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Integrating Canny Filter and Convolutional Neural Networks for Quality Defect Detection in Injection Molding Process

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Abstract **-** Detection of quality defects in injection molding manufacturing remains one of the most challenging tasks due to its heavy reliance on human visual inspection, which has inherent limitations. Computer vision, which addresses image-based problems, offers promising solutions in this area. This article explores the application of machine vision models to identify quality defects in products from the injection molding process. The methodology is divided into two main steps: first, the application of the Canny filter to extract edge characteristics; and second, the use of Convolutional Neural Networks (CNN) to classify parts as either good or defective. The results demonstrate that the combined method outperforms the use of CNN alone, achieving an accuracy of 99.57%, a precision of 99.44%, a recall of 100%, and an F1-score of 99.72% with the Canny filter, compared to an accuracy of 95.31%, a precision of 94.24%, a recall of 100%, and an F1-score of 97.03% without the Canny filter. These findings confirm that the integrated model can be implemented in online production systems to enhance the detection of defects in injection molding processes.

Keywords**:** Injection Molding Process, Quality Defect Detection, Canny Filter, Convolutional Neural Networks

1. Introduction

The injection molding process is widely used in manufacturing to produce high-precision plastic parts[1]. The process involves injecting plastic material into a mold cavity under high pressure, which can range from hundreds to thousands of bars[2]. Once injected, the plastic cools and solidifies within the mold cavity, taking the shape of the mold and producing a specific plastic product. Fig.1 depicts the main primary stages of the standard production cycle. However, quality defects in injection molding can lead to significant challenges[3]. When customers receive defective parts, it results in both direct costs, such as product returns and replacements, and indirect costs, including loss of reputation and customer trust. Consequently, identifying and addressing quality defects in injection molding is critical for maintaining product standards and customer satisfaction[4].

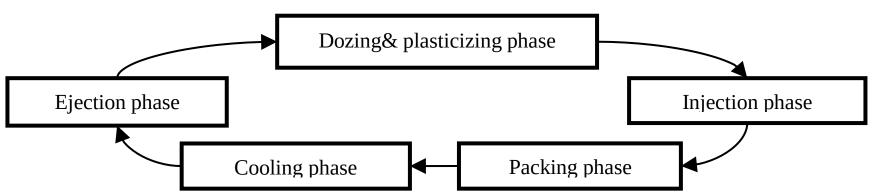

Fig. 1: The Five stages of a standard injection molding process

Quality defect detection remains a particularly challenging task in injection molding due to the intricate nature of the process and the high standards required for the final products[5]. Traditional inspection methods often fall short in terms of accuracy and efficiency, prompting the need for more advanced solutions[6].

In response to these challenges, this study focuses on harnessing the capabilities of vision models to augment the detection of quality defects in injection molding. By leveraging advanced image processing and analysis techniques, the objective is to refine the accuracy, efficiency, and reliability of defect detection processes. Through the integration of vision models, manufacturers can not only minimize costs associated with defective parts but also proactively mitigate customer claims, thereby enhancing operational efficiency and bolstering brand reputation.

Numerous studies have explored the integration of deep learning techniques into visual quality inspection applications. Lee et al. (2021)[7] introduce a novel framework for identifying defective products in injection molding manufacturing, aiming to improve upon the limitations of manual visual inspection. Their approach integrates Canny Edge Detection with Mask R-CNN, a neural network known for its speed and precision in object detection, using ResNet101 as the backbone for enhanced accuracy. They optimize image capture with LEDs to adjust sizes and scales, ensuring detection of even minor defects. This strategy enhances the reliability of defect detection, advancing automated quality inspection in a human-free production environment. Liu et al. (2021)[8] tackle the challenge of automatic appearance defect detection in manufacturing, seeking to overcome the limitations of manual visual inspection. They propose a knowledge reuse strategy to train CNN models, which enhances both accuracy and robustness in defect inspection. This strategy integrates model-based transfer learning and data augmentation, leveraging knowledge from other vision tasks to improve industrial defect detection. Experiments on injection molding products demonstrate a detection accuracy of around 99% with only 200 images per category, outperforming traditional CNN models and support vector machine methods. The proposed method effectively identifies complex defects with diverse appearances, as evidenced by visualization techniques that highlight precise feature extraction from defective regions. Overall, this approach represents a significant advancement in automatic defect detection within manufacturing. Yang et al. (2015) [9] assessed the effectiveness of four edge detection operators—Roberts, Sobel, Prewitt, and Canny—in digital image processing (DIP) to enhance the quality of injection molding processes. They integrated DIP with model-free optimization (MFO) to tackle challenges in injection molding. DIP was utilized to monitor surface defect magnitudes, while MFO employed online feedback to identify optimal settings. This method, successfully applied to an injection molding machine, effectively eliminated defects in molded parts. Reckert et al. (2024)[10] aim to improve part quality consistency in Multi-Material Jetting (MMJ), an additive manufacturing process for ceramics and hard metals. They propose using surface measurements and CNNs to automate the classification of process parameterization adequacy on green parts. Training data consists of demo part structures with various overlap settings, and the models achieve high accuracy. Significantly, analyzing only the first layer effectively predicts the quality of subsequent layers. im et al. (2023)[11] aim to create a neural network algorithm for predicting the quality of injection molding products. Their approach incorporates machine vibration data, temperature and pressure data from each cavity, and visual features from images. They establish an infrastructure for gathering vibration, cavity sensor, and image data. Statistical features extracted from the vibration and sensor data are utilized as independent variables, while quality grades are determined from images using indicators like housing flexion and pinhole alignment with the Canny-edge algorithm. The effectiveness of the neural network-based algorithm is subsequently assessed to improve quality prediction in injection molding.

In terms of the literature review, the primary gap highlighted is the scarcity of studies that integrate both the canny edge technique and convolutional neural networks (CNNs) for classifying faulty parts. Considering the diverse forms and shapes of products in injection processes, each product essentially constitutes a unique case. The key contribution of this article lies in:

- Utilizing a two-step detection approach involving filtering and subsequent CNN analysis.
- Demonstrating the application of this method on real-world data extracted from actual injection products.

2. Methodology

In this study, the methodology comprises four distinct steps, Fig2. The first step involves assembling a comprehensive dataset for training and testing purposes. This dataset includes 3000 data points for training, consisting of 2100 images of good parts and 900 images of bad parts. Additionally, there are 340 images for testing, categorized into 110 images of good parts and 230 images of bad parts. The second step involves applying edge detection techniques to the plastic parts, enabling the extraction of crucial edge characteristics essential for subsequent analysis. In the third step, Convolutional Neural Networks (CNN) are used to classify the parts as either good or bad. By leveraging the power of deep learning, the CNN facilitates accurate and efficient classification based on learned patterns and features. The final step involves conducting a comparative analysis based on standard classification metrics. By rigorously evaluating the model using metrics such as accuracy, precision, recall, and F1-score, the effectiveness and reliability of the classification model are assessed. This comprehensive analysis provides insights into the model's performance and its potential for real-world application in detecting and mitigating quality defects in injection molding.

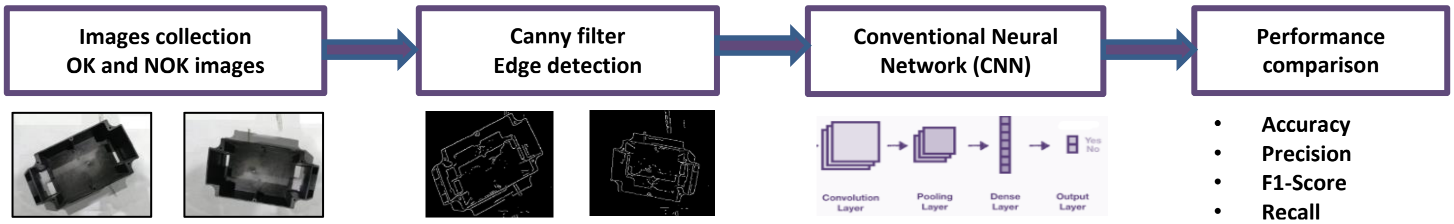

Fig. 2: Research methodology flowchart

2.1. Images acquisition

For this investigation, the images were sourced from a plastic injection molding facility situated in northern Morocco. The study concentrated on the packaging of plastic boxes for industrial goods. The collected data comprised both 2210 representing good parts and 1130 representing b a parts, with a specific anomaly studied in this paper: Burrs around the functional assembly hole, Fig3. This area is functional, as any material inside could prevent proper closure or sealing of the assembled part. The images were manually captured from the production line, with a resolution of 900 x 1200 pixels. Subsequently, the pixel size was reduced to 256x256 for feature extraction and model testing purposes. The figure 4, shows samples of the images used in this study.

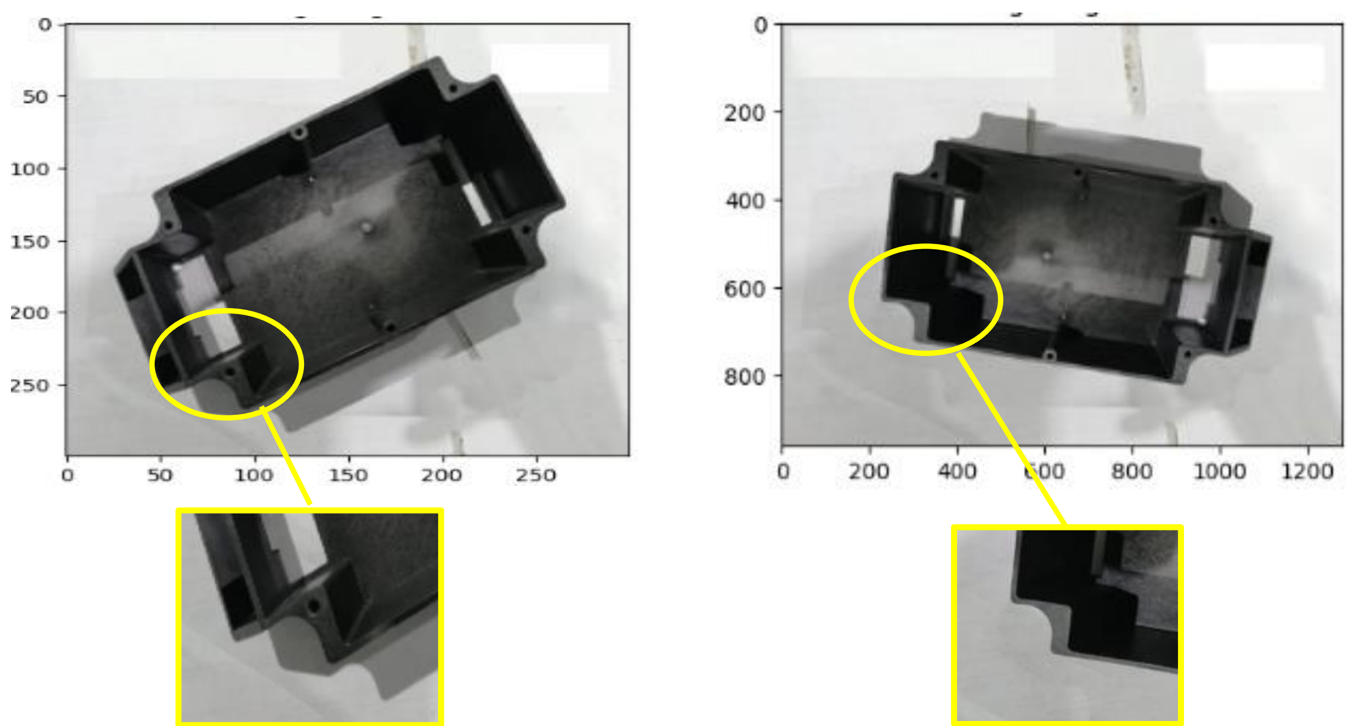

Fig. 3: Defect in plastic part hole position (Good part in the left, Bad part in the right)

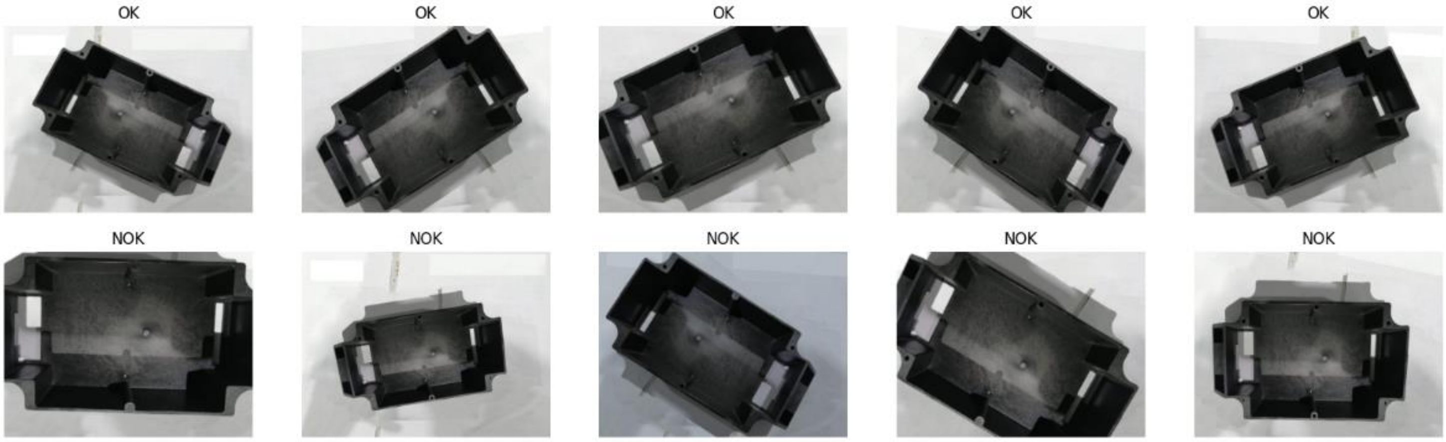

Fig.4: Dataset samples (Good vs. Bad)

2.2. Canny edge detection

The Canny edge detection algorithm is a popular technique used in computer vision and image processing for detecting edges in images. It was developed by John F. Canny in 1986 and is widely used due to its effectiveness and robustness[12].

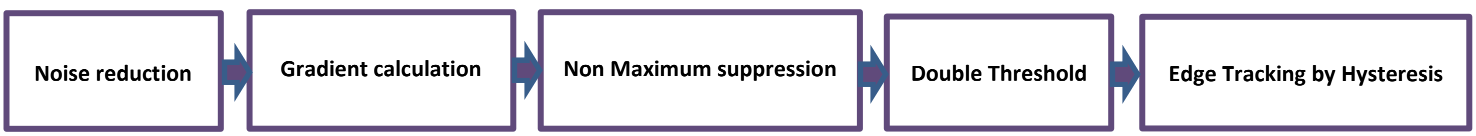

Fig. 5: Flowchart of the Canny edge detection algorithm

Figure 5 illustrates the key stages of the algorithm, which can be summarized into five main steps, while figure 6 shows the output of the Canny edge. The basic outline of how the Canny edge detection algorithm works can be summarized as follow:

- Noise Reduction: Before detecting edges, the image is often smoothed to reduce noise. This is typically done using a Gaussian blur[13].
- Gradient Calculation: The intensity gradients of the image are calculated using techniques like Sobel or Prewitt operators[14], [15]. These operators compute the gradient magnitude and direction for each pixel.
- Non-maximum Suppression: This step thins out the edges by suppressing all gradient values except for the local maxima, which are considered to be on the actual edges. Essentially, it finds the local maxima in the gradient magnitude along the direction of the gradient[16].
- Double Thresholding: This step categorizes edge pixels into strong, weak, and non-relevant based on their gradient values. The two thresholds are used to identify strong and weak edge pixels. Pixels with values above the high threshold are marked as strong edges, and those below the low threshold are considered non-edges. Pixels with values between the two thresholds are marked as weak edges[17].
- Edge Tracking by Hysteresis: Finally, this step tracks edges by suppressing weak edges that are not connected to strong edges. It considers a weak edge pixel to be part of the edge if it is connected to a strong edge pixel. This is typically done using techniques like edge following or connectivity analysis[18]

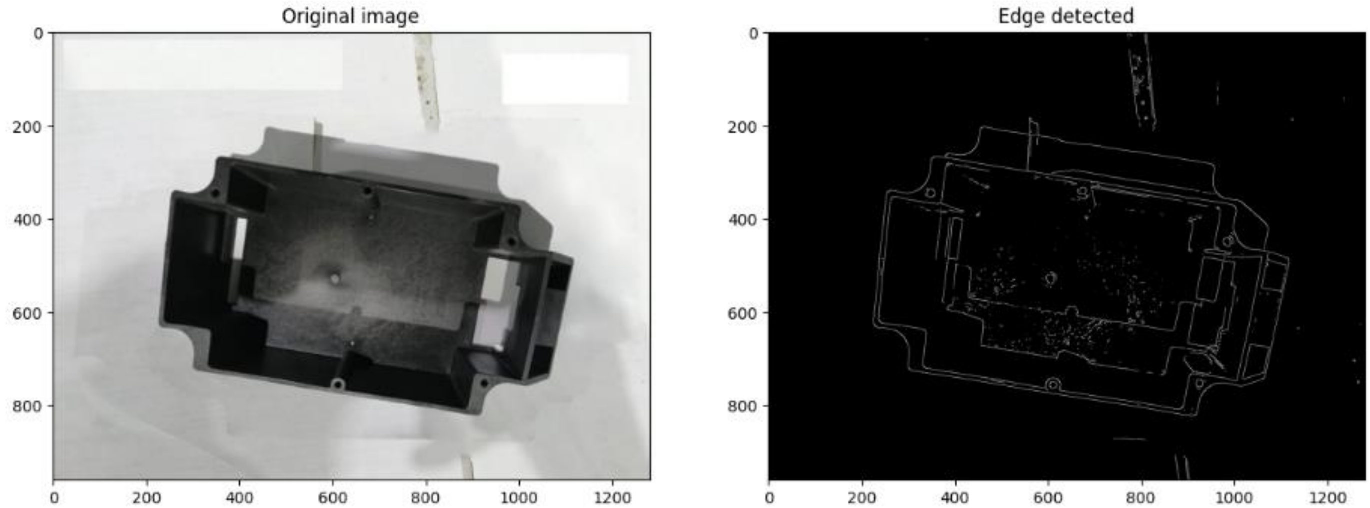

Fig 6: Original image (Left) and Canny edge detection output (Right)

2.3. Conventional Neural Network

CNNs are deep learning models designed for visual data analysis[19]. They consist of layers that extract features from images through convolution, introduce non-linearity with activation functions, downsample with pooling, and make high-level predictions through fully connected layers. They're widely used for tasks like image classification, object detection, and segmentation due to their ability to learn hierarchical representations from raw data.

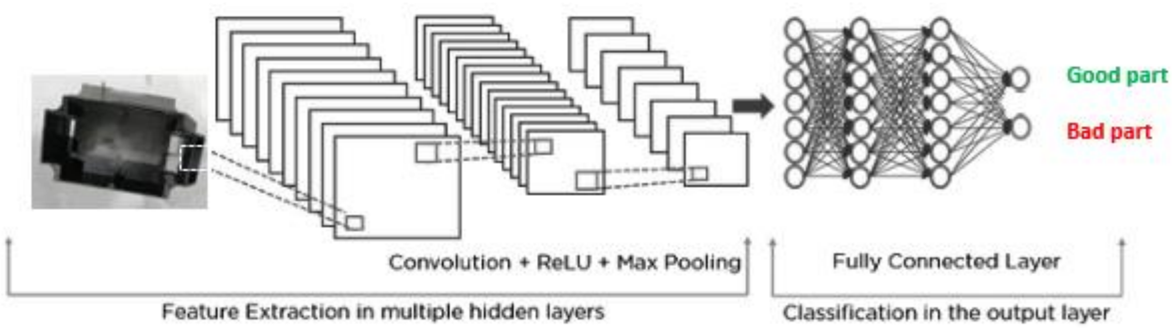

Fig 7: Convolutional Neural Networks architecture

Figure 7 displays the main steps of CNN, they can be listed as follow:

- Convolutional Layers: These layers use learnable filters to extract features from input images, creating feature maps. This allows the network to develop hierarchical representations of the input data.
- Activation Function: ReLU is commonly used to introduce non-linearity, which enables the network to learn intricate patterns effectively.
- Pooling Layers: Pooling layers reduce the spatial dimensions of feature maps, downsampling them to enhance computational efficiency in the network. Common operations include max pooling and average pooling
- Fully Connected Layers: These layers connect neurons across layers, enabling high-level reasoning and complex pattern recognition.
- Softmax Layer: In classification tasks, the softmax function converts the network's output into class probabilities, enabling it to make predictions.

- Backpropagation: CNNs are trained using backpropagation, adjusting weights based on the difference between predicted and true outputs. Optimization algorithms like stochastic gradient descent are used to minimize loss during training.

CNNs have found success in various applications beyond image processing, including natural language processing, to their ability to learn intricate patterns from data.

In our study, we utilized a specific architecture consisting of two convolutional layers followed by max-pooling layers for feature extraction from input images. The first convolutional layer has 16 filters with a 3x3 size and ReLU activation, followed by max-pooling. The second convolutional layer employs 32 filters of the same size and activation function. A flattening layer converts 2D feature maps into a 1D vector, followed by a densely connected layer with 32 neurons and ReLU activation. Dropout regularization with a rate of 0.5 is applied before the output layer, which has a single neuron with sigmoid activation for binary classification. This configuration ensures the network's ability to learn and extract relevant features from input images, while the regularization techniques enhance generalization and prevent overfitting, ultimately facilitating effective binary classification.

2.4. Performance comparison

To evaluate the performance of the trained model in identifying quality defects, we utilized the confusion matrix[20]. It serves as a vital instrument in classification tasks, providing a detailed breakdown of the model's predictions compared to the actual labels within the dataset. Each cell of the confusion matrix represents a specific outcome[21]:

- True Positives (TP): Cases where the model correctly identifies the existence of a quality defect.
- False Positives (FP): Cases where the model inaccurately identifies a quality defect that is absent.
- True Negatives (TN): Cases where the model correctly identifies the absence of a quality defect.
- False Negatives (FN): Cases where the model overlooks a quality defect that is genuinely present.

By examining these components, we can derive key performance metrics such as accuracy, precision, recall, specificity, and the F1 score[22]. These metrics offer nuanced insights into various aspects of the model's effectiveness, including its ability to minimize false identifications, capture all instances of defects, and maintain overall accuracy.

The Accuracy, which measures the proportion of correct predictions out of all predictions made by the model. we can calculate the MAE using the following formula:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

The Precision is a measure of the accuracy of the positive predictions made by a model. The formula is:

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

The Recall, also known as Sensitivity, quantifies the proportion of positive cases correctly identified by the classifier among all actual positive cases in the dataset. Its formula is expressed as follows:

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

The F1-Score, a measure that combines precision and recall, is often defined as the harmonic mean of the two metrics. Harmonic mean is favored for ratios, like precision and recall, as it balances extreme values more effectively than the arithmetic mean. The formula for calculating the F1-Score is given by:

$$F1Score = \frac{2 * Recall * Precision}{Reclall * Precision} \tag{4}$$

3. Main results and discussion

To compare the performance of the models, we conducted two tests. In the first trial, the model operated without the the Canny filter, while in the second trial, it operated with the Canny filter. The results of these tests are illustrated in the the figure8.

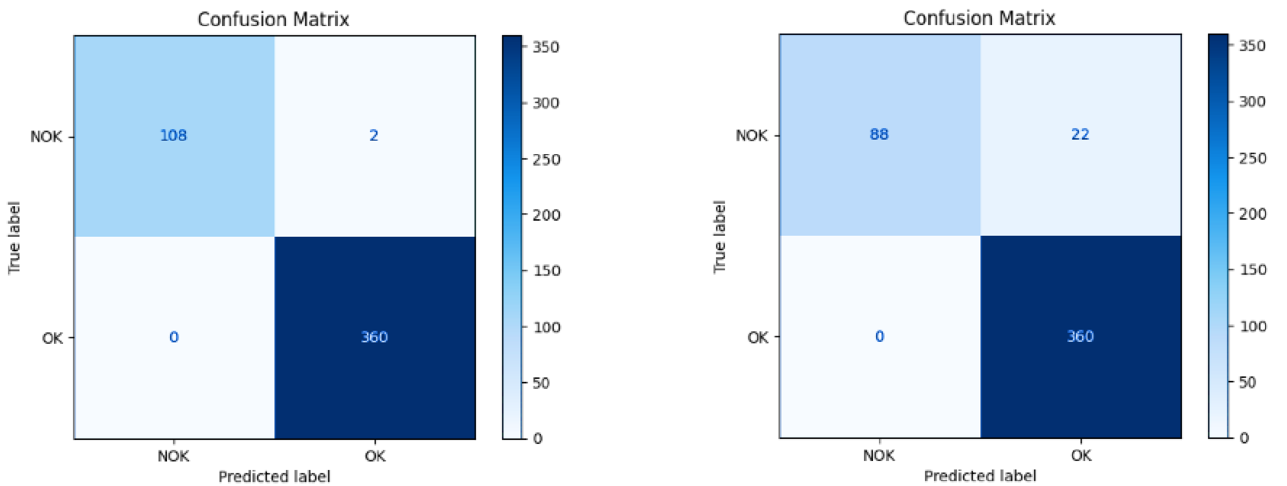

Fig 8: Comparison of confusion matrices: Model without vs. with Canny filter

Table 1 : Performance comparison

Configuration	Train data set	Test data set	Accuracy	Precision	Recall	F1- Score
(1) CNN Without Canny Filter	3000	470	95.31%	94.24%	100%	97.03%
(2) CNN with canny	3000	470	99.57%	99.44%	100%	99.72%

Table 1 provided results compare two configurations of a Convolutional Neural Network (CNN) used for image classification tasks, specifically evaluating the impact of applying a Canny edge detection filter to the input images.

Firstly, let's consider the configuration details. Configuration (1) involves a CNN model that processes raw images without any pre-processing through the Canny filter. In contrast, Configuration (2) applies the Canny edge detection filter to the images before feeding them into the CNN. Both configurations were trained on a data set of 3000 images and tested on a data set of 470 images, ensuring a fair and consistent comparison.

When examining the accuracy, the CNN without the Canny filter achieved an accuracy of 95.31%, while the CNN with the Canny filter achieved a notably higher accuracy of 99.57%. This significant improvement suggests that edge detection as a pre-processing step helps the model focus on essential features of the images, leading to better overall performance.

Looking at the precision metric, the CNN without the Canny filter had a precision of 94.24%, whereas the CNN with the Canny filter had a precision of 99.44%. Precision measures the proportion of true positive predictions among all positive predictions. The substantial increase in precision indicates that the Canny filter helps the model reduce false positives by emphasizing the most relevant features of the images.

The recall for both configurations remained at 100%, indicating that all actual positive cases were correctly identified by both models. This consistency shows that both models are excellent at identifying positive cases when they exist, demonstrating strong performance in recognizing relevant instances in the dataset.

The F1-Score, which balances precision and recall, was 97.03% for the CNN without the Canny filter and improved to 99.72% for the CNN with the Canny filter. This significant enhancement in the F1-Score suggests a more robust overall model when edge detection is used, as it excels in both identifying relevant positives and minimizing false positives

The results strongly indicate that applying the Canny edge detection filter before feeding images into the CNN greatly enhances model performance across all evaluated metrics. This pre-processing step allows the model to better capture and utilize important features of the images, leading to higher accuracy, precision, and F1-score without compromising recall. The significant improvements in precision and F1-score highlight the effectiveness of the Canny filter in reducing false positives and achieving more reliable performance in practical applications

When considering the baseline from previous studies, Lee et al. (2021)[7] achieved an accuracy of 96.94% using a model combining Canny filters and CNN (ResNet101) with 10,000 trained images. Meanwhile, Ha et al. (2021) [23]reached around 93% accuracy utilizing CNN and edge detection with approximately 3,800 images for injection molding. Despite the superior performance of our model, it's important to acknowledge that in injection molding, each plastic part is treated as unique. Therefore, comparing models across different types of parts introduces bias into the evaluation process.

4. Conclusion

This research investigated the effectiveness of combining a Canny edge filter with a Convolutional Neural Network (CNN) for defect detection in injection molded parts, specifically focusing on burrs around functional areas of packaging boxes with simple shapes. The results demonstrate that the combined approach using the Canny edge filter prior to CNN processing leads to improved defect detection compared to using the CNN alone. This improvement was achieved even with a moderate dataset size. By implementing a combined Canny edge filter and CNN approach, workshops across the manufacturing industry can potentially gain significant benefits in terms of improved defect detection and reduced quality control costs.

However, the study did not explore the generalizability of the trained models to other types of plastic parts. This opens an interesting avenue for future research, where the developed approach could be tested on a wider variety of parts and materials to assess its efficacy and potential need for adjustments. Overall, this work highlights the potential of combining Canny edge filtering with CNNs for enhanced defect detection in injection molding, particularly for parts with simple geometries. Further research is needed to explore the broader applicability of this approach across different plastic parts and molding processes. Additionally, the study focuses only on one type of anomaly, specifically burrs. Future research could investigate other defects such as shrinkage, sink marks, burns, and more. Applying digital detection techniques to each type of defect could significantly broaden the scope of research opportunities.

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