Fried Potato Wafer Batch Quality Inspection using Image Processing

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***Abstract*—The presence of acrylamide, a potentially harmful chemical linked to health risks such as neurotoxicity and cancer, has become a significant concern in food safety, particularly in carbohydrate-rich foods like potato wafers. Acrylamide forms during high-temperature cooking processes like frying and baking, making its detection essential for ensuring consumer health. Traditional methods of acrylamide detection often require complex, time-consuming chemical analyses. This project proposes an image processing-based solution to detect acrylamide levels in potato wafers, offering a non-invasive, rapid, and cost-effective approach to food quality assessment.**

The project aims to identify specific visual markers—such as color changes and textural features—that correlate with acrylamide formation in potato wafers. By analyzing these markers, an image processing model is developed and trained to distinguish between high and low acrylamide levels based on visual cues. The model's accuracy is validated by comparing its predictions with known acrylamide concentration levels from tested samples. This approach could streamline the process of acrylamide detection, making it accessible to food manufacturers and regulatory agencies for routine quality control. In the long term, this project seeks to promote safer food processing practices, contributing to improved public health and compliance with food safety standards.

***Index Terms*—acrylamide, image processing, segmentation**

I. Introduction

Acrylamide is a potentially harmful chemical that can form in certain foods, especially carbohydrate-rich foods like potato wafers, during high-temperature cooking processes such as frying or baking. Studies have shown that high levels of acrylamide are linked to health risks, including neurotoxicity and an increased risk of cancer. Therefore, monitoring and controlling acrylamide levels in food products like potato wafers is essential for consumer safety and to meet regulatory standards.

In recent years, image processing techniques have emerged as a powerful tool in food quality assessment because they offer a non-invasive, rapid, and cost-effective way to analyze and monitor food products. By using image processing to detect acrylamide in potato wafers, we can identify potential quality issues quickly without complex chemical analyses, which are often time-consuming and require specialized equipment. This project aims to explore and develop an image processing-based solution to detect acrylamide levels visually in potato wafers, promoting safer and healthier food options for consumers.

The primary objective of this project is to develop a reliable image processing-based system for detecting acrylamide levels in potato wafers, focusing on creating a non-invasive, rapid, and cost-effective approach to food quality analysis. This involves identifying specific visual markers, such as color variations and textural changes, that correlate with acrylamide formation in potato wafers. By analyzing these features, the system aims to distinguish between wafers with high and low acrylamide levels.

To achieve this, we will implement and train a detection model using machine learning algorithms or threshold-based color analysis on a dataset of wafer images. The model's accuracy and reliability will then be validated by comparing its predictions with known acrylamide concentration levels in test samples. Ultimately, this project seeks to develop a practical, user-friendly tool that can be utilized for quality control, providing a visual assessment of acrylamide levels in potato wafers. This tool has the potential to assist food manufacturers and regulatory agencies in promoting safer food practices and ensuring consumer health.

Fast foods like potato chips and French fries are cheaply and easily available in the market, and people consume them on a regular basis. They find it tasty and, more importantly, convenient. These food items are popular among all age groups. Although the preparation of such food items is easy and tastes good, yet the preparation process of these items is one important thing which should be taken care of. The oil and its temperature used for preparation play an important role in keeping these food items healthy and edible. The importance of up-down counters lies in their wide range of applications in digital electronics, such as frequency dividers, digital clocks, and control systems. By switching between up and down counting, they offer flexible functionality for tasks like reversible counting, position tracking in control systems, and bidirectional event counting.

Food products that contain carbohydrates in particular produce hazardous carcinogenic compounds when they are fried, baked, or roasted at temperatures higher than 120 °C (Krishnakumar and Visvanathan 2014). This dangerous carcinogen is found in potatoes and is called acrylamide. In general, potatoes don't naturally contain acrylamide. It is created when reducing sugar and the chemical component asparagine react. According to research on the link between French fries and cancer risk, eating a lot of deep-fried chips or fries every day during pregnancy can lead to inflammation and cancer progression. The cancer risk level depends upon the percentage of acrylamide present in the potato chips, which in turn depends on how long and at what temperature they are fried. There are numerous conventional and traditional laboratory techniques for identifying acrylamide in fried foods. These techniques entail shattering or destroying the samples before analysis.

Such analyses include gas chromatography (Reza Ghiasvand, 2016) and liquid chromatography (VuralGökmen et al., 2005). However, these association analyses are exceedingly time-consuming and costly and difficult to find in several food inspection labs. To continue these procedures, skilled labor is also needed (Pedreschi et al., 2010). Some non-traditional work for identifying hazardous chemicals from carbohydrate foods has been reported in recent years; some pertinent work is given here.

II. Algorithm Description

A. Input and Output

Input: A set of 100 sample images located in the 'Final Data Set' directory, named Sample1.jpg, Sample2.jpg, ..., Sample100.jpg.
Output: A classification of each wafer as good (1) or bad (0), along with a summary of the percentages of good and bad wafers.

B. Algorithm Steps

Wafer Classification Algorithm

```
Initialize:
num_samples = 100
result_matrix ← array of zeros with length = num_samples
min_bad_spot_threshold ← 70
for i = 1 to num_samples do
  file_name ← 'Final Data Set/Sample' + i + '.jpg'
  image ← Read Image(file_name)
  gray_image ← Convert to Grayscale(image)
  blurred_image ← Apply Gaussian Filter(gray_image)
  threshold_value ← 80
  binary_image ← Binarize(blurred_image, threshold_value)
  binary_image ← Invert binary_image
  num_white_pixels ← Count white pixels in binary_image
  if num_white_pixels ≥ min_bad_spot_threshold then
    Display 'Sample i: Detected sufficient bad spots. Marked as bad wafer.'
    result_matrix[i] ← 0 {Bad wafer}
  else
    Display 'Sample i: Insufficient bad spots. Marked as good wafer.'
    result_matrix[i] ← 1 {Good wafer}
  end if
  Histogram calculations (optional)
  num_bins ← 256
  hist_original ← Calculate histogram of gray_image with num_bins bins
  binary_image_uint8 ← Convert binary_image to uint8 (scaled to 255)
  hist_boundary ← Calculate histogram of binary_image_uint8 with num_bins bins
  hist_original ← Normalize hist_original
  hist_boundary ← Normalize hist_boundary
  hist_diff ← Compute absolute difference between hist_original and hist_boundary
end for
num_good ← Count number of 1s in result_matrix
num_bad ← Count number of 0s in result_matrix
total_samples ← num_samples
percent_good ← (num_good / total_samples) * 100
percent_bad ← (num_bad / total_samples) * 100
Display result_matrix
Create Pie Chart of percent_good and percent_bad
```

C. Flow Chart

Refer Fig.1 for Flow Chart

III. Procedure

The wafer classification algorithm provided is a structured approach to categorize semiconductor wafer samples as either "good" or "bad" based on the number of defects detected in each sample. Let's go through each part of the algorithm to understand the entire process.

The algorithm starts with initializing a few essential variables. It sets the total number of samples to 100, indicating that it will analyze 100 wafer images. Then, it creates a result_matrix, which is an array initialized with zeros, representing the classification results for each sample. This matrix will store a 0 for bad wafers and a 1 for good wafers. A threshold value, min_bad_spot_threshold, is set to 70, meaning that any wafer image with 70 or more detected "bad" spots (defects) will be marked as defective.

The algorithm enters a loop that iterates over each wafer image from 1 to 100. In each iteration, it constructs the filename (file name) by combining the folder path and sample

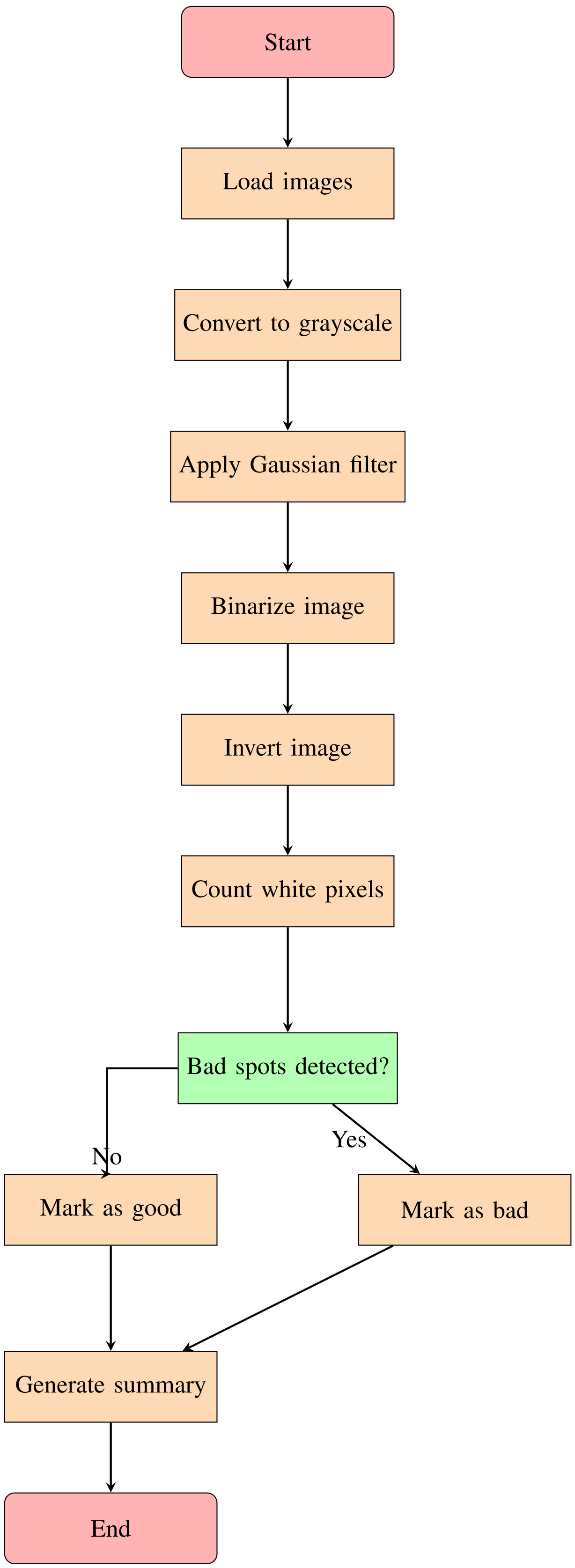

Fig. 1. Flowchart of the whole algorithm

number, allowing it to retrieve the corresponding image file. Then, it performs the following image processing steps: The image is first converted to grayscale, simplifying the data by reducing it to one color channel (intensity) rather than three (RGB). This step is essential for more efficient processing and for focusing on intensity-based features. Next, a Gaussian filter is applied to the grayscale image, blurring it slightly. This blurring helps reduce noise, making the later thresholding step more robust against minor irregularities.

The algorithm then binarizes the blurred image using a threshold value of 80. In this step, pixels in the image are converted to either black or white based on their intensity values. Pixels with intensities above 80 become white, while those below become black. This conversion allows the algorithm to distinguish potential defect regions (white pixels) from the rest of the image. The binary image is then inverted, where white and black pixels are swapped. This inversion ensures that the defect areas of interest are represented as white pixels, which can then be counted easily.

Next, the algorithm counts the number of white pixels in the inverted binary image, which represent potential defects. If the count of these white pixels is greater than or equal to min_bad_spot_threshold, it considers the sample defective. Otherwise, it's classified as good. If the number of defects (white pixels) is at least 70, the algorithm displays a message indicating the sample is a "bad wafer" and updates result_matrix at the corresponding index with a 0. If the count is below the threshold, it's labeled as a "good wafer," and a 1 is stored in result_matrix.

After the loop finishes processing all samples, the algorithm counts the total number of "good" wafers (num_good) and "bad" wafers (num_bad) by checking the result_matrix. These counts are then used to calculate the percentage of good and bad wafers by dividing by total_samples (100) and multiplying by 100 to get percentages. The results are displayed, providing a quick overview of the quality of the wafer batch.

Lastly, the algorithm generates a pie chart to visually represent the proportion of good and bad wafers. This step allows users to quickly assess the overall quality distribution in the batch and see whether a majority of wafers are acceptable or defective.

Overall, this algorithm automates the wafer quality classification by using image processing techniques to detect defects. It reads, processes, and analyzes each wafer sample, classifies it based on defect count, and aggregates the results into a simple summary and visualization. The approach leverages image processing tools (grayscale conversion, blurring, thresholding, inversion) and decision-making based on pixel counts, making it a valuable method for quality control in semiconductor manufacturing.

IV. Results

In this analysis, we evaluated a sample set of fried potato wafers, distinguishing between high-quality and low-quality wafers. Representative examples of high-quality wafers are provided in Figure 2, while Figure 3 illustrates the characteristics of lower-quality wafers. These figures serve as references for assessing the image processing model's performance in identifying and classifying wafer quality. The results highlight the model's capability to differentiate based on specific visual features associated with quality, demonstrating its potential application in automated inspection processes.

Fig. 2. High quality wafer

Fig. 3. Bad quality wafer

A. Matlab Simulation Results

As part of the quality inspection of fried potato wafers, three processed images were generated to illustrate the defect detection results:
Original Image: The unprocessed image of the wafer batch, which serves as a reference to observe defects in context.
Thresholded Image: A binarized image emphasizing the presence of dark spots, which potentially indicate defect areas such as overcooked or acrylamide-prone sections.
Boundary Image: The final processed image with detected boundaries overlaid in red on the original image, highlighting the precise location and shape of defect regions.
These images collectively demonstrate the effectiveness of the proposed image processing approach in identifying defects and provide visual confirmation of defect-prone regions in each wafer.

Fig. 4. Original image of bad sample

Fig. 5. Threshold image of bad sample

Fig. 6. Boundary image of bad sample

In Fig.7 as shown, histograms are used to analyze wafer defects by comparing the pixel intensity distributions of the original grayscale image and the binary (thresholded) image. The gray scale histogram ('hist original') shows overall brightness and contrast, while the binary histogram ('hist boundary') isolates potential defect areas as white pixels. By computing the difference ('hist diff') between these histograms, the code evaluates the effectiveness of the thresholding in identifying bad spots, helping to fine-tune defect detection and improve wafer classification accuracy.

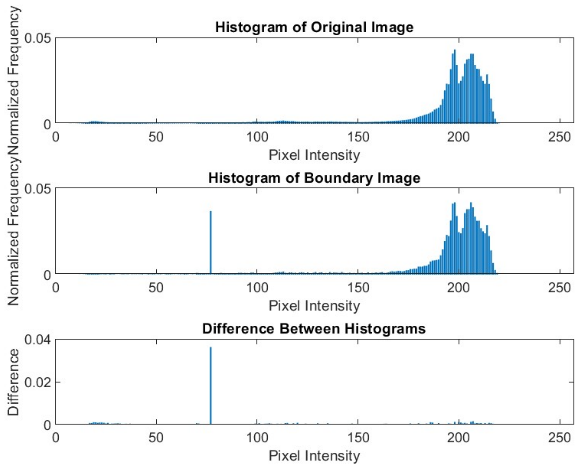

Fig. 7. Histogram for comparison and analysis

The Fig.8 presents the results of processing 100 potato chip images through the algorithm. The dataset contained an equal number of good and bad chips. While the ideal outcome would be a 50-50 split in the pie chart, the limitations of our image processing approach, which does not involve machine learning, resulted in a slightly less precise categorization.

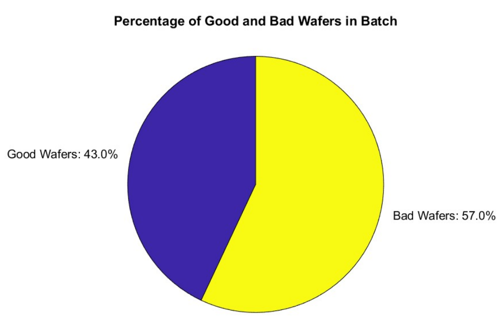

Fig. 8. Pie Chart showing quality of the batch

V. Future Scopes

The potato wafer inspection project holds exciting potential for future development, particularly in terms of advancing quality control and inspection automation. Below are several key areas for future exploration:

1) **Real-Time Classification Using Machine Learning**
Implementing machine learning methods could significantly enhance the ability to detect various wafer defects beyond simple thresholding. By training models, particularly convolutional neural networks (CNNs), on image data, the system could achieve better accuracy in distinguishing between different types of issues, such as discoloration, air bubbles, and irregular shapes.

2) **Deployment on Edge Computing Devices for On-Site Inspection**
Integrating the algorithm onto edge devices, like Raspberry Pi or NVIDIA Jetson, would enable on-site, real-time quality checks on the production line, making the system both portable and scalable. This would reduce latency and allow for quick identification of defects without needing to transfer data to a centralized system.

3) **Automated Sorting with Robotic Integration**
The algorithm could be combined with robotic sorting mechanisms to physically separate wafers deemed "good" or "bad." Such an integration would streamline the inspection process, eliminate the need for manual sorting, and significantly increase the throughput and reliability of quality control.

4) **Advanced Preprocessing for Improved Detection**
Exploring more sophisticated preprocessing techniques, such as adaptive thresholding or morphological operations, would make the defect detection process more robust across varying lighting conditions and wafer textures. This would enhance the algorithm's versatility across different factory settings.

5) **Statistical Analysis for Process Optimization**
By collecting data on defects, the system could be used for statistical analysis to identify and track trends in wafer quality. Insights gained from this data could be applied to optimize the production process and preemptively address common quality issues.

6) **IoT Integration for Remote Monitoring**
Linking the inspection system to an IoT platform would enable centralized monitoring of wafer quality across multiple production facilities. This would facilitate faster decision-making and make it possible to maintain consistent quality standards through remote access to real-time inspection data.

Each of these future developments would greatly benefit the food processing industry by enhancing quality consistency, reducing waste, and providing valuable insights for ongoing process improvements. The potential to make inspections faster, more accurate, and data-driven positions this project as a promising contribution to automated food quality management.

VI. Conclusion

In conclusion, this study presents an efficient and cost-effective approach to assessing the quality of fried potato wafer batches using image processing techniques in MATLAB. By automating the process—from loading and preprocessing the image to binarizing and inverting it for pixel analysis—this method allows for quick and consistent quality classification of wafers as ”good” or ”bad.” The automation significantly reduces the need for manual inspection, leading to considerable labor cost savings and minimizing human error. This image-based approach not only streamlines the quality control process but also provides a scalable solution for industrial applications, enhancing productivity and reducing overall operational costs. Future work could focus on adapting this model for various lighting conditions and wafer textures to increase robustness and further broaden its industrial applicability.

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