A Machine Learning-Based Framework for Image Quality Inspection of Automotive Metal Stamping Parts

W. S. Widodo[1,*] and T. Supriyono[2]

[1]Faculty of Mechanical Engineering and Technology, Universiti Teknikal Malaysia Melaka, Malaysia
[2]Teknik Mesin, Universitas Pasundan Bandung, Indonesia
Email: wahyonosapto@utem.edu.my (W.S.W.); supriyono.toto@unpas.ac.id (T.S.)
*Corresponding author

Manuscript received October 5, 2025; accepted November 19, 2025; published December 19, 2025

Abstract*—Traditional quality control for automotive metal stamping parts relies heavily on Checking Fixtures (C/Fs). These fixtures are custom-engineered for individual components, resulting in high initial design and manufacturing costs, limited versatility, and time-consuming processes for each new part. Moreover, C/F inspection is a manual and subjective process, which introduces human error, measurement variability, and slower throughput in high-volume production environments. This study proposes an automated imaging-based quality inspection framework utilizing a 3D laser scanner and the k-Nearest Neighbors (k-NN) machine learning algorithm. The framework systematically analyzes complex point cloud data of scanned parts through a structured sequence of steps: Data Acquisition, Segmentation, Pre-processing, Feature Recognition, Data Analysis, Post-processing, and Final Decision-making. To ensure both high accuracy and maximum speed, each step involves direct and immediate comparison with nominal Computer-Aided Design (CAD) data or a pre-established training set. The k-NN algorithm plays a central role in the analysis phase, effectively using Euclidean distances to distinguish noise from true features, recognize geometric elements such as holes, and reliably detect defects including material burrs and dimensional springback. The proposed system offers significant advantages over traditional C/Fs, including greater versatility across diverse component geometries and substantially reduced labor costs through full automation. Additionally, it ensures faster inspection times and consistent, objective accuracy, thereby eliminating the subjectivity, human error, and physical degradation associated with conventional fixtures. This automated framework represents a more sustainable, efficient, and robust quality control solution, aligning with the future needs of the automotive stamping industry.

***Keywords*—metal stamping parts, checking fixture (C/F), quality control, k-NN method**

I. Introduction

Metal stamping is a crucial manufacturing process that involves shaping metal sheets into specific forms or parts using a punch and a die by means of a stamping press machine. Metal stamping has been widely used, especially in the automotive industries, since the introduction of the T-model Ford mass production in 1908 [1]. The punch exerts significant force to drive the metal sheet into the die, which is designed with the desired shape of the part [2]. Fig. 1 shows a die set for a roof metal part, consisting of a lower die and an upper die. Metal stamping can produce a wide range of parts, from simple brackets and washers to more complex components like automotive body panels or electronic connectors, which consist of several stamping operations such as punching, coining, bending, perforating, piercing, notching, lancing, and embossing [3]. This process is widely employed across various industries due to its ability to produce high-quality parts in large quantities at a low cost with speed and high accuracy [4].

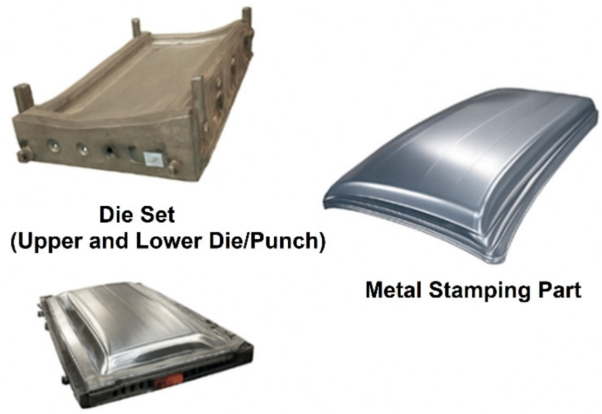

Fig. 1. Sample of a metal stamping part (a roof component).

For quality control of a metal stamping part, a tool called a Checking Fixture (C/F) is used (shown in Fig. 2) while Fig. 3 shows a sample of a Quality Inspection Sheet of a metal part. A checking fixture is a specialized tool in the manufacturing process that verifies dimensions, shapes/contours and positional accuracy and consistency of parts during assembly. It serves as a physical template or gauge to quickly assess whether a part meets the specified design shape and dimensional tolerances. The C/F is manufactured using metal parts and Araldite blocks, where the metal parts are typically used as structural support, while the Araldite blocks are used for measurement purposes due to their low thermal expansion characteristic. Each C/F is only applicable to a single metal stamping part or a single assembled part.

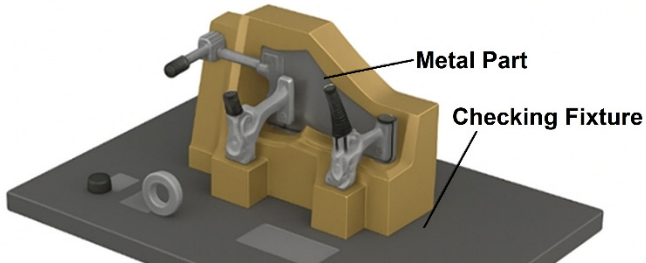

Fig. 2. Sample of a C/F.

The quality inspection process using the C/F is done manually. The part is placed in the C/F, and the operator measures and records discrepancies between the dimensions of the part and the C/F at specific locations. The total tolerance is then evaluated to decide whether the part meets acceptable quality standards or should be repaired or rejected.

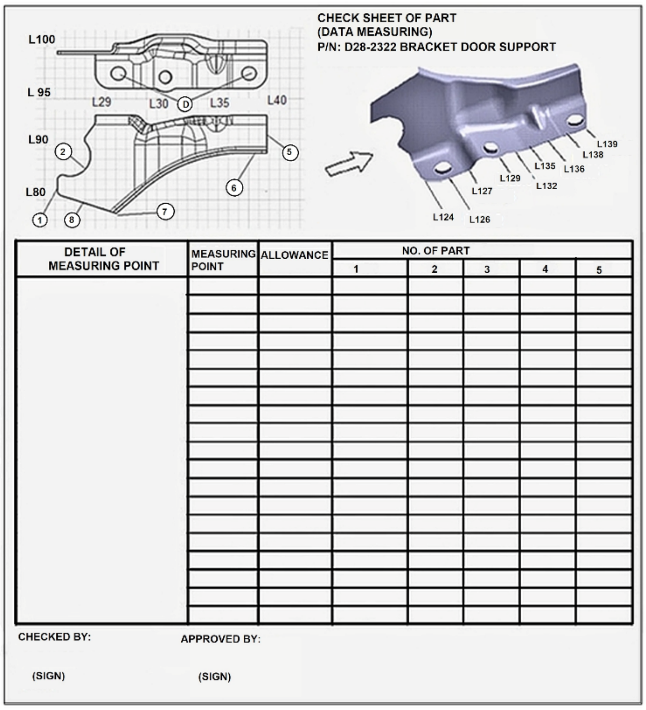

Fig. 3. Sample of a quality inspection sheet for a metal stamping part.

While essential for quality control, checking fixtures have several disadvantages. They involve high initial costs for design and manufacturing, especially for complex parts, which can be a barrier to small and medium-sized enterprises [5, 6]. Regular maintenance and calibration are necessary to ensure accuracy, adding to operational costs and requiring skilled personnel [5, 6]. Checking fixtures are typically designed for specific parts, limiting flexibility and necessitating new fixtures for each new design, which is both costly and time-consuming [6]. Many fixtures require manual placement and inspection, introducing human error and variability [6]. Setting up and aligning parts can be time-consuming, slowing down the inspection process, particularly in high-volume production lines. Over time, fixtures can wear out or become damaged, leading to inaccurate measurements and frequent replacements or repairs [6].

To address these disadvantages and eliminate the reliance on physical fixtures, this study proposes an innovative imaging quality inspection framework for metal stamping parts. The framework combines a 3D laser scanner for highly accurate, non-contact data acquisition with an intelligent machine learning model, specifically the k-Nearest Neighbors (k-NN) method.

The originality and key contribution of this framework are threefold:

1) Digital replacement for physical fixtures. The framework introduces a digital, versatile, and rapidly deployable alternative to physical C/Fs. Unlike the single-use nature of C/Fs, the framework uses the point cloud data directly against the master CAD model, making it adaptable to multiple part geometries through simple software reconfiguration, thereby drastically cutting tooling costs and lead times.
2) Strategic computational efficiency. The strategic selection of the k-NN algorithm ensures a balance of high predictive accuracy with minimal computational overhead and inherent interpretability. This lightweight approach makes the system viable for real-time deployment in high-volume manufacturing, distinguishing it from systems reliant on complex models.
3) Enhancing speed and sustainability. This framework transforms the time-consuming, labor-intensive C/F inspection process into an automated, non-contact measurement and classification system, substantially improving inspection speed, reducing manual errors, and increasing the overall sustainability and agility of the quality control process in automotive manufacturing.

The proposed framework, which addresses the irgency and speed of real-time industrial defect classification to maintain throughput and prevent scrap, finds a strong parallel in the rapid deployment of machine learning for novel disease diagnosis [7]. Both applications face significant challenges in handling uncertainty, whether it's an evolving disease with variable presentation or high-dimensional variability and diverse, changing defect types in manufactured parts. The approach's originality addresses this need for speed and robustness by prioritizing model simplicity: instead of complex, heavy models, the k-Nearest Neighbors (kNN) algorithm is intentionally adapted. This computationally light choice highlights the practicality of using kNN to process 3D point cloud features quickly, efficiently meeting stringent production cycle times while ensuring decision-making capability even from limited data.

II. Materials and Methods

A. 3D Model to Points Cloud

The general process to obtain CAD data from a physical model/part is shown in Fig. 4.

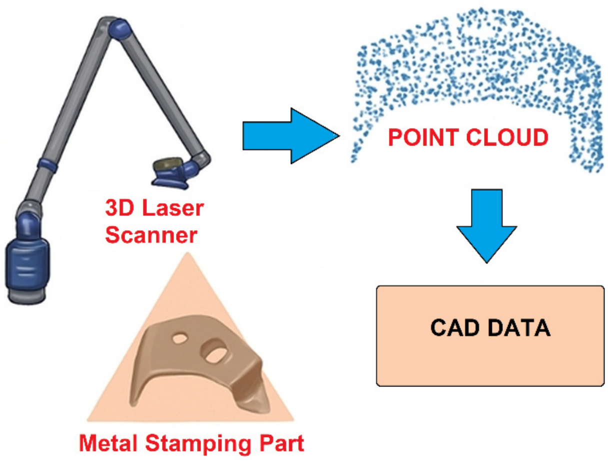

Fig. 4. Retrieving of CAD data using 3D laser scanner.

The process of converting a 3D part into CAD data involves several steps. First, 3D scanning captures the physical geometry using a 3D scanner, creating a point cloud (a dense mesh of points in formats like STL, OBJ, or PLY). Next, data cleaning and preprocessing are performed to remove noise and outliers from the point cloud using software like Geomagic. The cleaned point cloud is then converted into a mesh model by triangulating the points. Finally, the mesh model is imported into CAD software to create parametric

CAD models through 2D sketches, 3D features, and the application of constraints.

B. k-Nearest Neighbourhood (k-NN) Method

The k-NN algorithm is a non-parametric, instance-based learning method. It is used for classification and regression tasks and is widely applied in pattern recognition, data mining, and machine learning [8–11]. The review by Kausik *et al.* [8] highlights that Industry 4.0 has accelerated the use of Machine Learning in manufacturing, facilitating capabilities such as automated defect detection and predictive maintenance. This simplicity, combined with its effectiveness in handling high-dimensional feature vectors common in imaging data, makes the k-NN approach particularly useful for real-time applications in visual quality inspection, including the following:

- Defect detection in manufactured components by comparing visual features with known defect-free samples.
- Surface anomaly classification, such as identifying scratches, dents, or discoloration on metal or plastic surfaces.
- Pattern recognition in printed circuit boards (PCBs) to detect missing or misaligned components.

The k-NN algorithm has been effectively applied in various aspects of visual quality inspection, enhancing accuracy and efficiency across multiple domains. Liu and Liu [12] demonstrated its use in improving visual recognition tasks such as action, scene, object, and face recognition. Xu *et al.* [13] integrated the Shearlet transform with the k-NN for surface inspection, achieving high classification rates for complex surface defects. In dimensional analysis, the k-NN ensures products meet precise tolerances by comparing dimensions against standards. Li *et al.* [14] introduced a novel approach using the k-Nearest Neighbors (k-NN) algorithm for defect classification in wafers, aiming to enhance the accuracy and efficiency of the classification process. Priya *et al.* [15] developed an automated visual inspection system using the k-NN to classify defects in production line images, streamlining quality control. Buongiorno *et al.* [16] applied the k-NN with infrared thermography for weld defect detection, achieving high accuracy. Huang *et al.* [17] introduced a spike camera and SNN-based system utilizing k-NN for high-speed object detection, outperforming conventional cameras. Yuanhang *et al.* [18] used the k-NN for online monitoring and classification of welding defects, demonstrating real-time efficiency. Papananias *et al.* [19] proposed the inspection by exception method, reducing inspection volume with the k-NN. Ashwini *et al.* [20] integrated the k-NN into an automated quality inspection system, enhancing productivity and reliability. Yuekai *et al.* [21] reviewed the k-NN's application in machine vision-based condition monitoring and fault diagnosis, highlighting advancements and future directions in condition-based maintenance. Grochowalski and Chady [22] discuss the utilization of Pulsed Multifrequency Excitation and Spectrogram Eddy Current Testing (PMFES-ECT), an advanced Nondestructive Testing (NDT) technique, combined with the supervised learning algorithm k-Nearest Neighbors (k-NN).

Building upon these proven applications, this study integrates the k-NN algorithm into an imaging quality control framework specifically designed for metal stamping parts. The next section details the algorithm's implementation, showing how its core mathematical principles, including the selection of k and the calculation of Euclidean distance are directly applied to analyze the 3D point cloud data acquired from the laser scanner. This approach allows for the objective identification of part features, noise, and defects, forming the analytical engine of the proposed framework.

C. Performance Evaluation and Validation

To ensure the proposed framework possesses the necessary rigor for industrial quality control, the k-NN model's performance in defect prediction must be quantitatively validated. This process involves comparing the automated system's classification (OK/NG) against a ground truth dataset established by expert manual inspection or highly accurate conventional methods (like CMM or destructive testing). This approach aligns with successful data-driven monitoring frameworks in manufacturing [23].

The model's performance will be evaluated during the Data Analysis and Post-processing steps (Steps 5 and 6 of the framework) using the following key classification metrics:

- Accuracy: The overall ratio of correctly classified parts (both OK and NG) to the total number of parts inspected.
- Sensitivity (Recall): The proportion of all actual defective parts that are correctly identified as 'Not Good' (NG). This is critical for ensuring that defects are not missed (minimizing False Negatives).
- Specificity: The proportion of all actual good parts that are correctly identified as 'OK'. This measures the system's ability to avoid rejecting non-defective parts (minimizing False Positives).
- False Positive Rate (FPR): The ratio of good parts incorrectly classified as 'Not Good' (NG), which is essential for managing production cost and rework.

These quantitative validation steps are necessary to demonstrate that the automated imaging system offers a reliable and objectively measurable improvement over traditional checking fixtures (C/Fs) in terms of defect prediction robustness.

D. k-NN Algorithm in Imaging Quality Inspection Using Machine Learning

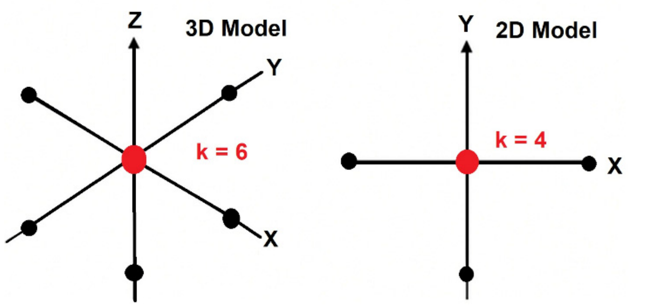

Fig. 5. k-NN model for 3D and 2D.

The k-Nearest Neighbors (k-NN) algorithm involves selecting the number of nearest neighbors (k), calculating the distance between the query point and all other points in the dataset using metrics like Euclidean, Manhattan, or Minkowski distances, sorting these distances to identify the k nearest neighbors [8–10, 16], and then either assigning the most common class label among the neighbors for classification or averaging their values for regression [10]. Euclidean distance is one of the most common metrics used to measure the distance between two points in Euclidean space, where this distance is the straight-line distance between the two points [9]. Fig. 5 shows the k-NN method used to identify and classify the points in a 3D model ($k = 6$) or 2D model ($k = 4$).

The distance between the number of nearest neighbors (k) to consider for the classifi-cation or regression can be calculated using the equation:

Euclidean distance for 3D:

$$E_{3D}= \sqrt{(X2-X1)^2+(Y2-Y1)^2)\ +\ (Z2-Z1)^2} \quad (1)$$

Euclidean distance for 2D:

$$E_{2D}= \sqrt{(X2-X1)^2+(Y2-Y1)^2} \quad (2)$$

Eq. (1) represents the distance of k for a 3D model and Eq. (2) represents the distance of k for a 2D model of the part. Based on these equations, a point in the point cloud can be verified as a noise (outlier) or as a feature of the part by assigning the maximum Euclidean distance value. If there is a point with the Euclidean distance exceeding the maximum value, then the point is considered as a noise.

1) Noise and feature of a surface

Fig. 6 depicts an example of the k-NN Algorithm to identify noises and features. The blue dots indicate the points in the point cloud data. Point/noise 1 and noise 2 are considered as noises due to their Euclidean distance between the set points exceeding the maximum value. The other points in the Fig. 6 are considered as surface and edges (features) due to their Euclidean distance being below the maximum distance.

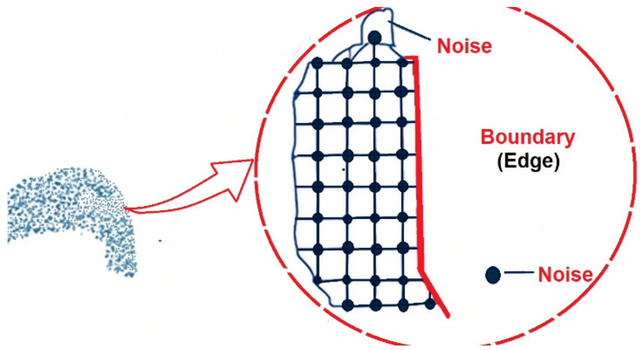

Fig. 6. k-NN Algorithm to identify noises and features.

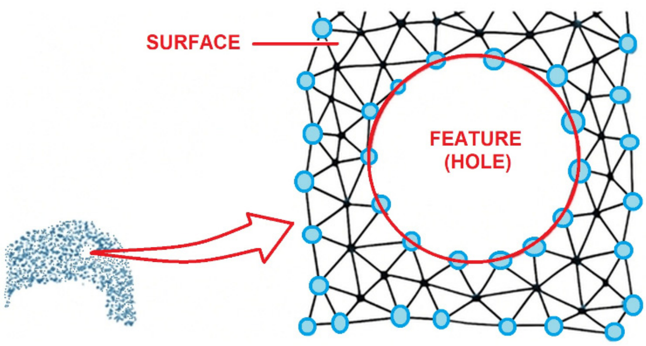

Fig. 7. k-NN Algorithm to identify hole features and surfaces.

Fig. 7 shows an example of the k-NN Algorithm to identify the hole feature of a sur-face. The hole is detected as a fully connected curve which develops a closed loop of a circle. The surface is defined by identifying the total number of k with the accepted Euclidean distance which exceeding the minimum number.

2) Defects identification

Fig. 8 illustrates the application of the k-NN algorithm for a defect identification. The lower area of the part/model (CAD data/training set data) is flat. Upon comparison with the point cloud data, the circled area in the left side is identified as a defect or burr.

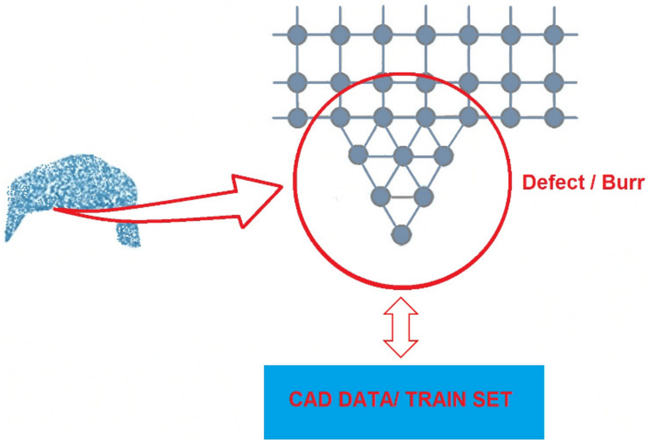

Fig. 8. k-NN Algorithm to identify defects.

III. Result and Discussion

A. Proposed Framework

The proposed quality inspection process using the k-NN machine learning method is shown in Fig. 9.

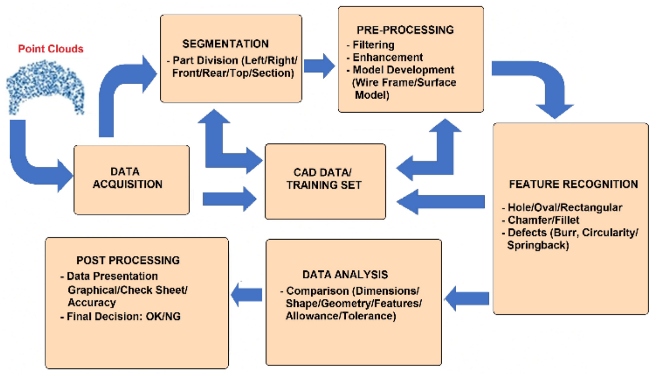

Fig. 9. Proposed imaging machine learning process.

The machine learning process will be performed according to the following steps:

Step 1: Data Retrieval/Acquisition. This step consists of obtaining datum position/coordinates from CAD and point cloud data. The objective of this step is to establish crucial reference points for accurately aligning the scanned data with the CAD model.

Step 2: Segmentation. This stage involves developing offset data and sectioning (orthographic projection) from CAD data for detailed analysis. Generating offset lines or surfaces from the CAD model at specified intervals is essential for creating cross-sectional views used for comparison with the point cloud data.

Step 3: Pre-processing. This stage consists of filtering/removing points located outside the offset position of the point cloud data. Removing points that lie outside the defined offset boundaries ensures that only relevant data points are considered for further processing, improving accuracy and reducing noise.

Step 4: Feature Recognition. In this stage a geometric representation of the part is created. The filtered and enhanced point cloud from the previous step is then used to generate a wireframe or surface model by connecting points to form a mesh representing the surface geometry. During this step, key features are detected and labeled to identify critical features such as holes, edges, and surfaces on the wireframe or surface model. These features are essential for detailed comparison and analysis.

Step 5: Data Analysis. This step compares the developed wireframe/surface model with CAD data to assess the accuracy of the scanned model. The wireframe or surface model is overlaid onto the CAD data, involving the measurement of deviations and discrepancies between the scanned and CAD models to identify any inaccuracies.

Step 6: Reporting and Tolerance Check. The step consists of developing a table that lists the accuracy of the scanned model, identified features, and any detected defects, including the allowable tolerances to determine if the deviations are within acceptable limits.

Step 7: Final Decision. The objective of this step is to make a final quality assessment. Based on the comparison and the table of findings, a decision is made on whether the part meets the required specifications (Good condition) or has defects that need correction (Not Good condition). A clear conclusion on the part's quality is then provided in the final decision report.

It can be seen also form the Fig. 9 that all of the steps directly interact and compared with the CAD data/training set data during the process to increase the accuracy, the processing speed and the effectiveness.

B. *Comparative Analysis and Advantages*

Each Checking Fixture (C/F) is specifically designed for a particular part, making it unique and discrete. This specificity means that a new C/F must be created for every new part, which can be both time-consuming and costly. In contrast, a single imaging system can be used for multiple parts, offering versatility that allows for a more streamlined and efficient inspection process. The same imaging system can adapt to different parts without the need for new C/Fs, significantly enhancing operational efficiency.

The cost associated with C/Fs includes significant expenses for designing each unique fixture, the raw materials and standard parts required for construction, the manufacturing process, and the skilled labor needed for both design and manufacturing. On the other hand, the costs of imaging machine learning systems include the initial purchase of hardware such as a PC and a 3D laser scanner, investment in machine learning software, and labor costs for developing and maintaining the software. These costs are generally lower compared to the labor-intensive process of creating C/Fs.

The checking fixture process involves a time-consuming design phase for each new part and a slower quality inspection process due to the manual nature of using fixtures. In contrast, the initial development of machine learning software for imaging is a one-time investment. Once set up, the quality inspection process becomes much faster due to automation and the system's ability to quickly adapt to different parts.

The quality inspection process using C/Fs is manual and subjective, leading to variability in results and a higher potential for human error. Additionally, physical fixtures can wear out over time, affecting accuracy. In contrast, imaging systems with ma-chine learning provide consistent and objective inspections, reducing the likelihood of human error and maintaining accuracy over time. This automated approach ensures a higher and more reliable standard of quality control.

In essence, imaging machine learning fully automates the inspection process, reducing subjectivity and ensuring consistency. Automation and machine learning algorithms minimize human errors, and the reliance on digital imaging eliminates the physical wear and tear associated with traditional fixtures.

IV. Conclusion

This study successfully developed and detailed an automated imaging quality inspection framework for metal stamping parts using the k-Nearest Neighbors (k-NN) machine learning method. The proposed structured and efficient process involves key steps: data acquisition, segmentation, pre-processing, feature recognition, data analysis, reporting and tolerance check, and final decision-making, where each step interacts with CAD data to enhance accuracy and processing speed.

The comparative analysis confirms the substantial advantages of the imaging system over traditional Checking Fixtures (C/Fs). While C/Fs require time-consuming and costly design and manufacturing for each unique part, the versatile imaging system, based on initial hardware and software investments, allows for streamlined inspections across multiple parts with significantly lower ongoing labor costs. Crucially, the automated approach eliminates the subjectivity and human error associated with C/F, providing consistent, objective, and accurate results without physical wear and tear.

In summary, this framework offers a more sustainable and agile quality control solution essential for modern high-volume manufacturing. Future work should focus on validating the framework using larger and more varied industrial datasets and comparing the k-NN performance against other suitable machine learning algorithms, such as Support Vector Machine (SVM) or Convolutional Neural Networks (CNNs).

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Widodo contributed to resources, conceptualization, methodology, investigation, and writing of the original draft, while S. Toto was responsible for visualization and writing review and editing. Both authors have read and approved the final version of the manuscript.

ACKNOWLEDGMENT

Special acknowledgement to the Fakulti Teknologi dan Kejuruteraan Mekanikal (FTKM), Universiti Teknikal Malaysia Melaka (UTeM) for providing the resources and facilities for the research.

REFERENCES

[1] C. D. Horvath, "Advanced steels for lightweight automotive structures," *Journal of Materials, Design and Manufacturing for Lightweight Vehicles*, pp. 39–95, 2020.

[2] Y. P. Fan, "Sheet metal cover drawing forming process analysis," *Advanced Materials Research*, pp. 971–973, 2014.

[3] L. Yu, X. Chen, and Y. Yang, "The stamping process simulation of plate using CAE technology," *Advanced Materials Research*, pp. 538–541, 2012.

[4] N. Baluch, N. Nordin, and S. Mohtar, "AHSS auto structural metal stampings: Crucial role of lubricant," *Applied Mechanics and Materials*, vol. 590, pp. 289–293, 2014.

[5] M. Hafizzul, "Design and development of a checking fixture for an automotive press part," Project Report, Faculty of Manufacturing, Universiti Teknikal Malaysia Melaka, Malaysia, 2017.

[6] E. Hoffman, *Jig and Fixture Design*. Singapore: Delmar, pp. 1–86.

[7] M. M. Mijwil1, I. Adamopoulos, and P. Pudasaini, "Machine learning helps in quickly diagnosis cases of 'New Corona'," *Mesopotamian Journal of Artificial Intelligence in Healthcare*, vol. 2024, pp. 16–19, 2024.

[8] A. K. Kausik, A. B. Rashid, R. F. Baki, and M. M. J. Maktum, "Machine learning algorithms for manufacturing quality assurance: A systematic review of performance metrics and applications," *Array*, vol. 26, 100393, 2025.

[9] M. David and M. A. Firdaus, "Defect rate prediction in manufacturing process using K-nearest neighbor algorithm," *International Journal of Informatics, Economics, Management and Science*, vol. 3, no. 2, pp. 161–173, 2024.

[10] R. K. Halder, M. N. Uddin, and M. A. Uddin, "Enhancing K-nearest neighbor algorithm: a comprehensive review and performance analysis of modifications," *Journal of Big Data*, vol. 11, pp. 113–120, 2024.

[11] P. K. Syriopoulos, N. G. Kalampalikis, and S. B. Kotsiantis, "k-NN Classification: A review," *Annals of Mathematics and Artificial Intelligence*, vol. 9, pp. 1–12, 2023.

[12] Q. Liu and C. Liu, "A novel locally linear k-NN method with applications to visual recognition," *IEEE Transactions on Neural Networks and Learning Systems*, pp. 2010–2021, 2017.

[13] K. Xu, S. Liu, and Y. Ai, "Application of shearlet transform to classification of surface defects for metals," *Image and Vision Computing*, vol. 35, pp. 23–30, 2015.

[14] W. Li, E. Nilsson, and F. Chen, "Defect classification in wafer inspection through k-nearest neighbors," *Optimizations in Applied Machine Learning*, vol. 3, no. 3, pp. 1–23, 2023.

[15] S. Gupta, N. Bhadoria, and P. Satpute, "Survey paper on visual inspection of a mechanical part using machine learning," *International Journal of Engineering Research & Technology (IJERT)*, vol. 9, pp. 106–109, 2015.

[16] M. Buongiorno, M. Prunella, S. Grossi, S. M. Hussain, A. Rennola, N. Longo, G. D. Stefano, V. Bevilacqua, and A. Brunetti, "Inline defective laser weld identification by processing thermal image sequences with machine and deep learning techniques," *Applied Sciences*, vol. 12, p. 6455, 2022.

[17] T. Huang, Y. Zhang, Z. Yu, R. Cheng, Y. Li, R. Xiong, L. Ma, J. Zhao, S. Dong, L. Zhu, J. Li, S. Jia, Y. Fu, B. Shi, S. Wu, and Y. Tian, "Faster camera and machine vision with ordinary devices," *Engineering*, vol. 25, pp. 110–119, 2023.

[18] Y. Bo, C. Bo, Y. Yao, and C. Tan, "A spectroscopic method based on support vector machine and artificial neural network for fiber laser welding defects detection and classification," *NDT and E International*, vol. 108, pp. 1–9, 2019.

[19] T. Papananias, T. E. McLeay, O. Obajemu, and M. Mahfouf, "Inspection by exception: A new machine learning-based approach for multistage manufacturing," *Applied Soft Computing*, vol. 97, 106774, 2020.

[20] K. Ashwini and S. B. Rudraswamy, "Automated inspection system for automobile bearing seals," *Materials Today: Proceedings*, vol. 46, pp. 4709–4715, 2021.

[21] Y. Liang, L. Guo, H. Gao, Z. You, and Y. Ye, "Machine vision-based condition monitoring and fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 164, 108217, 2022.

[22] J. M. Grochowalski and T. Chady, "Rapid identification of material defects based on pulsed multifrequency eddy current testing and the k-nearest neighbor method," *Materials*, vol. 16, 6650, 2023.

[23] M. M. Rosli, A. Rachini, and M. K. Mahmood, "Data-driven melt pool monitoring and defect prediction in LPBF of Ti-6Al-4V alloy," *Babylonian Journal of Mechanical Engineering*, pp. 51–67, 2025.