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A Comparative Study between AI-based and Manual Quality Inspection Techniques

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ABSTRACT

This paper analyzes the effectiveness of artificial intelligence (AI)-based (AI-based) visual quality inspection compared to conventional manual quality inspection in manufacturing. Manual inspection methods, though widely used, are prone to human error, fatigue, and inconsistency, often leading to quality disputes between suppliers and customers. In this study, a convolutional neural network (CNN)–based visual inspection system was developed and evaluated through a blind test conducted at both supplier and customer facilities. The results were benchmarked against manual inspections performed by multi-trained operators. The AI model achieved 98% accuracy and 100% repeatability across two evaluation rounds, significantly outperforming human inspectors whose accuracy ranged from 93% and 98% accuracy and showed lower consistency. Furthermore, the AI-based approach demonstrated adaptability to process variations and scalability across production environments, maintaining uniform standards regardless of operator differences. The findings confirm that AI-driven visual inspection offers a more reliable, repeatable, and efficient solution for high-precision manufacturing applications. By reducing inspection time, minimizing errors, and improving overall quality control, AI-based inspection systems represent a transformative step toward intelligent, data-driven manufacturing and operational excellence.

1. INTRODUCTION

The objective of this paper is to present a detailed and objective analysis of the effectiveness of artificial intelligence (AI)-based (AI-based) visual quality inspection compared to manual quality inspection. Quality inspection is crucial in manufacturing and other industries (Hamid et al., 2019) and requires reliable and efficient methods to ensure high-quality products. However, manual quality inspection is susceptible to

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human error, fatigue, and physical limitations, leading to inconsistent results and quality disputes between customers and suppliers.

Therefore, this paper seeks to provide a detailed and objective analysis of the potential benefits of using AI-based visual quality inspection, comparing it with manual quality inspection using a blind-test methodology. The study, conducted by Glow AI Inc, USA, illustrates how AI can enhance accuracy and efficiency in the visual quality inspection process, offering a more reliable alternative to human inspection.

Utilizing AI in visual quality inspection offers numerous advantages. In production, it helps overcome human limitations and provides real-time feedback (Cho et al., 2019), improving efficiency and accuracy. For engineering, it introduces statistical insights and helps set data-driven quality standards (Gökalp et al., 2021). In quality management, AI aids in standard alignment and efficient dispute resolution with suppliers (Pedersen, 2019). Overall, AI-driven visual quality inspection represents a significant advancement, enhancing manufacturing processes and outcomes.

Before the invention of the printing press, books were painstakingly copied by hand, requiring the skilled work of scribes who relied on their eyes, hands, and educated minds. The introduction of the printing press transformed this manual process, making book production faster and more efficient. Similarly, AI-based visual quality inspection streamlines and improve quality-control processes in manufacturing. The paper aims to discuss the implications of these findings for manufacturing and other sectors and to propose directions for future research.

1.1. The Need for Efficient Quality Inspection Methods

Manual quality inspection has several drawbacks, including operator factors such as personality, attitude, fatigue, emotional state, and physical limitations including visual acuity. In addition, method and machine factors present challenges such as lighting-contrast effects (different operators perceive varying levels of contrast between defects), training and expertise levels, and the reliance on sampling rather than full inspection (Drury & Watson, 2002). These limitations can result in inconsistent quality inspection outcomes, leading to quality disputes between customers and suppliers.

1.2. Prevention: The Key to Effective Quality Improvement

The current approach to improving quality emphasizes the necessity of shifting focus from passive quality inspection—performed after a defect has occurred—to active quality inspection that prevents defects before they occur. This involves transitioning from inspecting events to anticipating them and from inspecting results to inspecting processes (Borkowski & Knop, 2016). The investment in manufacturing increases throughout the production cycle: the bill of materials (BOM), labor costs, and capital tied up in production all grow from the acquisition of raw materials to the delivery of the finished product. Consequently, the cost of identifying a defect also rises as the product advances through the manufacturing cycle, as shown in Fig. 1.

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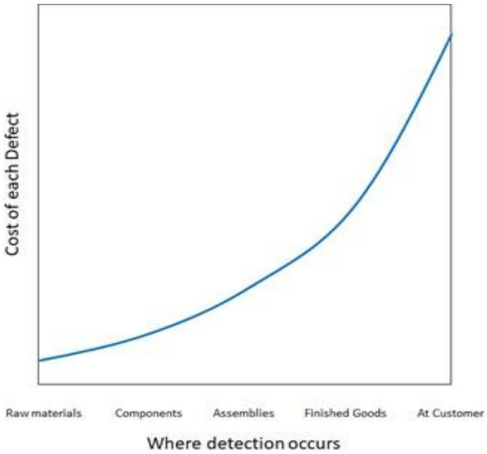

Fig. 1. The cost of detecting defects increases as the product moves through the manufacturing cycle

Source: Authors' illustration based on the quality-cost concept discussed in the literature

Fig. 1 implies that early quality efforts can significantly reduce the overall cost of defects. Ensuring quality at the start of production helps minimize nonconformity costs. Early investments in quality assurance—such as improved product designs and the implementation of AI-based visual inspection—can substantially decrease total defect costs (Kuc, 2009). Fig. 2 illustrates two scenarios from Kuc's model and their respective effects on defect-related expenses.

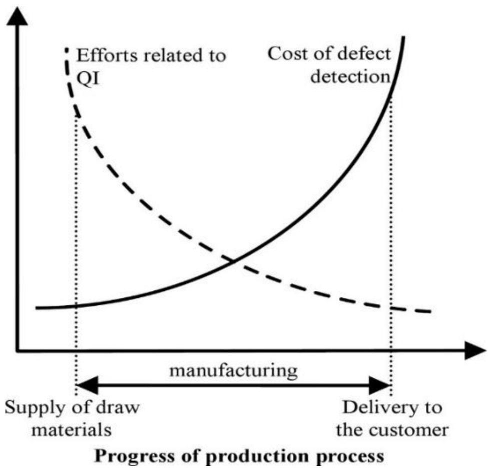

Fig. 2. The cost of defect detection and efforts put into quality inspection

Source: Authors' illustration based on the quality-cost concept discussed in the literature

1.3. AI-based Visual Quality Inspection and Its Potential Benefits

Technological advancements have made AI-based quality inspection a key solution for improving accuracy and efficiency in inspection processes. AI-based visual inspection methods have been widely studied for industrial defect detection and classification because they can support consistent, automated evaluation of product surfaces and visual anomalies (Czimmermann et al., 2020). AI-based methods offer

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several advantages over manual inspection, including reduced human error, consistent quality metrics, clearer quality standards, and the preservation of golden samples and inspection records. They also enable automated tracking, recording, and continuous learning for quality improvement, thereby increasing efficiency and reducing product lifecycle costs. The effectiveness of visual inspection is influenced by individual, environmental, organizational, social, and task-related factors (See et al., 2017). Implementing AI in visual quality inspection can effectively address challenges in these domains. AI transforms task-related inspection into a data-driven and statistically superior process compared to manual methods. For more details on these influencing factors, refer to Table 1 (See et al., 2017).

Table 1. Factors impacting inspection performance

Task	Individual
•Defect Rate •Defect Type •Defect Salience •Defect Location •Complexity •Standards •Pacing •Multiple Inspections •Overlays •Automation	•Gender •Age •Visual Acuity •Intelligence •Aptitude •Personality •Time in Job •Experience •Visual Lobe •Scanning Strategy •Biases
Environmental	**Organizational**
•Lighting •Noise •Temperature •Shift Duration •Time of Day •Vigilance •Workplace Design	•Management Support •Training •Retraining •Instructions •Feedforward Information •Feedback •Incentives •Job Rotation
Social	
•Pressure •Consultation	•Isolation •Communications

Source: Authors' compilation based on the literature reviewed in this study

2. METHODOLOGY: BLIND TEST FOR AI VISUAL QUALITY INSPECTION

Effective application of AI in visual inspection requires close collaboration among multiple stakeholders. The factory and trained personnel must generate and label test parts for data collection. The Glow AI Inc, USA team, together with factory staff, collects image data of parts, which are later associated with their known (expert-labeled) conditions. The data science team processes the raw data into formats suitable for model building and optimizes computer vision models for specific use cases. Generally, all available data are divided into three sets: training data (approximately 70%), validation data (around 20%), and test data (around 10%). Care is taken during this split to avoid "leaking" information between datasets. In this application, because multiple images of each area of interest are captured, the data must be split by part to ensure that images in the training dataset do not overlap with those in the validation or test datasets.

The validation dataset is used to select the best-performing model. Models are trained using training data, and their performance is evaluated using the validation data—allowing scoring based on previously unseen samples. As a final step, the test data serves as a measure of expected performance in practical use. After model decisions and test results are finalized, all available data are typically used in one final training

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round with fixed parameters, achieving the most robust model possible at that stage. In many industrial applications, fully blind testing is not standard practice because data collection is both time-consuming and costly; AI and data-science teams therefore aim to maximize the use of every available dataset.

In this study, Glow AI Inc, USA conducted an extensive blind-test study to demonstrate its expertise and the underlying technology of convolutional neural-network (CNN) computer-vision (CV) models. A large group of parts was used to train the models. Initially, the data were split into training and validation sets, and the so-called pre-blind-test data served as the test dataset. After validating the model's ability to detect defects accurately, all data from the original parts were used for final training, and blind-test results were subsequently obtained from that model.

The combination of CNNs and blind testing provides a powerful framework for visual quality inspection tasks. CNNs can learn complex image features and recognize patterns that are difficult for humans to detect, making them suitable for automated feature extraction in industrial inspection (LeCun et al., 2015; Weimer et al., 2016). Blind testing ensures objective and accurate evaluations by concealing part identities and preventing evaluators from being influenced by prior knowledge or bias. In this experiment, plastic parts were randomized and coded to mask their identities from both evaluators and the AI model. The inspection conditions for both manual and AI evaluations were identical. The same surface-lighting setup was used in all tests, comprising four centrally arranged patented prism panes with plano-convex lenses and black fields. The plano-convex lenses evenly distributed light across the part's surface, while the black fields reduced glare and reflections that might obscure defects. The lighting operated at 120–277 V AC ±10%, 50/60 Hz, making it suitable for a wide range of industrial environments. By combining CNN-based learning with controlled blind-testing procedures, this approach ensured high accuracy and consistency in evaluation, which were crucial for assessing the performance and reliability of the AI model.

2.1. Background: Manual Visual Inspection in Current Manufacturing

This study focuses on high-gloss plastic parts produced through injection molding for automotive Class A components. These parts have stringent cosmetic requirements and are subjected to 100% visual inspection at the supplier's facility before being shipped to the customer. The customer also performs additional inspections during production, prior to assembly, which often leads to disagreements regarding quality-acceptance criteria. Because these defects are primarily cosmetics in nature, they are difficult to quantify objectively, and inconsistencies in manual visual inspection frequently lead to quality disputes between suppliers and customers.

2.2. Objectives of the AI Visual Quality Inspection Blind Test

The objective of this blind test is to evaluate the performance of the AI model and compare it with manual visual inspection. This comparison was carried out by examining the accuracy and repeatability of both methods at the customer's facility and the supplier's facility. By analyzing the results of manual inspections performed by both parties, discrepancies in their evaluation methods could be identified. Furthermore, the performance of the AI model was compared directly with the manual inspections conducted by both the customer and the supplier to assess their effectiveness. These objectives are fundamental to ensuring that the AI model delivers accurate and consistent results that meet or surpass the standards of manual visual inspection.

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2.3. Data Collection and Preparation for AI Visual Inspection Test

2.3.1. The Role of Different Datasets in the Development of Accurate AI Models

A well-designed dataset is fundamental to the success of any AI project, requiring careful attention to the selection and preparation of training, validation, and test datasets. The training dataset is used to teach the AI model from examples, enabling it to accurately predict or classify new data. To achieve this, the dataset must be sufficiently large and balanced to reflect real-world diversity and minimize the risks of overfitting or underfitting. The validation dataset is used to evaluate and fine-tune the model's performance during training by adjusting hyperparameters such as learning rate and model depth. These hyperparameters, which define the model's architecture and learning behavior, are optimized through repeated trials to achieve the best validation score and to prevent overfitting. The test dataset serves as an independent measure of the model's final performance. In this study, blind-test part images validated by a senior quality inspector served as the ground truth. To maintain the integrity of the evaluation, the blind-test data were sealed, and signed to prevent tampering and were only revealed by the customer at a later stage.

2.3.2. Unbiased Data for Accurate and Fair AI Models

Unbiased data are essential for ensuring the accuracy, reliability, and fairness of AI models. Biased datasets can result in inaccurate predictions and reinforce systemic biases, leading to unfair or inconsistent outcomes. To develop effective and equitable AI models, it is therefore critical to use datasets that represent diverse perspectives and conditions. This inclusive approach improves model accuracy and helps mitigate bias during decision making processes—a topic that remains an active area of discussion in the AI research community.

For this study, the parts used were drawn from mass-production samples collected randomly over a three-month period across different production batches. Suspected defective parts were also collected from both the supplier's factory and the customer's rejected items, ensuring that the dataset was diverse and representative of the actual production environment. After collection, each part was inspected by a senior quality-inspection specialist from the customer's side, referred to as Customer Operator Number 1. This individual, who had undergone formal quality inspection training and served as the decision-maker in production-related quality disputes, provided the ground-truth labels for the dataset. Although the operator's judgments may inherently include some degree of error, these results were treated as the reference standard for model evaluation.

To ensure consistent inspection conditions, the same lighting setup was used across all manual and AI inspections. The surface-lighting system consisted of four centrally arranged patented prism panes with plano-convex lenses and black fields, operating at 120–277 V AC ±10%, 50/60 Hz. This configuration ensured even illumination and minimized glare and reflections, providing consistent lighting conditions for reliable comparison between manual and AI-based inspection results.

2.3.3. Steps for Data Collection in Training, Validation, and Blind Test

The data-collection process for training, validation, and blind-test datasets followed a structured, multi-step procedure designed to ensure the accuracy and integrity of the samples:

(i) Over a three-month period, production parts—comprising both good and defective items—were randomly collected from ongoing manufacturing batches.

(ii) Customer Operator Number 1 inspected all collected parts and categorized them into "good" and "bad" groups.

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(iii) For the blind-test dataset, 60 parts were randomly selected from these groups, with the ratio of good to bad parts determined by Customer Operator Number 1's initial classifications. Each part was individually packaged in a sealed bag labeled BT1, BT2, BT3, and so on, with its corresponding quality status recorded. All bags were signed to prevent tampering. Although the initial target was 60 samples, only 56 were ultimately used in the blind test due to handling losses.

(iv) For the validation dataset, 40 good parts and 40 bad parts were randomly selected from the remaining samples. These parts were also inspected by Customer Operator Number 1, sealed in bags labeled PBT1, PBT2, PBT3, etc., and withheld from the training process. The validation results were revealed only after the AI model was finalized and were then used to evaluate model performance and optimize parameters.

(v) For the training dataset, the remaining parts were placed in individual bags and labeled "G" for good and "B" for bad. The final training dataset comprised 100 good and 86 bad samples, which were used to train the AI model.

(vi) To capture image data for all datasets, each labeled part was recorded using a 2D camera operating at 60 frames per second. An automated fixture equipped with surface-inspection lighting was used to highlight defects. Consistency was maintained by employing a high-quality camera and calibrating the lighting setup to ensure uniform illumination across all recorded videos.

Overall, the data-collection process combined systematic inspection, random sampling, labeling, sealing, and detailed record-keeping to guarantee the accuracy and validity of the datasets used for AI model training, validation, and blind testing. Table 2 illustrates the complete data-collection workflow.

Table 2. Steps for data collection for training, validation, and blind testing.

Steps	Descriptions	Customer		Supplier		Glow-AI
		Operator #1	**Operator #2**	**Operator #1**	**Operator #2**	**Artificial Intelligence**
1	COLLECT RANDOM SAMPLES					
	Randomly collect samples over a 3-month period	X	X	X	X	
	Collect samples from different production batches at both the customer and supplier sides					
	Include both good and defectives parts					
2	CATEGORIZE SAMPLES					
	Categorize samples into good and bad	X				
	Serves as the ground truth					
3	BLIND TEST SAMPLES					
	Randomly choose 60 parts					
	Ultimately, only 56 parts were available because four were lost during handling	X				
	Results were documented and sealed					
4	VALIDATION SAMPLES					
	Randomly choose 40 good and 40 bad parts					
	Total 80 samples					
	Video was captured (2D camera, 60 fps)					X
5	TRAINING SAMPLES					
	Remaining parts were used to train the AI model					
	Remaining: 100 good parts					
	Remaining: 86 bad parts					
	Video was captured (2D camera, 60 fps)					X

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Steps	Descriptions	Customer		Supplier		Glow-AI
		Operator #1	**Operator #2**	**Operator #1**	**Operator #2**	**Artificial Intelligence**
6	BLIND TEST FIRST REVIEW					
	Randomly inspect blind-test samples	X	X	X	X	X
	Results were documented and sealed					
7	BLIND TEST SECOND REVIEW					
	Randomly inspect blind-test samples			X		X
	Results were documented and sealed					

Source: Authors' own work

3. BLIND TEST INSPECTION: MANUAL AND AI-BASED INSPECTION RESULTS

The blind-test inspection process involved both manual and AI-based evaluations of the blind-test samples by operators from the customer and supplier sides. Customer Operator Number 1 and Supplier Operator Number 1 each conducted two separate inspections of the same parts, recording and sealing their results after each session. In addition, Customer Operator Number 2 and Supplier Operator Number 2—both experienced in inspecting this specific component—each performed a single round of inspection, with their results similarly sealed for comparison. The AI model developed by Glow AI Inc, USA was then applied to the same blind-test dataset to evaluate its performance against human inspectors.

4. BACKGROUND ON THE DATA PROCESSING AND MODELING

This study focused on a plastic housing component for vehicle-mounted antennas, installed on the roof of finished vehicles. As noted earlier, the outer surface of these housings is fully visible and subject to stringent cosmetic requirements. During the development of the molded part, it was observed that variations in molding conditions could cause dimensional inconsistencies on the outer surface, particularly in regions surrounding the internal screw bosses. Issues such as excessive shrinkage in these areas could be mitigated through careful monitoring and control of the molding process.

To accentuate surface irregularities, an industrial banded light source was employed. Initially, human operators manually held the housings and moved them through the light field; defective regions were identified by the curvature or distortion of the light bands as they passed across the affected areas.

For this study, an electro-pneumatic-mechanical fixture was developed to hold the housings using vacuum suction onto a shaped boss, ensuring consistent part placement. The fixture was capable of horizontal motion and rotation about the part's longitudinal axis. This rotational capability enabled the inspection of both sides of the housing using a single fixture and a single camera—an essential requirement for this application. Fig. 3 shows a part in the fixture at two rotational positions with similar horizontal alignment. In the lower image of Fig. 3, surface distortions are visible where the light bands appear bent or misaligned, indicating defect areas.

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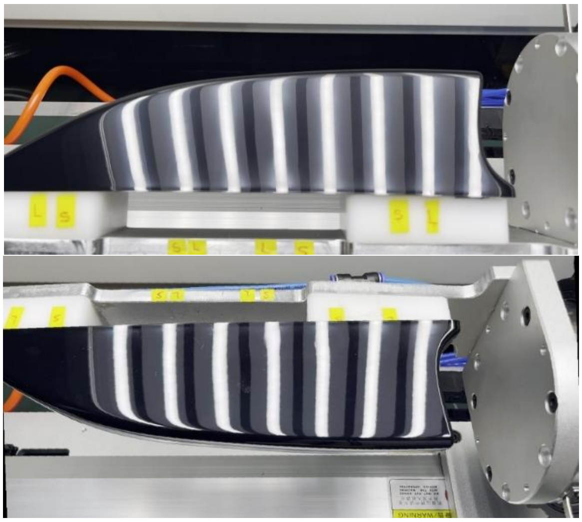

Fig. 3. A test part on the fixture in two positions

Source: Authors' own photograph

Images were captured in video format and post-processed through an automated pipeline. Fixture position markers were used to identify and locate regions of interest (ROIs) within each video frame. Computer vision software developed in Python was employed to extract these ROIs accurately. During the model development phase, the extracted ROIs were organized and used as input data for training the computer vision model. Fig. 4 illustrates several typical ROI samples: the top row represents "bad" regions, while the bottom row represents "good" regions. In total, approximately 500,000 images of this type were captured and processed for model development.

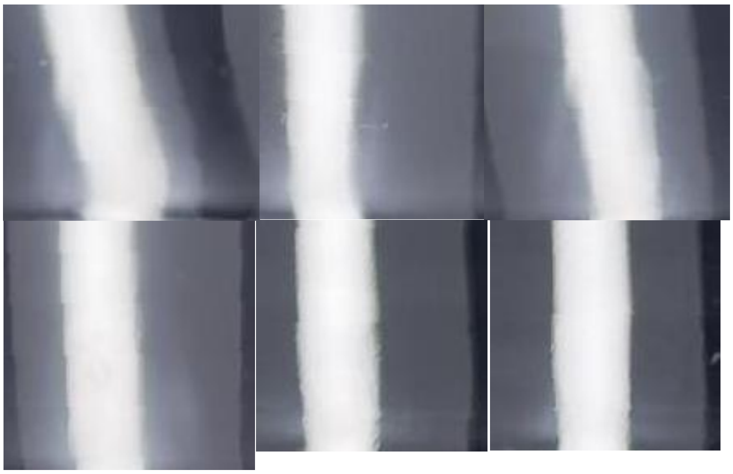

Fig. 4. Examples of regions of interest (ROIs): top row—bad regions; bottom row—good regions

Source: Authors' own image-processing output

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The distinct differences in the shapes of the light-band edges between acceptable and defective regions of the part make this case well suited for the application of a convolutional neural network (CNN). The convolutional layers in a CNN are designed to learn spatial features such as edge curvature and contrast variations, which are critical for distinguishing subtle surface defects. The architecture of the CNN employed in this study is shown in Fig. 5.

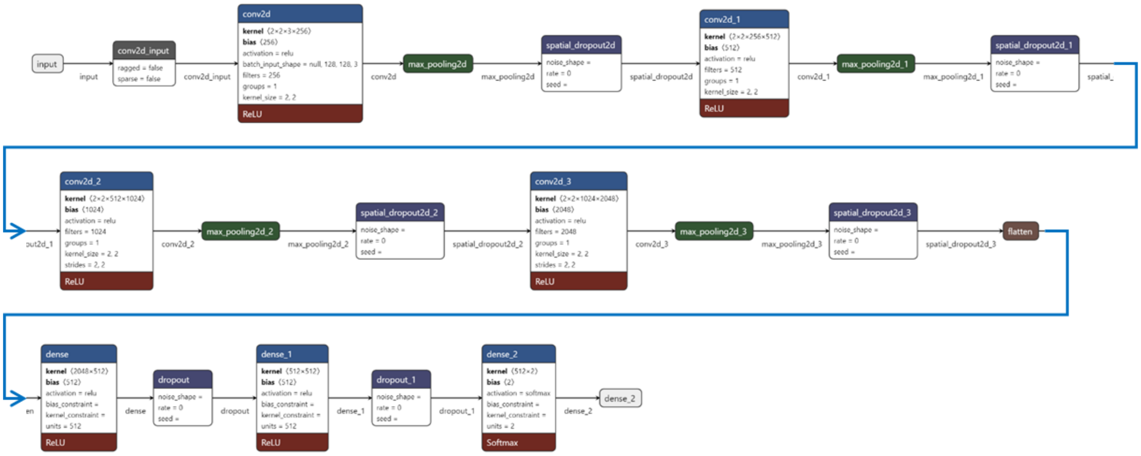

Fig. 5. Architecture of the convolutional neural network (CNN) used in this study

Source: Authors' own illustration

In accordance with standard practice, the image dataset was divided into training, validation, and test subsets. Multiple models with different hyperparameter configurations were trained using the training set, and their performance was evaluated on the validation set. The final model was selected based on its performance on the validation data. Expected field performance was then estimated using the test set. The selected model was subsequently applied to analyze data from the blind-test samples and to predict their ground-truth quality classifications. The remainder of this paper presents those results and compares the behavior of human inspectors with that of the computer vision–based inspection system.

5. BLIND TEST RESULTS: MANUAL VS. AI-BASED INSPECTION

The blind-test samples were evaluated by multiple human operators and the AI model, with the results summarized as follows.

(i) Customer Operator Number 1—the inspector who conducted the original evaluations used to establish the datasets and the ground truth—inspected the blind-test parts and achieved 96% accuracy, correctly identifying 54 out of 56 samples compared with the ground-truth data. This outcome indicates some inconsistency between the two inspection passes of the same parts, with a repeatability rate of 96% (i.e., the same classification of "good" or "bad" was achieved across both inspections). The results are illustrated in Fig. 6.

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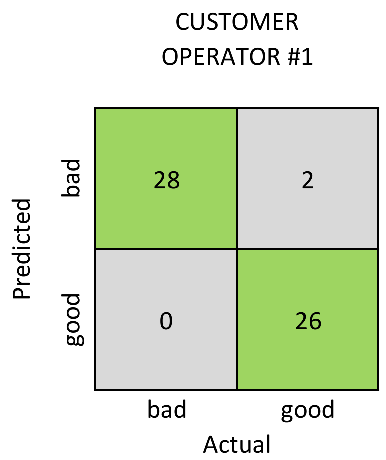

Fig. 6. Customer Operator Number 1 Actual vs. Predicted

Source: Authors' analysis based on the blind-test results

(ii) Customer Operator Number 2 reviewed the blind-test samples and achieved 98% accuracy, correctly identifying 55 out of 56 samples compared with the ground-truth results. The corresponding outcomes are presented in Fig. 7.

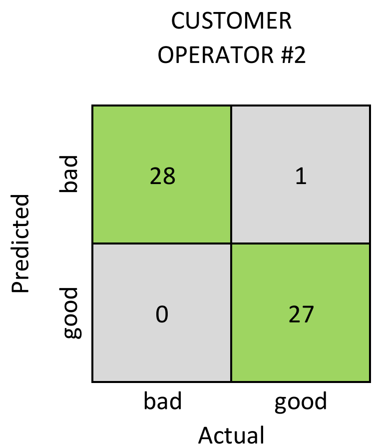

Fig. 7. Customer Operator Number 2 Actual vs. Predicted

Source: Authors' analysis based on the blind-test results

(iii) Supplier Operator Number 1 inspected the blind-test parts and achieved 93% accuracy, correctly identifying 52 out of 56 samples compared with the ground-truth results. During the second inspection of the same parts, however, the operator achieved 100% accuracy, correctly classifying all 56 samples. From a consistency standpoint, this corresponds to a repeatability rate of 93%, indicating variability between the two inspection rounds. The detailed results are shown in Figs. 8 and 9.

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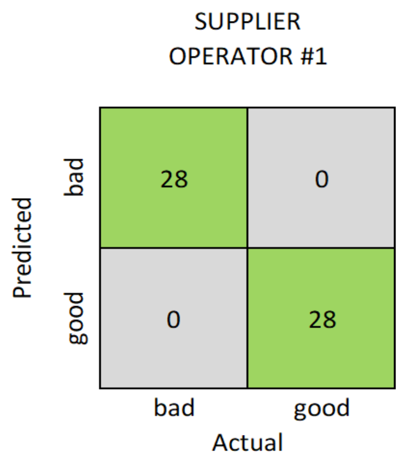

Fig. 8. Supplier Operator Number 1 Actual vs. Predicted First Inspection

Source: Authors' analysis based on the blind-test results

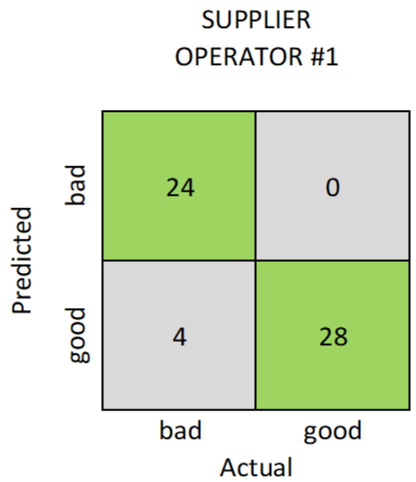

Fig. 9. Supplier Operator Number 1 Actual vs. Predicted Second Inspection

Source: Authors' analysis based on the blind-test results

(iv) Supplier Operator Number 2 reviewed the blind-test samples and achieved 93% accuracy, correctly identifying 52 out of 56 parts compared with the ground-truth results. The corresponding findings are illustrated in Fig. 10.

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Fig. 10. Supplier Operator Number 2 Actual vs. Predicted

Source: Authors' analysis based on the blind-test results

(v) The AI model achieved 98% accuracy, correctly identifying 55 out of 56 samples during both the first and second evaluations. More importantly, the model demonstrated 100% repeatability across the two reviews, producing identical classifications of "good" or "bad" across both inspection passes. This consistency indicates that the AI system maintained complete reliability when re-inspecting the same parts. The corresponding results are presented in Figs. 11 and 12.

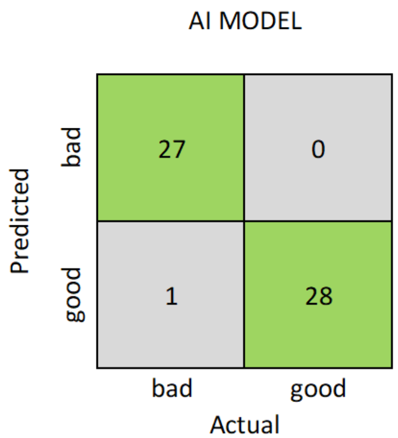

Fig. 11. AI Model Actual vs. Predicted First Inspection

Source: Authors' analysis based on the AI-model blind-test results

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Fig. 12. AI Model Actual vs. Predicted Second Inspection

Source: Authors' analysis based on the AI-model blind-test results

(vi) The results revealed considerable variation among the different human inspectors when evaluating the same parts. In contrast, the AI model developed by Glow AI Inc, USA produced consistent outcomes across repeated inspections of the same samples. A summary of these comparative results is presented in Figs. 13 and 14.

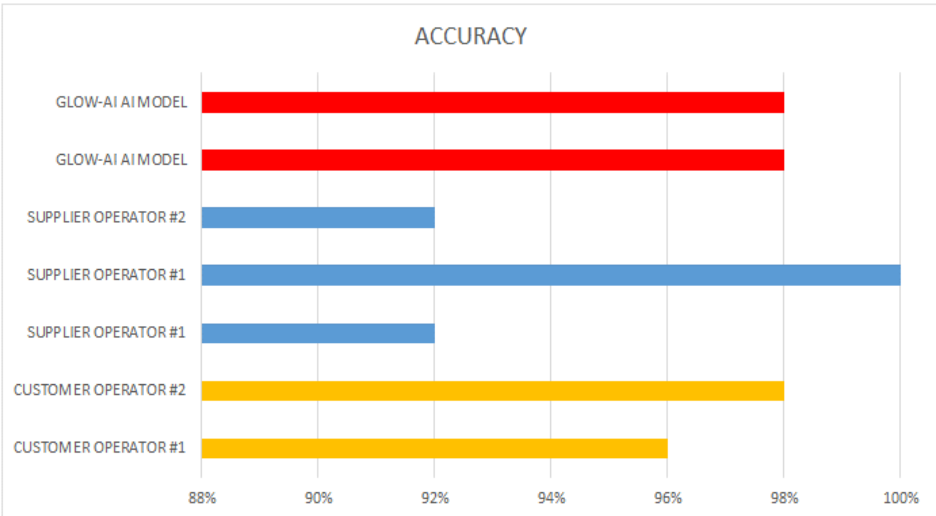

Fig. 13. Blind test overall accuracy summary

Source: Authors' analysis based on the blind-test results

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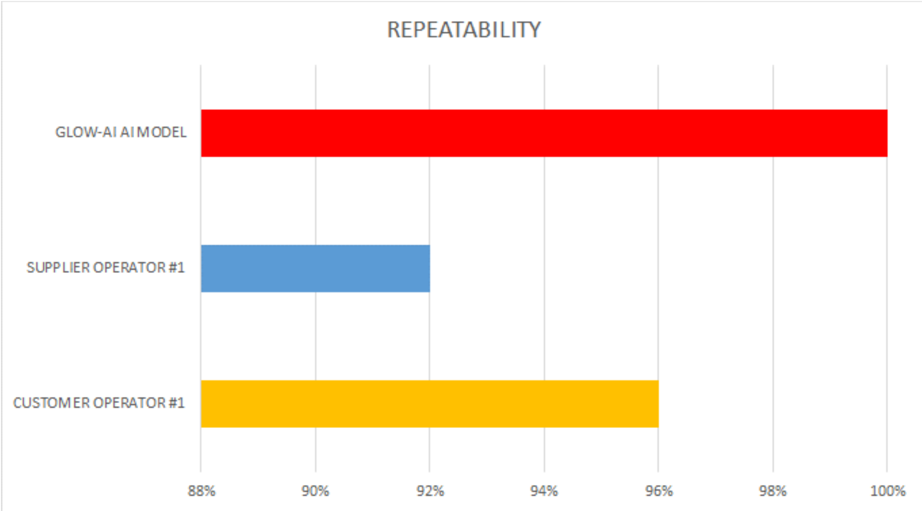

Fig. 14. Blind test overall repeatability summary

Source: Authors' analysis based on the blind-test results

6. DISCUSSION

The blind-test data clearly demonstrate the superiority of AI-based inspection over traditional manual methods. The AI model consistently achieved 98% accuracy in both evaluations and 100% repeatability across the two reviews, confirming its reliability and consistency. Such precision and stability directly enhance product quality, reduce defect risk, and ensure adherence to established quality standards. It is important to note that during blind testing, manual inspections may still be influenced by human-factor variables such as psychophysical, organizational, workplace, and social conditions (Kujawińska & Vogt, 2015).

Considering these influences, even in an optimistic scenario for manual visual inspection, the rate of a good part being mistakenly identified as defective (Type I error) is approximately 17.8%, while the rate of a defective part being incorrectly accepted as good (Type II error) is roughly 29.8% (Stallard et al., 2018). In other words, manual inspection correctly classifies parts only about 52.4% of the time when both error types are considered. From a customer standpoint, AI-based inspection provides greater assurance that received products meet quality expectations. The consistency and dependability of AI evaluation reduce the likelihood of defects reaching end users, thereby improving customer satisfaction and loyalty.

AI-based inspection systems also maintain consistent standards regardless of personnel changes and can be scaled or adapted to accommodate variations in manufacturing processes or product lines. This adaptability strengthens quality-management practices and promotes alignment throughout the supply chain, helping prevent defects in subsequent production runs. Moreover, AI introduces a proactive quality-assurance paradigm that contrasts with conventional inspection methods that primarily emphasize post-production verification (Borkowski & Knop, 2016).

Adopting AI-based inspection yields additional benefits. AI models can rapidly and accurately analyze large datasets, uncovering patterns and insights that human inspectors might overlook. This capability leads to greater efficiency, cost reduction, and improved product quality. By continuously learning from historical inspection data, AI systems can further enhance accuracy and dependability over time. The blind-test

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findings collectively underscore the advantages of AI-based inspection—early defect detection, reduced rework and recall costs, high accuracy and repeatability, and scalable performance—all contributing to superior product quality and operational efficiency. Automated inspection thus ensures that customers consistently receive high-quality products, reinforcing confidence and satisfaction.

In this study, convolutional neural network (CNN) technology was employed to identify sink marks and stress marks on high-gloss molded plastic components, demonstrating its effectiveness in visual quality inspection. Furthermore, this approach can be extended to detect a broad range of molded-part defects—including splay defects, pulled surfaces, cold slugs, impression marks, and jetting—arising from both process and tooling conditions.

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8. CONFLICT OF INTEREST STATEMENT

The authors declare that this research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

9. AUTHORS' CONTRIBUTIONS

Wei Siong Tan conceptualized the research design, supervised the analysis, and wrote and revised the manuscript. Blaine Bateman developed the machine learning model, contributed to data analysis, and co-wrote the manuscript. Hsiao-Kuang Yu provided technical validation and reviewed the final version of the manuscript.

10. DECLARATION OF GENERATIVE AI IN THE WRITING PROCESS

During the preparation of this work, the authors used ChatGPT to improve the clarity, grammar, and readability of the manuscript. Following the use of this tool, the authors have reviewed and edited the content as necessary and take full responsibility for the final content of the publication.

11. DATA AVAILABILITY/SUPPLEMENTARY MATERIALS

The data supporting the findings of this study are available from the corresponding author upon reasonable request. However, access to certain data may be restricted due to the commercial confidentiality requirements of the participating organizations. No supplementary materials are associated with this article.

12. ETHICS STATEMENT

The authors declare that this study did not involve human participants, personal data, or animal subjects. The research was conducted using industrial components, inspection images, and quality inspection results obtained through controlled testing procedures. All experimental procedures were conducted in accordance with the applicable organizational safety, health, environmental, and industrial requirements.

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