Chapter 4

Advanced Segregation of Defective Cigarettes: Integrating Image Processing and Machine Learning

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Abstract:

This paper presents the design and development of a damaged cigarette segregation machine, aimed at automating the process of identifying and separating defective cigarettes from production lines. The system integrates advanced image processing techniques and machine learning algorithms to detect physical defects such as broken filters, damaged wrappers, or incorrect lengths in real-time. High-speed cameras capture images of cigarettes on the conveyor belt, while a custom-trained neural network identifies defective products with high accuracy. Upon detection, a pneumatic actuator removes the damaged cigarettes from the production line. Initial testing demonstrated an accuracy rate of over 95% in detecting defects, significantly reducing manual inspection efforts and improving overall production efficiency. This machine offers a scalable, cost-effective solution for maintaining product quality standards in the tobacco industry while minimizing human intervention. Future work will focus on optimizing the machine's performance and extending its application to other quality control processes.

Keywords: image processing, machine learning, defect detection, cigarette quality, automation

1. Introduction

In the tobacco manufacturing industry, product quality and consistency are paramount, particularly in maintaining the integrity of cigarettes during the production process. Defects such as broken filters, torn wrappers, and incorrect lengths can significantly affect both product quality and consumer satisfaction. Traditionally, quality control in cigarette manufacturing has relied heavily on manual inspection, which is time-consuming, labor-intensive, and prone to human error (Jones & Baker, 2014). As the demand for higher production efficiency and precision increases, automated systems for detecting and segregating defective products have become essential.

The shift toward automation in quality control has been driven by advancements in machine vision and artificial intelligence (AI). Automated inspection systems equipped with high-resolution cameras and intelligent algorithms offer greater accuracy and speed compared to manual inspections (Ramesh et al., 2017). The ability to detect defects in real-time and at high production speeds reduces the need for human intervention, thus improving productivity and ensuring consistent product quality.

Machine vision systems have been applied in various industries for quality inspection, including food, pharmaceuticals, and electronics (Kumar & Singh, 2019). In cigarette manufacturing, the application of machine vision and AI is still in its nascent stages, but recent developments have shown potential. Studies such as those by Wang et al. (2020) have demonstrated the use of image processing

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techniques to inspect cigarettes for wrapper integrity and filter defects, achieving high levels of accuracy. However, most systems are designed for specific defect types, and there is a need for more versatile solutions that can handle multiple defect categories in real-time.

Machine learning has revolutionized defect detection systems by enabling the identification of complex patterns that are not easily discernible by traditional methods (Zhang et al., 2018). Deep learning, particularly convolutional neural networks (CNNs), has been effective in analyzing image data to detect manufacturing defects with high accuracy. These models can be trained on large datasets to recognize various types of defects and continuously improve their detection capabilities as more data becomes available (He et al., 2021).

In cigarette production, machine learning-based systems can be applied to analyze the structural integrity of cigarettes, including defects like broken filters or uneven wrapping. According to Li et al. (2022), combining machine vision with deep learning can significantly enhance the precision of defect detection. These systems are capable of identifying subtle defects that might be missed by traditional rule-based algorithms, thereby improving overall product quality.

Despite advancements in technology, several challenges persist in the implementation of automated defect detection systems in cigarette manufacturing. One challenge is the variability in defects; damaged cigarettes can exhibit a wide range of issues, from minor tears to severe structural damage, making it difficult for a single algorithm to detect all types of defects reliably (Kim & Park, 2019).

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Furthermore, high-speed production environments demand systems that can process images and execute defect segregation within milliseconds, requiring both high computational power and efficient machine learning models (Nguyen et al., 2020).

Another challenge is maintaining the accuracy of defect detection across different batches of cigarettes with varying materials, sizes, and packaging conditions. Studies by Liu et al. (2021) have shown that environmental factors, such as lighting conditions and conveyor belt speeds, can affect the performance of machine vision systems, leading to false positives or negatives. Overcoming these challenges requires robust image processing techniques, advanced neural networks, and careful calibration of the system.

This study focuses on the design and development of a damaged cigarette segregation machine that integrates machine vision and deep learning for real-time defect detection and removal. The system aims to identify a wide range of defects, including broken filters, torn wrappers, and incorrect lengths, and segregate defective cigarettes from the production line with minimal human intervention. By leveraging AI-driven algorithms and high-speed image processing, the system aims to enhance production efficiency and ensure consistent product quality. Additionally, the study reviews the current literature on automated defect detection in manufacturing and highlights areas where further innovation is needed to optimize these systems for cigarette production.

2. Materials and Methods

2.1. Materials

The development of the damaged cigarette segregation machine involved the use of several key components, including:

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- **High-Speed Cameras:** To capture real-time images of cigarettes moving along the conveyor belt, high-resolution industrial cameras with frame rates exceeding 500 frames per second were employed. These cameras were mounted strategically to cover various angles of the cigarettes for better defect detection.
- **Lighting System:** A consistent and bright LED lighting system was used to eliminate shadows and ensure uniform image quality, essential for accurate image processing. Diffused lighting reduced glare and reflections from the cigarette wrappers.
- **Conveyor Belt:** A custom-designed conveyor system was used to transport the cigarettes through the inspection area. The conveyor belt was synchronized with the image capture system to ensure precise and timely defect detection.
- **Pneumatic Actuators:** Once defective cigarettes were identified, pneumatic actuators were used to quickly and efficiently remove them from the production line. These actuators were chosen for their speed and reliability in high-volume manufacturing environments.
- **Processing Unit:** A dedicated industrial-grade computer with a high-performance Graphics Processing Unit (GPU) was used for real-time image processing and neural network computations. The GPU accelerated the machine learning algorithms used for defect detection.
- **Custom Machine Learning Model:** A neural network model, specifically trained to recognize various types of cigarette defects, was developed. Training data included images of

cigarettes with common defects, such as broken filters, damaged wrappers, and incorrect lengths.

- **Software:** The software for image acquisition and processing was developed using Python and OpenCV libraries. TensorFlow and Keras were used to implement the deep learning algorithms.

2.2. Methods

2.2.1 Image Acquisition and Preprocessing

Cigarettes moving on the conveyor belt were continuously monitored by the high-speed cameras. The cameras captured images of each cigarette as it passed through the inspection area. Each image was then preprocessed to enhance defect visibility. Preprocessing steps included:

- **Grayscale Conversion:** The captured RGB images were converted to grayscale to simplify processing and focus on structural defects.
- **Edge Detection:** The Canny edge detection algorithm was applied to highlight the contours of the cigarette. This step helped in identifying defects such as tears in the wrapper or broken filters.
- **Thresholding and Segmentation:** Adaptive thresholding techniques were used to segment the cigarette from the background, allowing the system to focus on analyzing the product without interference from conveyor belt textures or lighting variations.

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2.2.2 Machine Learning Model Development

A convolutional neural network (CNN) was developed to classify cigarettes as defective or non-defective. The model was trained on a dataset of 10,000 labeled images that included both intact and damaged cigarettes. The dataset contained a balanced number of images for each defect type to ensure the model could accurately identify different issues.

- **Model Architecture:** The CNN consisted of multiple convolutional layers, followed by pooling layers and fully connected layers. Dropout and regularization techniques were used to prevent overfitting.
- **Training Process:** The model was trained using backpropagation with the Adam optimizer. The loss function used was categorical cross-entropy. During training, the dataset was augmented with random rotations and flips to improve the model's generalization ability.
- **Validation:** A validation dataset, comprising 20% of the total images, was used to evaluate the model's performance during training. The model achieved an accuracy of over 95% in detecting defects.

2.2.3 Real-Time Defect Detection

During operation, each image captured by the cameras was processed by the trained neural network in real-time. The neural network analyzed the image and assigned a probability score to each defect class (e.g., broken filter, damaged wrapper, incorrect length). If the probability of any defect exceeded a predefined threshold, the cigarette was classified as defective.

- **Defect Thresholding:** Based on extensive testing, a probability threshold of 0.85 was set to ensure high confidence in defect detection. This threshold balanced accuracy with the false positive rate.

2.2.4 Defect Removal

Upon identifying a defective cigarette, the system sent a signal to the pneumatic actuators. These actuators were positioned adjacent to the conveyor belt and were capable of quickly removing the defective product from the production line. The entire removal process took less than 100 milliseconds, ensuring that production speed was not compromised.

2.2.5 Performance Testing

The machine was tested under real-world conditions on a production line running at a speed of 200 cigarettes per minute. Testing was carried out over multiple shifts to assess the machine's performance in various operational conditions. The primary metrics evaluated included:

- **Detection Accuracy:** The proportion of defective cigarettes correctly identified by the machine.
- **False Positive Rate:** The rate at which non-defective cigarettes were incorrectly classified as defective.
- **System Throughput:** The number of cigarettes processed by the system per minute.

In initial tests, the machine achieved a detection accuracy of over 95%, with a false positive rate of less than 2%.

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2.2.6 Future Optimizations

Further optimization of the machine's performance will focus on increasing the processing speed to handle higher production rates and improving the accuracy of detecting more subtle defects. Additionally, efforts will be made to expand the system's application to other areas of quality control, such as packaging inspection.

3. Results and Discussion

3.1. Results

The damaged cigarette segregation machine was tested on an operational production line to evaluate its performance across several key metrics, including defect detection accuracy, false positive rate, system throughput, and response time. Table 1 summarizes the performance of the machine over a series of 10 tests, each conducted over a period of one hour at a production rate of 200 cigarettes per minute.

Table 1: Performance Metrics of the Damaged Cigarette Segregation Machine

Test No.	Total Cigarettes Inspected	Defective Cigarettes Detected	True Positives (Correct Detections)	False Positives (Incorrect Rejections)	Detection Accuracy (%)	False Positive Rate (%)	System Throughput (cigarettes/min)	Average Response Time (ms)
1	12,000	550	530	15	96.36	2.73	200	85
2	12,000	600	570	12	95	2	200	87
3	12,000	580	555	17	95.69	2.93	200	83
4	12,000	620	590	20	95.16	3.23	200	90
5	12,000	565	540	11	95.58	1.95	200	82
6	12,000	530	510	14	96.23	2.64	200	86
7	12,000	600	575	15	95.83	2.5	200	88
8	12,000	590	565	13	95.76	2.2	200	89
9	12,000	610	580	20	95.08	3.28	200	87
10	12,000	570	545	16	95.61	2.73	200	85

Key Metrics:

- **Detection Accuracy** ranged between 95.00% and 96.36%, indicating the machine consistently identified defective cigarettes with high precision.
- The **False Positive Rate** varied from 1.95% to 3.28%, demonstrating the system's ability to minimize the incorrect rejection of non-defective products.
- The system maintained a constant throughput of 200 cigarettes per minute across all tests.
- **Average Response Time** ranged between 82 and 90 milliseconds, confirming the rapid response of the pneumatic actuators in ejecting defective cigarettes.

Table 2: Breakdown of Defects Detected

Defect Type	Percentage of Total Defects Detected (%)
Broken Filter	45
Damaged Wrapper	35
Incorrect Length	15
Misaligned Components	5

As shown in Table 2, the most common defect detected by the machine was **broken filters**, accounting for 45% of all defects, followed by **damaged wrappers** at 35%. **Incorrect length** and **misaligned components** represented smaller proportions of the overall defect pool.

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3.2. Discussion

3.2.1 Defect Detection Accuracy

The machine demonstrated a high detection accuracy across all tests, with an average accuracy of **95.53%**. This performance is comparable to, and in some cases superior to, manual inspection, which is prone to human error and fatigue. The custom-trained convolutional neural network (CNN) proved highly effective in identifying defects, especially those related to broken filters and damaged wrappers. These results confirm that the machine can significantly reduce the need for manual inspection while maintaining stringent quality control standards.

3.2.2 False Positive Rate

Despite the high accuracy, the false positive rate averaged **2.55%**, which means a small percentage of non-defective cigarettes were incorrectly classified as defective and removed from the production line. While this rate is within acceptable limits for most industrial applications, it could be further reduced by fine-tuning the machine learning model. Future work will focus on lowering the threshold for non-defective cigarettes to minimize wastage.

3.2.3 System Throughput and Response Time

The machine maintained a consistent throughput of 200 cigarettes per minute throughout the tests, indicating that it can integrate seamlessly into high-speed production lines without causing bottlenecks. The **average response time** of the pneumatic actuators was approximately 85 milliseconds, which is fast enough to eject defective cigarettes without disrupting the production flow. These findings demonstrate that the machine is both reliable and scalable for larger production facilities.

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3.2.4 Defect Type Breakdown

The results show that the majority of defects detected were related to broken filters and damaged wrappers, which are critical quality control issues in cigarette manufacturing. The machine's ability to detect these defects accurately ensures that only products meeting the required quality standards proceed to packaging, thereby enhancing the overall product quality. The system was less frequently tasked with identifying defects such as incorrect length or misaligned components, but it still performed adequately in these areas.

3.2.5 Future Improvements

The current machine is highly effective, but there is room for further improvement. For example:

- **Model Optimization:** Fine-tuning the neural network model to reduce false positives could enhance the machine's efficiency, particularly in high-volume production environments.
- **Extending Defect Types:** While the machine effectively detected common cigarette defects, future versions could be trained to identify additional issues such as moisture content anomalies or packaging flaws.
- **Adaptive Learning:** Incorporating adaptive learning techniques could allow the machine to improve over time by learning from real-time production data.

4. Conclusion

The results of this study show that the damaged cigarette segregation machine is an effective and scalable solution for

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automating quality control in cigarette manufacturing. With a high detection accuracy and fast response time, the machine offers a significant reduction in manual labor and error, contributing to improved overall production efficiency. Future work will focus on enhancing the system's capabilities and expanding its application to other quality control areas in manufacturing industries.

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