International journal of science, engineering, and information technology
Volume XX, Issue XX, Moon YYYY
Journal homepage: https://journal.trunojoyo.ac.id/ijseit

AI-Based Visual Inspection for Torsion Spring Installation in Automotive Transmission Manufacturing

Departement of Informatics, Universitas KH. Bahaudin Mudhary Madura, Sumenep, Indonesia

A B S T R A C T

In the context of Industry 4.0, automotive manufacturing increasingly adopts artificial intelligence (AI) to improve quality assurance and reduce dependency on manual inspection. One critical issue in transmission assembly is improper installation of torsion spring components on the parking lock pole, which can lead to transmission malfunction and severe quality defects. Traditionally, this inspection process relies on human visual checking, which is time-consuming and prone to human error due to fatigue and varying operator conditions. This research proposes an AI-based visual inspection system to automatically detect incorrect torsion spring installation in a car transmission production line. The proposed system utilizes Convolutional Neural Network (CNN) models for image classification, deployed on an edge computing device integrated with Programmable Logic Controller (PLC) interlocking. Three CNN architectures (*MobileNet*, *EfficientNet*, and *ResNet*) are evaluated to identify the most suitable model for this application. The dataset consists of production images captured directly from the factory environment, with data augmentation applied to enhance robustness under varying lighting conditions. Model performance is evaluated using accuracy and *K-Fold Cross-Validation*. Experimental results show that the *ResNet* model achieves the highest performance, with an average accuracy of 99.66%, demonstrating its effectiveness in detecting improper torsion spring installation. The implementation of the proposed system eliminates the need for human visual inspection and reduces processing time in the production process. This study confirms that AI-based edge vision systems can significantly enhance quality assurance in automotive transmission manufacturing.

Keywords: Computer Vision, Deep Learning, Edge AI, Quality Inspection, Automotive Manufacturing.

Article History
Received 10 August 26 Received in revised form 12 November 26 Accepted 21 December 26

1. Introduction

In the era of Industry 4.0, automotive manufacturing is increasingly driven by automation, digitalization, and intelligent systems to improve production efficiency and product quality. One of the key challenges in modern manufacturing is ensuring consistent quality assurance while reducing reliance on manual inspection processes. Manual visual inspection, although widely used, is inherently limited by human factors such as fatigue, subjectivity, and inconsistent performance, which may lead to undetected defects in critical components.

In automotive transmission manufacturing, the correct installation of torsion spring components plays a vital role in ensuring proper mechanical function. Torsion spring components are responsible for storing and transmitting rotational energy and must be precisely installed on the parking lock pole at designated positions. Improper installation, such as missing or incorrectly positioned torsion springs, can result in transmission malfunction, reduced durability, and potential safety risks. Therefore, reliable detection of torsion spring installation defects is essential to maintaining product quality and preventing downstream failures in the production process.

Traditionally, the inspection of torsion spring installation is performed by human operators through visual checking. While this method is straightforward, it is time-consuming and prone to miss-checks caused by operator fatigue, variations in lighting conditions, and differences in individual judgement. As production volume increases, maintaining consistent inspection quality becomes increasingly difficult. These limitations highlight the need for an automated inspection system that can operate reliably under real production conditions.

Recent advancements in artificial intelligence (AI), particularly in computer vision and deep learning, have enabled automated visual inspection systems to achieve high accuracy and robustness. Convolutional Neural Networks (CNNs) have demonstrated strong performance in image-based classification and defect detection tasks across various industrial applications. By learning discriminative visual features directly from image data, CNN-based systems can outperform traditional rule-based inspection methods, especially in complex or variable environments.

In addition, the adoption of edge computing has made it feasible to deploy AI models directly on the production line. Edge AI systems allow real-time inference with low latency and reduced dependency on cloud infrastructure, making them suitable for integration with industrial equipment such as Programmable Logic Controllers (PLCs). This integration enables immediate responses to detected defects, such as stopping the production line to prevent defective products from proceeding to the next process, thereby supporting poka-yoke (error prevention) and zero-defect manufacturing principles.

* *Corresponding author.* Phone : +6285645123565
E-mail address: muhammadnajib@unibamadura.ac.id

E-ISSN 2548-4214

This research proposes an AI-based visual inspection system for detecting improper torsion spring installation in automotive transmission manufacturing. The proposed system utilizes CNN-based image classification models deployed on an edge computing device integrated with a PLC interlock mechanism. Several CNN architectures, including *MobileNet*, *EfficientNet*, and *ResNet*, are evaluated to determine the most suitable model for this application. The system is trained and tested using real production images collected directly from the factory environment, with data augmentation applied to enhance robustness under varying conditions.

The objective of this study is to evaluate the effectiveness of deep learning-based visual inspection in replacing human visual inspection for torsion spring installation. Model performance is assessed using accuracy and *K-Fold Cross-Validation* to ensure reliability and generalization. By implementing the proposed system, this research aims to demonstrate how AI-based edge vision can improve quality assurance, reduce inspection time, and contribute to cost reduction in automotive transmission manufacturing.

2. Materials

2.1. Torsion Spring Assembly Case

In automotive transmission manufacturing, torsion springs are critical mechanical components used to store and transmit rotational energy elastically. These springs play an essential role in providing damping, absorbing shocks, and ensuring stable mechanical operation within transmission systems, particularly in mechanisms requiring controlled rotational force such as parking lock systems [1]. One important application of torsion springs in transmission assembly is their installation on the parking lock pole, where correct positioning is required to guarantee proper engagement and release of the parking mechanism. Figure 1 shows the transmission assembly and a magnified view of the torsion spring installation area on the parking lock pole.

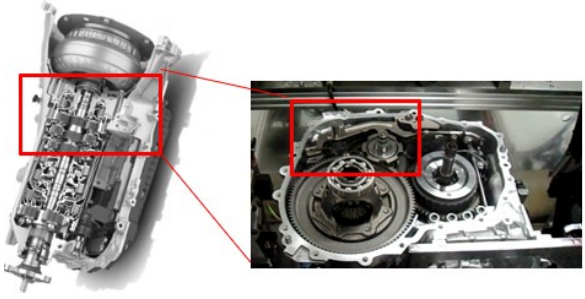


Figure 1. Torsion springs inside the transmission

The torsion spring assembly process involves mounting both the main torsion spring and the sub torsion spring onto designated positions on the parking lock pole, as illustrated in Figure 2. Each spring must be correctly hung at specific points to ensure balanced force distribution and reliable mechanical performance. Improper installation, such as missing springs or incorrect hanging positions, may lead to abnormal transmission behavior, including malfunction of the parking lock mechanism. Such assembly defects are known to cause quality issues, increased rework rates, and potential safety risks in automotive applications [2].

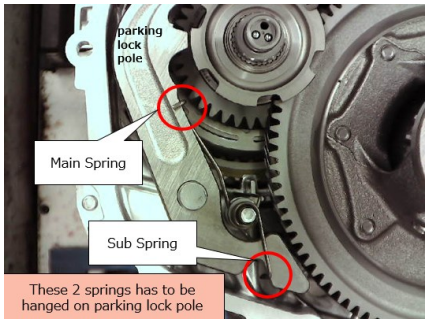


Figure 2. Torsion springs positions

Figure-based inspection is commonly used to verify the correctness of torsion spring installation. Under normal (OK) conditions, both torsion springs are properly mounted and securely positioned on the parking lock pole. In contrast, abnormal (NG) conditions occur when one or more torsion springs are missing, incorrectly positioned, or not properly engaged with the designated mounting points. These NG conditions are often difficult to detect reliably due to the similarity in appearance between correct and incorrect installations, especially when variations in lighting, angle, or component orientation are present.

In the existing production process, verification of torsion spring installation is primarily performed through human visual inspection. Operators are responsible for confirming the presence and correct positioning of both torsion springs before allowing the transmission assembly to proceed to the next process. However, as production speed increases and tasks are repeated continuously, human inspection becomes susceptible to fatigue and inconsistency, increasing the risk of miss-checks and allowing defective assemblies to pass through the production line [2].

Given the critical function of torsion springs in transmission systems and the potential consequences of improper installation, reliable and consistent inspection is essential. This assembly case therefore presents a suitable scenario for the application of automated visual inspection using artificial intelligence, where image-based inspection can enhance detection reliability and prevent defective products from advancing to subsequent processes.

2.2. Human Visual Inspection Limitation

In the current production process, the inspection of torsion spring installation is primarily performed through human visual inspection. Operators are required to verify the presence and correct positioning of both the main torsion spring and the sub torsion spring on the parking lock pole before allowing the transmission assembly to proceed to the next process. Although this method is widely applied, it presents several inherent limitations.

The main limitations of human visual inspection in torsion spring assembly include:

1. **Operator fatigue and reduced concentration**
   Visual inspection tasks are repetitive and continuous, particularly in high-volume production environments. Prolonged inspection activities can cause physical fatigue and decreased attention, increasing the probability of miss-checks over time [3].
2. **Environmental variability**

Variations in lighting conditions, viewing angles, shadows, and component orientation on the production floor can significantly affect visual perception. Subtle differences between OK and NG torsion spring installation conditions may become difficult to distinguish under such variable conditions [4].

3. **Production speed and takt time constraints**
   As production speed increases, operators must perform inspections within limited cycle times. This time pressure can compromise inspection accuracy, allowing defective assemblies to pass undetected [2].

These limitations highlight the challenges of relying solely on human visual inspection for critical assembly processes such as torsion spring installation. Therefore, an automated inspection approach that provides consistent, objective, and real-time evaluation is required to improve quality assurance and support poka-yoke (error prevention) and zero-defect manufacturing objectives.

2.3. AI-Based Visual Inspection Concept

AI-based visual inspection has become an effective solution for overcoming the limitations of human visual inspection in industrial manufacturing. Deep learning, especially Convolutional Neural Networks (CNNs), has shown strong performance in image classification and defect detection tasks, making it suitable for automated quality inspection in production environments [5]. Unlike manual inspection, CNN-based systems can analyze visual data consistently and objectively, without being affected by human fatigue or subjective judgement.

In industrial applications, CNNs automatically learn hierarchical visual features from raw input images, enabling them to distinguish between normal (OK) and abnormal (NG) conditions even when visual differences are subtle. This capability has been demonstrated across various manufacturing contexts, where automated defect detection using CNN architectures achieves high classification accuracy and supports consistent inspection under varying lighting and production conditions [6].

Compared to traditional rule-based inspection methods, which depend on manually designed features and thresholds, CNN-based approaches offer greater flexibility and robustness. Deep learning models can generalize more effectively by learning discriminative features directly from representative datasets, allowing reliable performance across diverse defect types and background variations [7].

2.4. Edge Computing and PLC Integration

The deployment of AI-based visual inspection systems in manufacturing environments requires real-time processing and seamless integration with existing production equipment. Cloud-based processing is often unsuitable for such applications due to network latency, bandwidth limitations, and reliability concerns, particularly in time-critical industrial processes. To address these challenges, edge computing has emerged as a preferred approach for implementing AI solutions directly on the production floor [8].

Edge computing refers to the execution of data processing and inference close to the data source, such as industrial cameras and sensors installed on production equipment. By deploying AI models on edge devices, inspection results can be generated with low latency and high reliability, enabling immediate decision-making within the takt time of the production line. This approach is particularly suitable for manufacturing inspection tasks that require fast and deterministic responses, including torsion spring installation inspection [8].

In this research, the AI-based visual inspection system is designed to operate on an edge computing device connected to an industrial camera. The edge device performs image preprocessing and deep learning inference locally, eliminating the need for continuous data transmission to external servers. Such architectures are widely adopted in industrial automation to enhance system robustness and ensure stable operation in environments with limited or variable network connectivity.

Automated process control is achieved through integration of the edge AI system with a programmable logic controller (PLC). The PLC functions as the central control unit of the production line, managing equipment operation and process flow. When an abnormal (NG) condition is detected by the AI system, a signal is transmitted to the PLC to activate an interlock mechanism, preventing the defective assembly from proceeding to the next process. Conversely, when a normal (OK) condition is detected, the PLC allows the production process to continue. This integration between edge AI and PLC supports *poka-yoke* (error-prevention) by ensuring immediate detection and handling of assembly errors, thereby improving inspection reliability and overall manufacturing efficiency [2].

3. Research Implementation

3.1 Research Framework

This research follows a structured framework to design, implement, and evaluate an AI-based visual inspection system for torsion spring installation in an automotive transmission production line. The research framework focuses on the sequential stages of the study, from problem identification to system evaluation, ensuring that both technical performance and industrial applicability are addressed.



Figure 3. Research framework

As illustrated in Figure 3, the research framework begins with the identification of inspection challenges in torsion spring assembly, particularly the limitations of human visual inspection under high-volume production conditions. This is followed by data collection from the production line using an industrial camera installed above the torsion spring assembly area. The collected images are then prepared through image preprocessing to improve data consistency and suitability for deep learning.

Subsequently, CNN-based models are developed and trained using the prepared dataset to classify torsion spring installation conditions. Model training and validation are conducted to evaluate classification performance and generalization capability. After selecting the most suitable model, the trained CNN is deployed on an edge computing device and evaluated under real production conditions. The final stage of the research involves system-

level evaluation, where the inspection results are integrated with the production line through PLC-based interlock control.

In addition to the research framework, the overall system architecture of the proposed AI-based visual inspection solution is presented in Figure 4. This figure illustrates the integration of the industrial camera, edge computing device, CNN-based inference, and PLC interlock mechanism with the production line, providing a practical view of how the proposed system operates in an actual manufacturing environment.

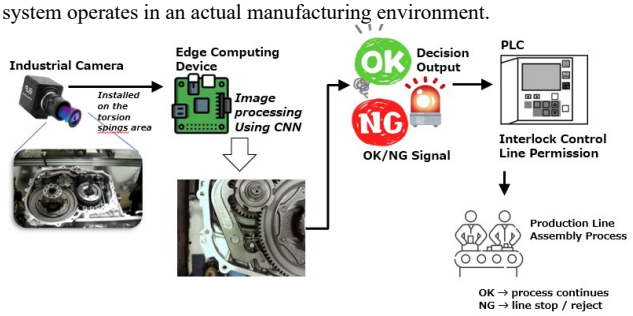


Figure 4. AI-based visual inspection integrated with edge computing and PLC

3.2 Data Collection and Dataset Preparation

Data collection was conducted directly on the automotive transmission assembly production line where torsion spring installation is performed. An industrial camera was installed above the torsion spring assembly area on the parking lock pole, as illustrated in Figure 4. The camera was positioned to capture a consistent top-view image of the assembly area, ensuring that both the main torsion spring and the sub torsion spring were clearly visible during inspection.

Images were captured during normal production operation to reflect real manufacturing conditions, including variations in lighting, component orientation, and minor positional differences caused by assembly tolerances. This approach was adopted to ensure that the dataset represents realistic production scenarios rather than idealized laboratory conditions. All images were acquired automatically and stored for offline analysis and model development.

The collected images were manually reviewed and labeled into two primary classes: OK and NG. The OK class represents images in which both torsion springs are correctly installed and securely positioned on the parking lock pole. The NG class includes images with abnormal installation conditions, such as missing torsion springs, incorrect hanging positions, or improper engagement with the designated mounting points. Labeling was performed based on standard assembly criteria used in the production line to ensure consistency with actual quality requirements.

The dataset classification scheme used in this study is consists of two torsion spring types: small-type torsion spring and medium-type torsion spring as described in Figure 5. For each type, five installation conditions are defined: OK**,** Not Installed**,** NG Both Springs**,** NG Main Spring**,** and NG Sub Spring, resulting in a total of ten classes across both torsion spring types. The OK class represents correct installation of both torsion springs, while the remaining classes correspond to abnormal installation conditions, including missing springs or incorrect positioning of the main and/or sub torsion springs. This classification reflects realistic assembly variations observed on the production line and provides a consistent basis for training and evaluating the CNN-based visual inspection model.

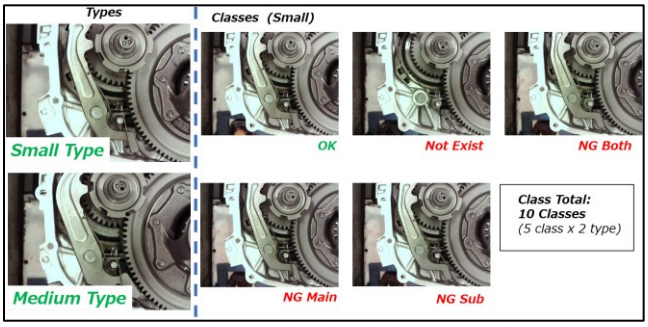


Figure 5. Captured Images that classified into OK and NG class

Prior to model training, the dataset was organized and prepared to support effective learning. Images with severe blur or incomplete views were excluded to maintain data quality. The labeled dataset was then divided into training and validation sets to enable performance evaluation during model development. This dataset preparation process ensures that the deep learning models are trained using representative and reliable data, forming a solid foundation for the CNN-based inspection system described in the subsequent sections.

3.3 Image Preprocessing

Image preprocessing was performed to improve data quality and enhance the robustness of the CNN-based visual inspection model. Since images were captured directly from the production line under real manufacturing conditions, variations in lighting, contrast, and background noise were present. Preprocessing steps were therefore applied to reduce these variations and ensure consistency across the dataset.

All input images were resized to a fixed resolution compatible with the CNN models used in this study. Resizing ensures uniform input dimensions and reduces computational complexity during training and inference. Pixel values were normalized to standardize the input data range, which helps stabilize the learning process and improves model convergence.

To further improve model generalization, data augmentation techniques were applied during training. These techniques include random rotation, slight translation, and brightness adjustment to simulate variations commonly encountered on the production floor. Data augmentation helps prevent overfitting and enables the model to learn invariant features related to torsion spring installation rather than being sensitive to minor visual changes.

No region-of-interest (ROI) cropping was applied, as the camera position was fixed and consistently captured the torsion spring assembly area. The original image resolution of 640 x 480 pixels was preserved throughout the preprocessing stage to maintain complete spatial information of the assembly components. This approach simplifies system deployment and ensures that the trained model remains compatible with real-time inference on the edge computing device, while avoiding additional computational overhead associated with dynamic ROI extraction.

3.4 Deep Learning Model Architecture

In this research, multiple Convolutional Neural Network (CNN) architectures were evaluated to identify the most suitable model for torsion spring installation inspection in an automotive transmission production

line. The selected models were chosen based on their proven performance in image classification tasks as well as their suitability for real-time inference on edge computing devices.

Three CNN architectures were considered in this study: *MobileNet*, *EfficientNet*, and *ResNet*. These models represent different design philosophies in deep learning. *MobileNet* is designed for lightweight computation and low latency, making it suitable for deployment on resource-constrained edge devices [9]. *EfficientNet* adopts a compound scaling approach to balance network depth, width, and resolution, offering improved accuracy with relatively efficient computation [10]. *ResNet* utilizes residual connections to enable deeper network architectures and has demonstrated strong performance in complex image classification tasks [11].

All CNN models were adapted for binary classification, corresponding to OK and NG torsion spring installation conditions. The final classification layer of each architecture was modified to match the target classes while maintaining the core feature extraction structure of the original networks. This approach allows fair comparison across models under the same dataset and preprocessing conditions.

The evaluation of multiple CNN architectures enables systematic comparison between accuracy and computational efficiency. This is particularly important for industrial applications, where inspection performance must satisfy both quality requirements and real-time processing constraints. The results of this comparison are presented and discussed in the following sections.

3.5 Model Training and Dataset Composition

The CNN-based visual inspection model was trained using the dataset collected from the automotive transmission production line, as described in the previous sections [12]. The dataset consists of images representing various torsion spring installation conditions and was organized into ten classes based on spring type and installation status. This class structure enables the model to distinguish not only between normal (OK) and abnormal (NG) conditions, but also among different types of installation errors [13].

Prior to training, the dataset was divided into training, validation, and testing subsets to ensure objective performance evaluation. The training dataset was used to learn discriminative visual features related to torsion spring presence and positioning, while the validation dataset supported hyperparameter tuning and overfitting prevention [14]. The testing dataset was reserved exclusively for final performance assessment using unseen data.

Data augmentation was applied to address class imbalance and improve model robustness [15]. Brightness adjustment was used to simulate variations in illumination conditions commonly observed on the production line, while preserving the original spatial structure of the torsion spring assembly. No resizing or cropping was performed, and all images were maintained at the original resolution of 640x480 pixels, ensuring compatibility with real-time inference on the edge computing device.

Model training was conducted using a supervised learning approach, where labeled images were iteratively fed into the CNN to minimize classification error. Standard optimization techniques were applied to improve convergence and generalization performance. The trained model outputs a classification result for each input image, indicating whether the torsion spring installation condition corresponds to an OK or NG category [16].

The trained CNN model was then deployed on an edge computing device for real-time inference. This deployment enabled on-site evaluation of inspection performance under actual production conditions and provided the foundation for integration with PLC-based interlock control, as described in the subsequent section.

3.6 Performance Evaluation and Validation

To evaluate the effectiveness of the proposed AI-based visual inspection system, both model-level and system-level performance evaluations were conducted. The evaluation focuses on the ability of the trained CNN model to accurately classify torsion spring installation conditions and its suitability for deployment in a real production environment.

At the model level, classification performance was assessed using standard evaluation metrics, including accuracy, precision, recall, and *F1-score*. These metrics provide a comprehensive understanding of model behavior, particularly in distinguishing between OK and NG classes. Special attention was given to NG classes, as false-negative results may lead to defective products passing through the production line. Confusion matrix analysis was also used to identify misclassification patterns among different torsion spring installation conditions [17].

At the system level, the inspection model was validated through real-time inference on the edge computing device. Images captured directly from the production line were processed within the takt time constraints, and the inference results were compared with ground-truth labels confirmed by experienced operators. This evaluation verifies that the system can operate reliably under actual production conditions, including variations in lighting and component orientation.

In addition, the response behavior of the integrated PLC interlock system was evaluated. When an NG condition was detected by the AI system, the corresponding signal was transmitted to the PLC, triggering an immediate line stop or reject action. Conversely, OK conditions allowed the production process to continue without interruption. This validation confirms that the proposed system not only performs accurate inspection but also effectively enforces quality control through automated process control.

The results of these evaluations demonstrate the feasibility of deploying the proposed AI-based visual inspection system as a *poka-yoke* mechanism in automotive transmission assembly. The detailed quantitative results and discussion are presented in the subsequent section.

4. Implementation Result

4.1. Model Performance Comparison

Model performance result can be seen in Table 1. The performance of the three CNN architectures (*MobileNet, EfficientNet, and ResNet*) was evaluated using the collected dataset with *K-Fold Cross-Validation*. The evaluation metrics included accuracy, precision, recall, and *F1-score*, providing a comprehensive assessment of classification quality.

Table 1. Model Performance Comparison of all CNN model

CNN Model	Accuracy (%)	Precision (%)	Recall (%)	*F1-score* (%)	Inference Time (ms)	Notes
Mobile-Net	97.84	97.70	97.90	97.80	12	Fastest, but slightly higher NG false negatives
EfficientNet	98.72	98.65	98.78	98.71	18	Good balance between accuracy and speed
ResNet	99.66	99.64	99.67	99.65	22	Highest accuracy, robust NG detection

MobileNet achieved satisfactory performance, with an average accuracy of 97.84%. While computationally lightweight and suitable for edge deployment, MobileNet exhibited a slightly higher rate of false negatives for NG torsion spring cases, indicating limited capability in detecting subtle installation errors.

EfficientNet improved upon *MobileNet*, reaching an average accuracy of 98.72%. Its balanced design between depth, width, and resolution allowed better feature extraction, particularly under varying illumination. However, inference time was slightly higher than *MobileNet*, which could impact takt time in high-speed production lines.

ResNet achieved the highest performance, with an average accuracy of 99.66%, precision of 99.64%, recall of 99.67%, and *F1-score* of 99.65%. The deep residual connections enabled effective learning of intricate visual features related to torsion spring installation. *ResNet* also maintained robust performance across all NG categories, minimizing the risk of defective products passing undetected.

4.2. Real-Time Edge Deployment

For real-time deployment, the *ResNet* model was selected due to its superior accuracy and robustness in detecting NG torsion spring conditions, especially under varying illumination and subtle installation errors. Despite its relatively deeper architecture, *ResNet* maintained inference speed compatible with the production line takt time, making it suitable for on-site industrial use.

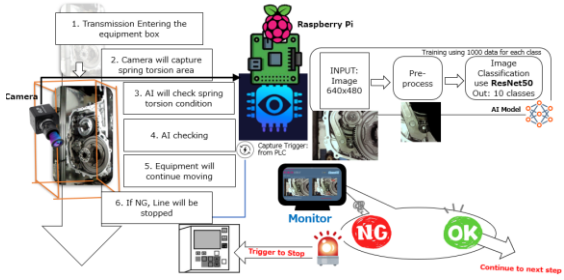


Figure 6. AI-Based Solution for torsion spring case

The *ResNet* model architecture used for inference is illustrated in Figure 6. It consists of residual blocks with skip connections, allowing deep feature extraction without gradient vanishing. This architecture enables reliable discrimination between OK and NG installation conditions, including minor misalignments or partial installations. The system was implemented on an edge computing device integrated with the existing PLC interlock system, enabling immediate production line control upon detection of NG conditions. Figure 2 shows the actual camera position mounted above the parking lock pole in the automotive transmission assembly line.

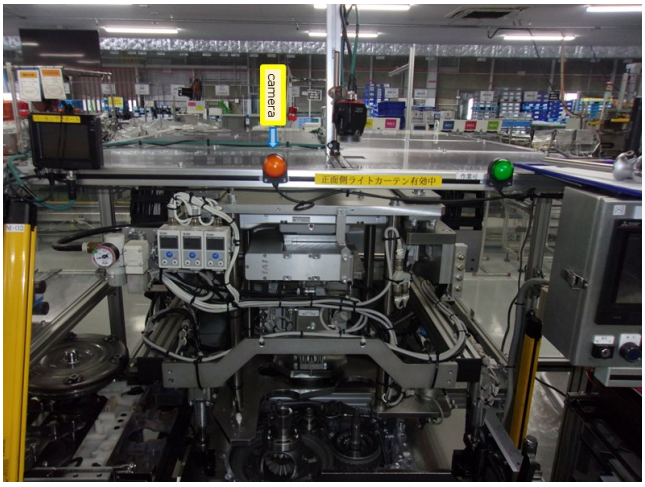


Figure 7. Camera Position in Actual Assembly Line

The inspection results are visualized on a Raspberry Pi-based application, as shown in Figure 8. The GUI displays both the live camera feed and the captured frame annotated with classification outcomes. NG conditions are highlighted with bounding boxes and red labels, while OK parts pass without interruption. This real-time feedback allows operators to monitor inspection outcomes directly and ensures seamless integration with automated line control.

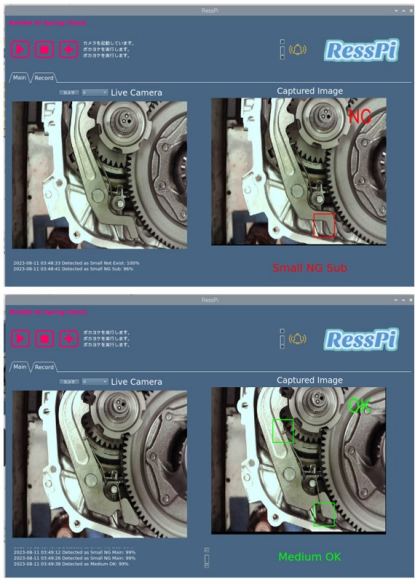


Figure 8. Visualization in Raspberry Pi-based application

Overall, the combination of *ResNet*, edge computing, and PLC interlock provides a robust, low-latency inspection system that effectively enforces quality assurance while maintaining production speed. *ResNet*'s selection ensures that detection accuracy is not sacrificed for speed, balancing operational constraints with defect detection reliability.

4.3. Practical Implications

The deployment of the ResNet-based visual inspection system provides a fully automated solution for torsion spring verification in automotive transmission assembly. By capturing high-resolution images directly from the production line (Figure 1), the system eliminates human inspection errors caused by fatigue, inconsistent attention, or subjective judgment.

Integration with the PLC interlock system allows immediate corrective actions: NG conditions trigger automatic line stops or part rejection, while OK components pass without interruption. The real-time feedback is visualized on a Raspberry Pi-based GUI (Figure 3), which displays both live camera feed and annotated inspection results, enabling operators to monitor outcomes without manually checking each part.

The selected ResNet architecture (Figure 2) ensures robust classification performance, even for subtle installation errors, balancing high accuracy with real-time inference constraints. By combining edge computing, deep residual CNNs, and PLC integration, the system functions as a reliable poka-yoke mechanism, enhancing quality assurance while maintaining production speed.

Overall, this implementation demonstrates that AI-based edge vision systems can effectively enforce automated quality control in industrial settings, reducing human dependency, minimizing defect rates, and ensuring consistent product quality across the transmission assembly process.

5. Conclusion

This study presents an AI-based visual inspection system for detecting improper torsion spring installation in automotive transmission assembly. Key findings include:

1. Among the three CNN models evaluated, ResNet achieved the highest accuracy (99.66%), demonstrating robust classification across all OK and NG conditions.
2. The system successfully operates in real-time on an edge device, maintaining compatibility with production line takt time.
3. Integration with PLC interlock ensures immediate corrective actions, effectively enforcing quality control.
4. Data augmentation improved model robustness under variable lighting conditions, supporting consistent detection performance.

Overall, the proposed system eliminates the need for manual visual inspection, reduces processing time, and enhances quality assurance in automotive transmission manufacturing.

Future research directions include exploring multi-modal inspection by combining visual data with torque or force sensors to detect installation defects that may be invisible to vision alone. Optimizing model architectures for faster inference on ultra-low-power edge devices without compromising NG detection accuracy is another promising avenue. Additionally, investigating continuous learning frameworks could enable the system to adapt to new torsion spring designs or slight variations in assembly processes.

Furthermore, this methodology could be extended to other automotive components where precise installation is critical, thereby generalizing the AI-based inspection framework. Such developments have the potential to significantly enhance manufacturing efficiency while establishing a broader foundation for intelligent, automated quality assurance in Industry 4.0 environments.

REFERENCES

[1] Wahl A M 2012 Mechanical Springs (McGraw-Hill, New York)

[2] Groover M P 2016 Automation, Production Systems, and Computer-Integrated Manufacturing (Pearson Education)

[3] Wickens C D, Lee J D, Liu Y and Gordon-Becker S 2004 An Introduction to Human Factors Engineering (Pearson Education)

[4] Xie X 2008 A review of recent advances in surface defect detection using texture analysis techniques (Electronic Letters on Computer Vision and Image Analysis vol. 7 no. 3) p 1–22

[5] Hütten N, Alves Gomes M, Hölken F, Andricevic K, Meyes R and Meisen T 2024 Deep Learning for Automated Visual Inspection in Manufacturing and Maintenance: A Survey of Open-Access Papers Appl. Syst. Innov. 7(1) 11. https://doi.org/10.3390/asi7010011 :contentReference[oaicite:0]{index=0}

[6] Wang Y, Liu Z and Zhou J 2024 A systematic review of deep learning approaches for surface defect detection in industrial applications Eng. Appl. Artif. Intell. 130 107717. https://doi.org/10.1016/j.engappai.2023.107717 :contentReference[oaicite:1]{index=1}

[7] Saberironaghi A, Ren J and El-Gindy M 2023 Defect Detection Methods for Industrial Products Using Deep Learning Techniques: A Review Algorithms 16(2) 95. https://doi.org/10.3390/a16020095 :contentReference[oaicite:2]{index=2}

[8] Shi W, Cao J, Zhang Q, Li Y and Xu L 2016 Edge Computing: Vision and Challenges IEEE Internet of Things Journal 3(5) 637–646

[9] He K, Zhang X, Ren S and Sun J 2016 Deep residual learning for image recognition Proc. IEEE Conf. on Computer Vision and Pattern Recognition (CVPR) pp 770–778

[10] Howard A G et al. 2017 MobileNets: Efficient convolutional neural networks for mobile vision applications arXiv:1704.04861

[11] Tan M and Le Q 2019 EfficientNet: Rethinking model scaling for convolutional neural networks Proc. Int. Conf. on Machine Learning (ICML) pp 6105–6114

[12] Saberironaghi A, Ren J and El-Gindy M 2023 Defect Detection Methods for Industrial Products Using Deep Learning Techniques: A Review Algorithms 16(2) 95. https://doi.org/10.3390/a16020095

[13] Arikan S, Varanasi K and Stricker D 2019 Surface Defect Classification in Real-Time Using Convolutional Neural Networks arXiv:1904.04671

[14] Schwebig A I M and Tutsch R 2020 Compilation of training datasets for use of convolutional neural networks supporting automatic inspection processes in Industry 4.0 based electronic manufacturing J. Sens. Sens. Syst. 9 167-178

[15] Yan F, Ma W, Xue J, Shao X, Li L 2025 Using Convolutional Neural Networks for Material Surface Quality Inspection and Classification Int. J. Comput. Intell. Syst.

[16] Ariefa I, Satrio H J, Kumalaningrum D, Handoko R, Harseno A and Nugraha F W 2025 Performance Enhancement of 2D CNN-Based Visual Inspection Using Data Augmentation for Defect Classification in Metal Casting Products Jurnal Rekayasa Mesin 20(3) 379-392. https://doi.org/10.32497/jrm.v20i3.7170

[17] Shaloo M, Princz G, Hörbe R and Erol S 2024 Flexible automation of quality inspection in parts assembly using CNN-based machine learning Procedia Computer Science 232 2921-2932. https://doi.org/10.1016/j.procs.2024.02.108