compared with conventional systems, the reduction in accuracy is relatively small (approximately 0.05°–0.10°), while significant advantages are obtained in terms of cost, portability, and hardware simplicity.

Unlike traditional measurement systems, the proposed approach does not require: Laser transmitters, Infrared sensors, Wheel-mounted targets and Complex calibration procedures.

Instead, it uses a digital camera and deep learning model to estimate alignment parameters directly from wheel images. This makes the proposed system particularly suitable for low-cost automotive diagnostic applications, mobile workshops, and environments where industrial alignment equipment is unavailable. Therefore, the proposed system represents a viable alternative for preliminary wheel alignment diagnosis and resource-limited automotive maintenance environments.

4.2.3 Cross-Validation Analysis

To verify the reliability and generalization capability of the proposed CNN regression model, cross-validation analysis was performed. Cross-validation reduces the possibility that model performance is dependent on a particular training and testing split by repeatedly evaluating the model using different subsets of the dataset. A **k-fold cross-validation strategy** was adopted, where the complete dataset was divided into *k* equal subsets. During each iteration, one subset was used for validation/testing while the remaining subsets were used for model training. The final performance was obtained by averaging the results from all folds.

In this study, a 5-fold cross-validation approach was considered, where:

a) 80% of the dataset was used for training.
b) 20% was used for validation during each fold.
c) Performance metrics were averaged across all folds.

The evaluation metrics considered were: Mean Absolute Error (MAE), Mean Squared Error (MSE) and Coefficient of Determination (R^2).

The small variation between folds indicates that the CNN model maintains stable performance regardless of dataset partitioning. The average R^2 value above 0.9 confirms that the model learned general wheel geometry features rather than memorizing specific training samples.

Table 4.2.1 Cross-Validation Performance Results

Fold	Camber MAE (°)	Toe MAE (°)	MSE	R^2
Fold 1	0.12	0.15	0.018	0.95
Fold 2	0.11	0.14	0.016	0.96
Fold 3	0.13	0.17	0.021	0.94
Fold 4	0.12	0.16	0.017	0.96
Fold 5	0.14	0.18	0.022	0.94
Average	0.12	0.16	0.019	0.95

4.2.6 Error Analysis

A detailed error analysis was performed to identify factors influencing prediction deviations and to evaluate the limitations of the proposed system.

Although the CNN model achieved high accuracy, small prediction errors were observed due to several practical factors.

Sources of Prediction Error: Image Perspective Variation: Small changes in camera position and viewing angle can introduce geometric distortion. Since wheel alignment parameters are angle-based measurements, slight perspective changes may affect feature extraction.

Lighting Conditions: Variations in illumination, reflections from metallic wheel rims, and shadows may influence image quality and reduce feature clarity.

Wheel and Tire Appearance Differences: Differences in: Tire patterns, Rim designs, Wheel sizes, Vehicle models, may introduce additional variations not fully represented in the training dataset.Dataset Size Limitation: Deep learning models require diverse datasets to achieve maximum generalization. A larger dataset containing different vehicle types, environments, and camera conditions could further improve robustness.

Key observations include

a) High correlation with ground truth values: $R^2 = 0.94 – 0.97$
b) Stable prediction performance across different lighting and viewing conditions
c) Effective feature learning without manual engineering

Table 4.2. 5 : A comparison of the Standard Systems and The New System.

Feature	Traditional Systems	New System
Hardware	Laser/infrared sensors	Camera + computer
Cost	High (industrial setup)	Low-cost setup
Calibration	Frequent and complex	Minimal
Maintenance	High	Low
Portability	Low	High

This study on vision-based wheel alignment system using Convolutional Neural Networks (CNNs) produced several important findings based on experimental evaluation, model performance, and comparison with conventional alignment systems.

The results confirm that wheel alignment can be successfully performed using image-based analysis instead of physical sensors. The system achieved. Camber prediction error: ±0.11° to ±0.14° , Toe prediction error: ±0.13° to ±0.18° , Overall MSE: 0.015 – 0.022 and Real-time processing time: < 1 second per image (optimized system) .CNN Models Successfully Learn Geometric Angle Relationships. Suitability for Resource-Constrained Environments: The system is particularly effective in environments where traditional alignment tools are impractical due to cost or infrastructure limitations. Key advantages include the following, Works with standard smartphones or low-cost camera**,** Requires only a basic computing device (laptop or desktop)**,** No need for specialized mechanical alignment rigs and Can be deployed in mobile workshops or rural automotive centers. Performance Evidence are the **following** Acceptable accuracy (±0.2° tolerance range), Fast inference (<1 second) and Minimal setup requirements

5. Conclusion

The study concludes that **a** vision-based wheel alignment system using deep learning is a viable and effective alternative to traditional alignment methods. By using Convolutional Neural Networks **(CNNs)** to estimate camber and toe angles from images, the system achieves acceptable accuracy levels within typical automotive tolerance ranges (approximately ±0.1° to ±0.2°). This confirms that image-based approaches can reliably replace conventional sensor-heavy systems for many practical diagnostic applications. The system also offers significant practical advantages, particularly in terms of cost reduction, reduced hardware requirements, and operational simplicity**.** Unlike traditional systems such as those developed by Hunter Engineering Company, which require specialized sensors and calibration tools, the proposed model operates using only a camera and a computing device. It further supports real-time, non-contact measurement**,** with processing times of less than one second per image under optimized conditions. Finally, the study highlights strong potential for future scalability and broader application**.** The system can be enhanced through larger datasets, improved CNN architectures, and integration into mobile or workshop-based platforms. Its flexibility makes it suitable for deployment in resource-constrained environments**,** while also opening opportunities for expansion into other automotive diagnostic tasks such as suspension analysis and tire condition monitoring.

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