T.C.
MANİSA CELAL BAYAR UNIVERSITY
GRADUATE SCHOOL OF

MASTER’s THESIS
DEPARTMENT of COMPUTER ENGINEERING

# IMAGE PROCESSING APPLICATIONS IN FOOD INDUSTRY

Ali Burak CEYLAN

Supervisor
Assoc. Prof. Dr. Övünç ÖZTÜRK

MANİSA-2025

ALİ
BURAK
CEYLAN

IMAGE PROCESSING APPLICATIONS IN FOOD
INDUSTRY

2025

## COMMITMENT

I declare that this thesis was written in Manisa Celal Bayar University, Faculty of Engineering, Department of Computer Engineering in accordance with academic and ethical rules, and all the literature information used is included in the thesis with reference.

Signature
**ALİ BURAK CEYLAN**

# ÖZET

**Yüksek Lisans Tezi**

**Ali Burak CEYLAN**
**Manisa Celal Bayar Üniversitesi**
**Lisansüstü Eğitim Enstitüsü**
**Bilgisayar Mühendisliği Anabilim Dalı**

**Danışman: Doç. Dr Övünç ÖZTÜRK**

Gıda endüstrisinde geleneksel kalite kontrol yöntemlerinin çoğunlukla manuel olması; sonuçların değişkenliği, insan hatası ve sınırlı ölçeklenebilirlik gibi önemli zorluklara yol açmaktadır. Endüstri otomasyon ve dijitalleşmeye yöneldikçe, görüntü işleme teknolojilerinin kalite kontrol süreçlerini iyileştirme potansiyeli giderek daha belirgin hale gelmektedir. Bu çalışma, özellikle makine öğrenmesi algoritmaları içermeyen deterministik görüntü işleme tekniklerini uygulayarak gıda üretiminde kalite kontrol denetimlerini sadeleştirmeye odaklanmaktadır. Bu yaklaşımın cazibesi, basitliği, daha az hesaplama gereksinimi ve mevcut üretim sistemlerine kolay entegrasyonunda yatmaktadır.

Belirli görevler için tanımlı algoritmalar kullanan deterministik görüntü işleme, öngörülebilir ve tekrarlanabilir sonuçlar sunar. Bu tezde eşikleme (global ve uyarlamalı yöntemler dahil), kenar tespiti (Sobel ve Canny gibi operatörlerle) ve morfolojik işlemler gibi tekniklerle gıda ürünlerinde kusur, yabancı madde ve yapısal tutarsızlıkların tespiti ele alınmıştır. Bu tür yöntemlerin uygulanması, kalite kontrollerinde tutarlılık sağlar ve insan denetçilerine olan bağımlılığı önemli ölçüde azaltarak gözden kaçma riskini ve insan hatasını en aza indirir. Örneğin, eşikleme sayesinde nesneler arka plandan ayrıştırılabilir; bu da yüzeydeki anormalliklerin ve kirlenmelerin tespiti için kritik önemdedir. Kenar tespiti ise ürün şekillerini ve olası düzensizlikleri belirleyerek kalite değerlendirmelerini daha doğru hale getirir. Bu doğrultuda bir algoritma yazılmamıştır. Çekilen resimler üzerinden Azure özel görüntü işleme apisi ile raporlamalar sağlanmıştır.

Araştırma yöntemi olarak, gerçek zamanlı görüntü yakalama ve analiz için özel olarak geliştirilmiş bir Unity uygulamasıyla entegre edilmiş Epson BT-350 akıllı gözlükler kullanılmıştır. Operatörler, önceden belirlenmiş yüksek riskli bölgeleri denetlemiş ve bu alanlardan toplanan görüntüler kural tabanlı algoritmalarla işlenmiştir. Bu deterministik yöntemler, işlem hızının ve güvenilirliğin kritik olduğu gerçek zamanlı uygulamalarda etkili olmaları nedeniyle tercih edilmiştir. İlk denemeler, bu sistemin yüzey kusurlarını ve kirlenmeleri manuel denetimlere kıyasla %30'a varan hata oranı düşüşüyle doğru şekilde tespit edebildiğini göstermiştir. Bu iyileşme yalnızca önemli maliyet tasarruflarına işaret etmekle kalmaz, aynı zamanda deterministik görüntü işlemenin operasyonel verimliliği artırma potansiyelini de vurgular.

Bu araştırmanın temel bulgularından biri, karmaşık makine öğrenimi modellerine ihtiyaç duyulmadan rutin kalite kontrollerinde deterministik görüntü işleme yöntemlerinin uygulanabilirliğidir. Makine öğrenimi uyarlanabilir ve yüksek doğruluk sağlayan çözümler sunabilse de, genellikle geniş çaplı eğitim verisi, yüksek hesaplama gücü ve uzmanlık gerektirir. Buna karşılık, deterministik yöntemler daha erişilebilir, uygulanması ve sürdürülmesi daha kolaydır; bu da onları orta ve küçük ölçekli gıda üretim tesisleri için uygun hale getirir.

Çalışma ayrıca gıda üretim ortamlarında görüntü işlemenin karşılaştığı özel zorluklara dikkat çekmektedir. Aydınlatma değişkenliği, ürün hareketi ve ürün çeşitliliği gibi faktörler otomatik denetimlerin doğruluğunu etkileyebilir. Bu zorluklar, aydınlatma koşullarına uyum sağlayan yerel eşikleme gibi uyarlanabilir tekniklerle ele alınmış; böylece araştırmanın performansı daha dayanıklı hale getirilmiştir ve alandaki karmaşıklıklar kapsamlı şekilde anlaşılmıştır.

Sonuç olarak, bu tez, makine öğrenmesi içermeyen görüntü işleme tekniklerinin gıda endüstrisinde kalite kontrol açısından önemli faydalar sağlayabileceğini göstermektedir. Bu faydalar arasında kusur ve kirlenmelerin daha iyi tespiti, insan hatasının azaltılması ve operasyonel verimliliğin artırılması yer alır. Sistemin uyarlanabilirliği ve düşük hesaplama yükü, onu kalite kontrol süreçlerini modernize etmek isteyen üreticiler için pratik ve uygulanabilir bir çözüm haline getirir.

**Anahtar Kelimeler: Görüntü İşleme, Kalite Kontrol, Gıda endüstrisi, Akıllı Gözlük (Epson BT-350), Gerçek Zamanlı Denetim, Azure Vision.**

**2025, 74 sayfa**

## ABSTRACT

**M.Sc. Thesis**



**Ali Burak Ceylan**
**Manisa Celal Bayar University**
**Graduate School**
**Department of Computer Engineering**

**Supervisor: Assoc. Prof. Dr. Övünç ÖZTÜRK**



Traditional quality control methods in the food industry are mostly manual, leading to significant challenges such as variability of results, human error, and limited scalability. As the industry shifts towards automation and digitization, the potential of image processing as a solution for enhancing quality control processes becomes increasingly evident. This study is dedicated to applying deterministic image processing techniques, specifically those not involving machine learning algorithms, to streamline quality inspections in food production. The appeal of this approach lies in its simplicity, lower computational requirements, and ease of integration into existing production systems.

Deterministic image processing, which employs defined algorithms for specific tasks, offers predictable and repeatable results. This thesis delves into techniques such as thresholding (including global and adaptive methods), edge detection (using operators like Sobel and Canny), and morphological processing to identify defects, contaminants, and structural inconsistencies in food products. Applying such methods ensures consistent quality checks and significantly reduces the reliance on human inspectors, thereby minimizing oversight and human error. For instance, thresholding allows for the segmentation of objects from the background, making it an essential tool for detecting surface anomalies and contamination. Edge detection methods facilitate the identification of product shapes and possible irregularities, contributing to more accurate quality assessments. Accordingly, no custom algorithm was written. Instead, reports were generated using Azure’s Custom Vision API based on the captured images.

The research methodology involves using Epson BT-350 smart glasses integrated with a custom-built Unity application for real-time image capture and

analysis. Operators inspected pre-determined high-risk zones, collecting images processed using rule-based algorithms. These deterministic methods were chosen for their effectiveness in real-time applications, where processing speed and reliability are critical. The results from initial trials indicated that this system could accurately detect surface-level defects and contamination, with error rates reduced by up to 30% compared to manual inspections. This significant improvement not only highlights the potential for substantial cost savings but also underscores the enhanced operational efficiency that can be achieved through the use of deterministic image processing.

One of the key findings of this research is the feasibility of implementing deterministic image processing methods in routine quality control without the need for complex machine learning models. While machine learning can offer adaptive and highly accurate solutions, it often requires extensive training data, higher computational resources, and specialized model development and maintenance expertise. In contrast, deterministic methods are more accessible and easier to implement and maintain, making them suitable for mid-sized and smaller food production facilities.

This study also underscores the importance of understanding the specific challenges associated with image processing in a food production environment. Factors such as lighting variability, product movement, and diverse product types can affect the accuracy of automated inspections. By addressing these challenges and implementing adaptive techniques, such as local thresholding, which adjusts to changes in lighting conditions, the research ensures more robust performance, providing a comprehensive understanding of the complexities in the field.

In conclusion, this thesis contributes to the field by demonstrating that non-machine learning-based image processing techniques can substantially benefit quality control in the food industry. These benefits include improved detection of defects and contamination, reduced human error, and enhanced operational efficiency. The system's adaptability and low computational overhead make it a promising and, importantly, practical and feasible solution for food manufacturers looking to modernize their quality control processes without significant infrastructure changes.

**Keywords: Image Processing, Quality Control, Food Industry, Smart Glasses (Epson BT-350), Real-Time Inspection, Azure Vision.**

**2025, 74 pages**

**ACKNOWLEDGEMENTS**

Completing this thesis has been a journey filled with challenges and achievements, and it would not have been possible without the valuable support and encouragement of many individuals and institutions. I would like to express my deepest gratitude to my thesis advisor, Assoc. Prof. Dr. Övünç ÖZTÜRK, whose guidance played a pivotal role in shaping both the direction and the outcome of my research. His expertise, insights, and constructive feedback have been essential to my academic development. The open, collaborative, and intellectually stimulating environment he fostered enabled me to make significant progress throughout this process.

I am also sincerely grateful to all the faculty members of the Computer Engineering Department at Manisa Celal Bayar University for their constructive critiques and thought-provoking discussions during the development of this project.

My special thanks extend to the technical support team and laboratory staff for their assistance during the experimental phase. Their dedicated efforts ensured the smooth execution of the tests and the consistent collection of high-quality data—support that was truly invaluable.

I would also like to thank my colleagues and fellow researchers at Chefseasons A.Ş. Their shared enthusiasm and collaborative spirit created a supportive environment for exchanging ideas. The late-night discussions, joint problem-solving sessions, and moments of discovery played a significant role in refining my research approach and overcoming technical challenges. In addition, I thank Chefseasons A.Ş. for providing the financial and logistical support necessary for developing the Unity application used in this study and for supplying the software and hardware required for data collection and processing.

On a personal note, I am profoundly grateful to my family for their unwavering support, patience, and confidence in me. Their encouragement—especially during moments of doubt—gave me the strength to continue moving forward. I am equally thankful to my friends, whose motivation and ability to provide balance helped me maintain perspective throughout this journey.

Ali Burak CEYLAN

Manisa, 2025

## LIST OF ABBREVIATIONS

| | |
|---|---|
| **QC** | Quality Control |
| **FAO** | Food and Agriculture Organization |
| **WHO** | World Health Organization |
| **FDA** | U.S. Food and Drug Administration |
| **EFSA** | European Food Safety Authority |
| **AR** | Augmented Reality |
| **ML** | Machine Learning |
| **AI** | Artificial Intelligence |
| **X-ray** | X-ray (Imaging/Analysis) |
| **SMEs** | Small and Mid-Sized Enterprises |
| **RGB** | Red–Green–Blue |
| **LoG** | Laplacian of Gaussian |
| **QR** | Quick Response (code) |
| **GPU** | Graphics Processing Unit |
| **LED** | Light Emitting Diode |
| **OCR** | Optical Character Recognition |
| **HACCP** | Hazard Analysis and Critical Control Points |
| **IR** | Infrared |
| **FPS** | Frames Per Second |
| **RAM** | Random Access Memory |
| **API** | Application Programming Interface |
| **GET** | HTTP GET (method) |
| **POST** | HTTP POST (method) |
| **MSSQL** | Microsoft SQL Server |
| **HD** | High Definition |
| **C#** | C Sharp |
| **BT-350** | Epson BT-350 (smart glasses model) |

## LIST OF FIGURES

## LIST OF TABLES

CONTENTS

## 1. Introduction

Ensuring consistent, accurate, and efficient quality control remains one of the most critical challenges in the food industry. As production volumes increase and regulatory standards tighten, traditional manual inspection methods—long relied upon for identifying defects, contaminants, and inconsistencies—are increasingly proving inadequate. Manual inspections are prone to human error, fatigue, subjectivity, and scalability limitations, especially in high-speed production environments where rapid and objective decision-making is essential. At the same time, machine learning-based image processing systems, while powerful, often require extensive training datasets, high computational resources, and continuous model retraining, making them impractical or cost-prohibitive for many food producers, particularly small and mid-sized enterprises.

In response to these challenges, this thesis presents a structured, evidence-based investigation into the practical applications of deterministic image processing for food quality control. Deterministic approaches rely on predefined, mathematically grounded algorithms—such as thresholding, edge detection, and morphological processing—to evaluate visual characteristics in food products. These methods offer a compelling balance between accuracy, computational efficiency, and real-time performance. Unlike machine learning solutions, deterministic image processing does not require large and labeled datasets or specialized hardware, and yet it can deliver highly consistent, repeatable, and objective inspection outcomes.

The motivation behind this research is twofold. First, it aims to demonstrate that deterministic image processing provides a viable, cost-effective alternative to both manual inspections and computationally intensive machine learning models. Second, it seeks to establish a scalable automation framework that is accessible to food manufacturers of varying sizes, ensuring that industry-wide adoption of automated quality control does not remain limited to organizations with significant financial or technological resources.

A key contribution of this study is its emphasis on automation. Deterministic image processing minimizes reliance on human inspectors, reducing variability caused by subjective judgment and operator fatigue. By enabling real-time, rule-based inspection, deterministic methods support consistent quality standards across production batches and align with global trends toward smart manufacturing and Industry 4.0. Moreover, the integration of emerging technologies—such as augmented reality (AR) smart glasses—further enhances operator capabilities by providing visual overlays, instant feedback, and streamlined data capture without introducing system complexity.

Beyond automation, this research highlights the importance of consistency, objectivity, and regulatory compliance. Deterministic algorithms ensure that each product is evaluated using standardized criteria, thereby reducing the risk of inconsistent inspections and supporting compliance with stringent food safety regulations enforced by agencies such as the FDA and EFSA. With quantifiable, traceable, and verifiable inspection outputs, deterministic image processing strengthens quality assurance frameworks and helps minimize the likelihood of product recalls, safety issues, and legal liabilities.

The practical implications of this study extend to multiple stakeholder groups. Food manufacturers gain an affordable and scalable alternative to machine learning-based systems; quality assurance professionals benefit from standardized, automated inspection capabilities; compliance officers can rely on rule-based, measurable decision criteria; and technology developers acquire a robust foundation for building lightweight, deployable inspection tools. The research also positions deterministic image processing as a pathway toward future innovations, including hybrid inspection models that selectively integrate machine learning components, multispectral imaging for enhanced defect detection, and broader applications across other industrial domains.

Ultimately, the significance of this thesis lies in its demonstration that high-performance automated quality control does not require complex or resource-intensive AI frameworks. Instead, deterministic image processing offers a scientifically rigorous, technically practical, and economically accessible solution capable of transforming inspection processes across the food industry. By bridging the gap between manual inspections and advanced AI-driven systems, this work contributes to a more efficient, safer, and technologically progressive food production ecosystem.

The remainder of this thesis is organized into a series of chapters that systematically develop the theoretical background, technical methodology, and experimental findings of the study. Chapter 2 examines the importance of quality control in the food industry, outlining regulatory requirements and common operational challenges. Chapter 3 discusses the limitations of traditional manual inspection methods, establishing the motivation for automated solutions. Chapter 4 presents an overview of image processing principles and core techniques relevant to industrial inspection. Chapter 5 explores frequently used image processing methods—such as thresholding, edge detection, and morphological operations—and evaluates their applicability to food quality assessment. Chapter 6 identifies the primary technical challenges encountered when applying image processing in food production environments. Chapter 7 highlights practical applications of image processing in quality control, supported by literature and real-world examples. Chapter 8 compares deterministic and machine-learning-based inspection strategies, emphasizing their advantages and limitations. Chapter 9 details the materials, hardware, software environment, and workflow used in the experimental system developed for this study. Chapter 10 presents the experimental results, including performance evaluations, user feedback, and comparative analyses. Finally, the thesis concludes with a summary of key findings and recommendations for future research directions.

## 2. The Importance of Quality Control in the Food Industry

The food industry is pivotal in global economic stability and public health. High-quality food production is critical for consumer safety and compliance with stringent regulatory standards. Contamination, inconsistencies, and defects in food products can lead to severe consequences, including health hazards, financial losses, and reputational damage for manufacturers. Quality control (QC) is the foundation for food safety, compliance, and consumer trust, making it a fundamental aspect of food production.

### 2.1. The Necessity of Quality Control in Food Production

Food safety and quality control are essential to maintaining the integrity of the food supply chain, from raw material sourcing to final product distribution. Several regulatory bodies and international organizations, such as the Food and Agriculture Organization (FAO), the World Health Organization (WHO), the U.S. Food and Drug Administration (FDA), and the European Food Safety Authority (EFSA), impose strict guidelines to ensure that food products meet quality and safety standards. These regulations require food manufacturers to implement preventive measures, systematic inspections, and corrective actions to mitigate risks associated with contamination, mislabeling, and defects.

Beyond regulatory compliance, product quality also strongly influences consumer trust and brand reputation. Increasing awareness about foodborne illnesses, allergens, and sustainability has heightened consumer expectations for transparency, quality assurance, and traceability in recent years. Recurring food safety scandals, such as contamination with pathogens like Salmonella or Listeria monocytogenes, reinforce the need for robust quality control mechanisms. Consumers demand clear labeling, consistent product quality, and assurances that food has been handled under hygienic conditions.

Food manufacturers must implement reliable and advanced quality control measures beyond traditional manual inspections to meet these demands and incorporate technological innovations such as image-processing-based automated inspection systems.

### 2.2. Challenges in Ensuring Effective Quality Control

Implementing effective quality control in the food industry presents multiple challenges, as food products are diverse, perishable, and susceptible to contamination at various stages of production. Some of the key challenges include:

*Product Variability and Complexity:* Unlike manufactured goods with fixed dimensions and uniform characteristics, food products can vary significantly in size, shape, color, and texture. This variability complicates quality assessment and standardization.

*Environmental Factors and Production Conditions:* Food processing environments are dynamic and complex, with fluctuations in temperature, humidity, and handling conditions that can affect product quality. Ensuring consistency under varying production conditions requires adaptive quality control mechanisms.

*Detection of Contaminants and Defects:* Some defects and contaminants are not easily visible to the human eye. Microbial contamination, chemical residues, and foreign particles (such as plastic or metal fragments) often require advanced detection methods.

*Scalability and Efficiency:* Traditional inspection methods struggle to keep up with high-speed production lines. As food production scales up to meet market demand, quality control systems must evolve to maintain high inspection accuracy without slowing down operations.

These challenges underscore the need for automated quality control solutions, particularly image processing techniques, which offer precision, speed, and scalability in detecting defects, contamination, and inconsistencies.

### 2.3. Advancements in Image Processing for Quality Control

As the food industry embraces digital transformation, image processing has become a powerful tool for automated quality inspection. Image processing involves capturing, analyzing, and interpreting visual data to assess product quality, detect irregularities, and ensure compliance with safety standards. Advantages of image processing in food quality control includes:

*Enhanced Accuracy*: Image processing systems can analyze microscopic details in food products, detecting irregularities, contamination, and inconsistencies more precisely than human inspectors.

*Speed and Efficiency*: Automated image-based quality control systems can inspect thousands of products per hour, maintaining high accuracy without slowing production.

*Non-Destructive Testing*: Unlike some traditional quality control techniques that require physical contact or sampling, image processing allows for non-invasive inspections, preserving the integrity of food products.

*Consistency and Objectivity*: Unlike human inspectors, image processing systems apply predefined algorithms, ensuring consistent and objective evaluations across all production batches.

Several image processing techniques are widely applied in food quality assessment including:

*Thresholding*: Segment objects from the background and detect size variations, shape inconsistencies, and foreign objects.

*Edge Detection*: Methods such as Sobel and Canny filters identify shape irregularities and surface defects.

*Morphological Processing*: Helps refine image structures and remove noise, improving the accuracy of quality assessments.

These automated inspection techniques reduce reliance on manual labor, improve traceability, and ensure that only high-quality products reach consumers.

## 3. Limitations of Traditional Inspection Methods

Traditional quality control methods in the food industry have relied mainly on manual inspections conducted by trained personnel. While human inspection can be practical, particularly in identifying visible defects and contaminants, it is inherently limited by subjectivity, fatigue, and processing inefficiencies. In a highly competitive and regulated industry where precision and consistency are paramount, these limitations introduce significant risks to food safety and quality assurance.

### 3.1. Human Error and Fatigue in Manual Inspections

One of the most critical limitations of manual inspection is human error, which can influence fatigue, concentration lapses, and environmental conditions. Quality control personnel must perform repetitive, visually demanding tasks for extended periods, increasing the likelihood of overlooking defects, contamination, or inconsistencies. Studies have shown that error rates in manual inspections rise significantly when workers are exposed to long shifts without breaks, particularly in high-speed production environments.

Unlike automated systems that maintain consistent performance throughout production, human inspectors are susceptible to fluctuations in judgment and attention. As production lines become faster and more complex, the risk of human oversight increases, leading to potentially hazardous products reaching consumers.

Prolonged manual inspection inevitably degrades human performance, and its impact on decision-making is both well-documented and operationally significant. Extended exposure to fast-moving products reduces visual acuity, making subtle defects increasingly difficult to detect as the shift progresses. Cognitive fatigue further contributes to declining focus; numerous human-factors studies indicate that attention reliability drops sharply after the first hour of repetitive visual inspection, resulting in a measurable rise in oversight and missed anomalies. Moreover, human judgment is inherently variable—inspectors may unintentionally apply inconsistent evaluation criteria, causing fluctuations in pass/fail decisions and undermining overall quality assurance integrity.

These limitations clearly demonstrate why relying exclusively on manual inspection introduces unacceptable variability into modern production environments. Automated, rule-based systems eliminate fatigue-induced errors, enforce consistent evaluation standards, and maintain high-precision detection capabilities regardless of operational duration, thereby significantly enhancing the reliability and accuracy of quality assessments.

### 3.2. Inconsistency and Subjectivity in Inspections

Another major limitation of manual inspection is subjectivity, as different inspectors may interpret quality standards differently, leading to variability in defect detection. Factors such as lighting conditions, inspector experience, and cognitive biases can significantly influence inspection outcomes, resulting in inconsistent product quality across batches. Challenges associated with subjective quality assessments include:

*Inconsistent Classification of Defects*: Inspectors may categorize the same defect differently, leading to non-uniform acceptance criteria.

*Cognitive Biases*: Human inspectors may develop biases over time, particularly if they inspect similar products daily. This can lead to desensitization to minor defects or over-scrutiny of less significant irregularities.

*Difficulty Detecting Subtle or Microscopic Defects*: Manual inspections rely on naked-eye assessments, which are inadequate for identifying tiny contaminants, bacterial growth, or internal defects.

As global food safety standards tighten, relying on human-based inspections introduces significant risks to manufacturers, including product recalls, legal penalties, and damage to consumer trust. These factors make adopting automated image processing techniques that provide standardized, objective, and repeatable quality assessments imperative. The potential risks of human-based inspections, such as overlooking defects due to fatigue or subjectivity, further underscore the need for automated solutions.

### 3.3. The Inefficiency of Manual Inspections in Fast-Paced Production

With the food industry operating at increasingly high production speeds, manual inspections struggle to keep pace with demand, resulting in bottlenecks, higher costs, and potential quality compromises. Unlike automated quality control systems, which can analyze thousands of items per hour, manual inspection remains labor-intensive and slow, making it difficult to scale production while maintaining consistent quality. Key limitations of human-based ınspections in fast-paced production lines include:

*Inability to Inspect Every Product:* Human inspectors can only evaluate a fraction of the total output, increasing the risk of defective products bypassing quality control.

*Time-Intensive Decision-Making*: Unlike automated systems, which make instantaneous pass/fail decisions, human inspectors require several seconds per product, slowing down the overall inspection process.

*Increased Labor Costs*: High-speed production lines require multiple inspectors to keep up with demand, leading to higher operational costs without a proportional increase in accuracy.

This comparison highlights the apparent disadvantages of manual inspections and emphasizes the numerous benefits of automated image processing for modern food production. These benefits include higher accuracy, faster throughput, and cost-effective scalability, making it a necessary upgrade for food manufacturers.

### 3.4. The Need for More Reliable and Consistent Quality Control Approaches

The limitations of manual inspections in the food industry present significant challenges for manufacturers trying to maintain high-quality standards while ensuring efficiency. These shortcomings—human error, subjectivity, slow processing, and scalability issues—increase the likelihood of defective or unsafe products reaching consumers. The main takeaways are as follows:

- Human inspections are unreliable due to fatigue, variability, and subjectivity.
- Manual quality control is too slow to keep up with high-speed production lines.
- Automated image processing is a necessary upgrade for food manufacturers seeking higher accuracy, faster throughput, and cost-effective scalability.
- With the growing demand for standardized, error-free, and scalable quality control solutions, the transition to automated inspection systems—particularly those utilizing image processing techniques—is essential for the future of food quality assurance.

In the next section, this thesis will explore how image processing has emerged as a transformative solution in addressing these limitations, providing a more reliable and objective approach to food quality control.

## 4. Overview of Image Processing

Image processing is a broad and interdisciplinary field that involves the acquisition, enhancement, analysis, and interpretation of digital images to extract meaningful information. It plays a crucial role in automating visual inspection tasks, enabling industries to achieve higher accuracy, efficiency, and reliability in their processes [1].

Image processing has become an essential tool for quality control and defect detection in the food industry. It offers a noninvasive, real-time, and automated approach to ensuring product consistency and safety. By leveraging image processing techniques, manufacturers can eliminate subjectivity, reduce the limitations of human inspection, and increase scalability in food production lines. Image processing delivers several critical benefits for industrial applications, including:

- *Non-Invasive Inspection*: Image processing allows for quality assessment without physical contact, preserving the integrity of food products.
- *Automation and Consistency*: Image processing provides repeatable and objective evaluations, unlike manual inspections.
- *Real-Time Processing*: Advanced computer vision algorithms enable instant defect detection and sorting of defective products.
- *Scalability*: Image-processing techniques can be integrated into high-speed production lines, ensuring continuous quality monitoring.

The increasing reliance on artificial intelligence (AI) and machine vision systems has expanded the scope of image processing, making it a cornerstone of modern industrial automation. However, this study focuses on deterministic image processing methods, which offer computational efficiency and reliability without the complexity of machine learning models.

### 4.1. Historical Context and Evolution of Image Processing

The field of image processing has evolved significantly over the past few decades. Early image processing applications were primarily used in medical imaging and satellite image analysis, where visual data was enhanced to improve interpretation and decision-making. With advancements in digital computing, image processing techniques were refined and expanded into industrial applications, including manufacturing, automotive safety, medical diagnostics, and food quality control. Milestones in the development of image processing can be outlined as follows:

1960s-1970s:

- Development of basic image enhancement techniques, such as contrast stretching and histogram equalization.
- Introduction of edge detection and segmentation algorithms for feature extraction.

1980s-1990s:

- Advancement of morphological operations and real-time image analysis.
- Early adoption of computer vision in quality control systems, particularly in manufacturing and food inspection [2].

2000s-Present:

- Emergence of high-resolution digital cameras and hyperspectral imaging.
- Integration of AI-driven image processing for automated defect detection.
- Miniaturization of embedded vision systems for real-time industrial automation [1].

The rapid evolution of hardware capabilities, image processing algorithms, and machine learning techniques has led to widespread adoption in automated industrial inspection systems, revolutionizing quality control in food production.

### 4.2. Fundamental Principles of Image Processing

At its core, image processing consists of several fundamental techniques that enable extracting helpful information from digital images. These techniques form the basis for automated quality inspection in the food industry.

*Image Acquisition:* The first step in image processing involves capturing digital images using various sensors, including cameras, infrared scanners, and hyperspectral imaging devices. The choice of acquisition method depends on the nature of the inspection task, such as:

- RGB cameras for color-based defect detection (e.g., ripeness assessment of fruits).
- Infrared cameras for moisture detection in food processing.
- X-ray imaging for detecting foreign objects inside packaged foods [2].

*Preprocessing and Enhancement:* Raw images often contain noise, uneven lighting, or distortions that must be corrected before further analysis. Standard preprocessing techniques include:

- *Noise Reduction:* Filters such as Gaussian smoothing remove unwanted artifacts.
- *Histogram Equalization:* Enhances image contrast to improve feature visibility.
- *Color Normalization:* Adjusts brightness and hue inconsistencies for better defect detection.

*Feature Extraction and Segmentation:* Feature extraction focuses on identifying relevant information within an image, while segmentation divides the image into meaningful regions for analysis. Key techniques include:

- *Thresholding (Otsu's Method):* Differentiates objects from the background based on intensity values.
- *Edge Detection (Sobel, Canny Operators):* This technique identifies the boundaries of objects to detect defects such as cracks or irregularities.
- *Morphological Processing:* Enhances structures within an image by removing noise, filling gaps, or refining object contours [1].

Object Recognition and Classification: Once the features are extracted, object recognition algorithms classify food items based on predefined criteria. Deterministic methods use rule-based classification, such as:

- *Size Filtering:* Ensuring that only uniform-sized products pass quality control.
- *Color-Based Sorting:* Identifying products that meet specific color thresholds.
- *Shape Matching:* Detecting irregularities in packaging or food structure.

These techniques provide a robust, fast, and computationally efficient means of automated quality inspection, making them ideal for real-time industrial applications.

### 4.3. Levels of Image Processing

Image processing consists of multiple hierarchical stages, each performing specific operations to extract, enhance, and interpret visual information. These stages range from basic pixel-level adjustments to advanced image analysis techniques, allowing for automated quality control system decision-making. The categorization of image processing into three primary levels—low-level, intermediate-level, and high-level processing—provides a structured approach to handling image-based data for industrial applications, including food quality inspection [3].

*Low-Level Processing:* Low-level image processing constitutes the foundational stage of an image-based inspection system, focusing on image acquisition and pre-processing. Its main purpose is to produce clear, distortion-free images suitable for subsequent analysis by enhancing image quality, reducing noise, correcting distortions, and normalizing intensity levels.

Key techniques include image acquisition—using sensors such as RGB cameras, infrared systems, X-ray scanners, or hyperspectral devices—while ensuring proper illumination, resolution, and focus. Noise reduction methods such as Gaussian filtering and median filtering help eliminate pixel-level variations caused by sensor errors or inconsistent lighting. Geometric corrections address distortions arising from lens aberrations or perspective issues through techniques like affine transformations and homography adjustments. Contrast and intensity normalization methods, including histogram equalization and adaptive contrast stretching, improve feature visibility and ensure consistent image brightness.

In food quality control, low-level processing plays a crucial role by ensuring that images used for defect detection and feature extraction are clear and standardized. It supports color consistency for tasks such as ripeness assessment and contamination detection [3] and reduces false positives and negatives in later segmentation and classification stages.

*Intermediate-Level Processing:* Intermediate-level processing comprises advanced operations designed to identify structures, objects, and regions of interest within an image, enabling the division of an image into meaningful components for further analysis. This stage relies heavily on segmentation techniques such as thresholding (e.g., Otsu's method), edge-based segmentation using Sobel and Canny operators to detect boundaries, and region-growing methods [2][4] that group similar pixels into coherent areas. Once segmented, objects are represented and described mathematically through feature extraction methods, including histogram-based descriptors for analyzing color intensity, Fourier descriptors for shape analysis, and Haralick texture features for identifying surface patterns on food products. Morphological processing further refines these segmented regions by removing noise, filling gaps, and strengthening object boundaries through operations such as dilation, erosion, opening, and closing.

In the context of food quality inspection, intermediate-level processing plays a critical role in distinguishing defective items from acceptable ones by highlighting irregularities in shape. It also supports real-time monitoring of product consistency by detecting variations in size, color, and texture, while improving computational efficiency by excluding irrelevant regions from analysis, thereby enabling faster and more accurate defect classification.

*High-level processing:* High-level processing is the most advanced stage of image analysis, focused on interpreting and classifying segmented objects to support automated decision-making and defect recognition. At this level, image-processing systems assess object features to detect defects, measure quality parameters, and execute real-time pass/fail decisions in industrial environments. Key techniques include object recognition and classification, where labels are assigned based on characteristics such as shape, color, texture, and size. Rule-based classifiers—such as feature matching, decision trees, statistical models, and geometric matching [2][4][5]—compare extracted features against predefined templates or quality thresholds. Defect detection and pattern recognition methods identify anomalies, contamination, and structural defects using tools like blob analysis and template matching [6][7][8] to evaluate products relative to ideal models. High-level processing also facilitates automated sorting and decision-making by categorizing items into pass, rework, or reject classes, enabling mechanical or robotic handling systems, and providing real-time feedback to optimize quality control processes [9].

In the food industry, high-level processing supports applications such as detecting foreign objects like glass, plastic, or metal fragments; classifying defects to distinguish minor issues from critical failures; and performing automated grading and sorting of products based on predefined quality standards.

Although many modern high-level image processing systems rely on machine learning approaches—such as neural networks—to improve recognition accuracy, this study focuses on deterministic methods for several important reasons. Deterministic approaches require significantly less computational power, provide predictable and rule-based decision-making [4][5], and do not depend on large training datasets, making them particularly suitable for small and medium-sized food manufacturers [9].

Image processing in food quality control progresses through three structured levels: low-level processing for image acquisition and enhancement, intermediate-level processing for segmentation and feature extraction, and high-level processing for object classification and final decision-making. Each stage contributes to achieving accurate, consistent, and reliable inspection outcomes.

This study places particular emphasis on deterministic techniques within the intermediate and high-level stages to enable real-time, cost-effective quality control without the added complexity of machine learning algorithms [2][3]. By applying these methods, food manufacturers can improve defect detection, maintain compliance with food safety standards, and enhance production efficiency.

### 4.4. Principles of Image Processing in Quality Control

The primary function of image processing in food inspection is to automate the detection of product attributes, irregularities, and potential contaminants. This is accomplished through well-defined image acquisition, enhancement, and analysis techniques, allowing precise and repeatable quality assessments. Key steps in Image-Processing-Based Quality Control can be listed as follows:

*Image Acquisition:* High-resolution cameras and optical sensors capture images of food products in real time. These images may be obtained using visible light, infrared, or hyperspectral imaging techniques, depending on the inspection requirements.

*Preprocessing and Enhancement:* The captured images undergo contrast enhancement, noise reduction, and normalization to improve clarity and highlight defects or contaminants.

*Feature Extraction:* Critical product attributes such as color, texture, shape, and size are extracted to evaluate compliance with quality standards.

*Defect Detection and Classification:* Advanced image analysis techniques identify surface irregularities, contamination, or size variations, allowing defective products to be flagged for removal.

*Decision-Making and Sorting:* Based on the analysis, automated sorting systems can separate defective items from acceptable ones, reducing human intervention and ensuring consistent quality control.

By leveraging these systematic image-processing steps, food manufacturers can enhance quality inspections' speed, accuracy, and reliability while minimizing waste and recall risks.

### 4.5. Future Trends in Image Processing for Quality Control

As technology advances, image processing in food quality control evolves with more sophisticated algorithms and hardware innovations. Some of the key future trends include:

*AI-Enhanced Image Processing:* Integration of machine learning models to improve pattern recognition and anomaly detection.

*Multi-Spectral and Hyperspectral Imaging:* Development of high-resolution, multi-wavelength imaging systems for enhanced contaminant detection.

*Integration with Robotics:* Automated sorting and removal of defective products using robotic vision systems.

*Edge Computing for Real-Time Processing:* Implementation of edge AI processors for instant decision-making on production lines.

These innovations will enhance image-based food quality control systems' accuracy, efficiency, and intelligence, making food safety measures more robust and reliable.

## 5. Common Techniques in Image Processing for Quality Control

The application of image processing in quality control relies on various computational techniques that enhance image clarity, extract critical features, and enable automated decision-making. Each method serves a distinct role in ensuring accurate defect detection, object classification, and process optimization within industrial settings. The food industry, in particular, benefits from real-time image analysis, enabling manufacturers to identify defects, contaminants, and inconsistencies at an early stage [1].

This section explores three fundamental image-processing techniques widely used in food quality inspection systems: thresholding, edge detection, and morphological operations.

### 5.1. Thresholding

Thresholding is one of the simplest yet most effective image-processing techniques for image segmentation. It differentiates objects from the background based on pixel intensity levels. By applying a threshold value, pixels are classified into foreground (object) or background categories.

Global thresholding applies a single, fixed intensity threshold across the entire image, classifying pixels above the threshold as objects and those below it as background. While this method is straightforward, it may be limited in environments with uneven lighting. Otsu's method, an adaptive global thresholding technique, automatically determines the optimal threshold by minimizing intra-class variance. It is particularly effective when the image histogram exhibits a bimodal distribution, such as in quality control scenarios distinguishing defective from non-defective food products [10]. In contrast, adaptive thresholding computes threshold values locally for different regions of the image, making it highly effective for handling variable illumination and non-uniform lighting conditions.

Thresholding techniques play an essential role in various food quality control applications, including defect detection in fruits and vegetables by distinguishing blemished areas from normal surfaces, identifying foreign contaminants that contrast with the surrounding food material, and analyzing moisture levels in baked goods through grayscale intensity variations. Owing to its simplicity, processing speed, and effectiveness in producing clear binary segmentations, thresholding remains one of the foundational methods used in industrial image processing for quality assessment.

### 5.2. Edge Detection

Edge detection is a technique used to identify object boundaries and discontinuities in an image. It plays a crucial role in shape analysis, defect localization, and structural verification in quality control systems [1].

Common edge detection techniques play a critical role in analyzing the geometric and structural properties of food products. The Sobel operator uses discrete differentiation filters to compute horizontal and vertical intensity gradients, effectively highlighting regions with significant intensity changes and helping define product shapes. The Canny edge detector applies a multi-stage process—Gaussian smoothing for noise reduction, gradient calculation, non-maximum suppression, and hysteresis thresholding—to detect fine, well-connected edges while minimizing false detections, making it highly suitable for detailed quality control tasks. The Laplacian of Gaussian method identifies second-order intensity variations, enabling the detection of subtle surface imperfections. In food quality control, these edge detection methods are used to identify cracks in eggshells and baked goods, detect bruises and shape irregularities in fruits and vegetables, and verify packaging shape and seal integrity. Collectively, edge detection provides a consistent and structured approach to shape analysis, ensuring products comply with predefined geometric and structural standards.

### 5.3. Morphological Operations

Morphological operations, thorough and precise, are shape-based transformations applied to binary or grayscale images. These operations refine segmented regions by removing noise, filling gaps, and enhancing object structures, ensuring the highest level of accuracy in food quality control.

Morphological techniques play a vital role in refining segmented images and enhancing the accuracy of food quality assessments. Dilation expands object boundaries by adding pixels, making it useful for bridging small gaps within segmented regions. Erosion performs the opposite operation by removing pixels from object boundaries, effectively eliminating minor noise artifacts such as specks or irregularities that could interfere with analysis. Combining these operations produces more specialized techniques: opening, which applies erosion followed by dilation to remove small noise points while preserving the overall structure of objects, and closing, which uses dilation followed by erosion to fill small holes and gaps within objects, improving the completeness of segmented food items. In food quality control, morphological operations support more accurate defect detection by removing unwanted noise, improve segmentation precision for tasks such as seed counting and grain quality assessment, and assist in evaluating the structural integrity of food packaging. These techniques are essential for refining image features and ensuring reliable, high-quality inspection results.

### 5.4. Comparative Analysis of Image Processing Techniques

Each of the discussed techniques addresses specific challenges in food quality control. Table 5.1 highlights their comparative strengths and applications.

| **Technique** | **Key Strength** | **Common Application Area** |
|---|---|---|
| Thresholding | Fast and simple segmentation | Defect detection, contamination, moisture analysis |
| Edge Detection | Shape accuracy and structural analysis | Crack detection, bruises, packaging seal integrity |
| Morphological Operations | Noise removal and structure enhancement | Segmentation accuracy, structural quality, seed counting |

Table 5.1. Summary of Key Deterministic Image Processing Techniques and Their Applications.

These techniques are often combined in industrial food quality control to ensure high-precision inspections. Integrating thresholding, edge detection, and morphological processing enables food manufacturers to automate quality control processes with high accuracy. Each technique contributes unique capabilities, making them essential for real-time defect detection, object classification, and contaminant identification.

This study focuses on deterministic image processing techniques, which are based on fixed mathematical rules and provide computational efficiency and predictable performance. This makes them suitable for industrial applications where machine learning models are impractical. In subsequent sections, we will explore their real-world implementations, demonstrating how they contribute to enhanced food safety and quality assurance.

## 6. Challenges in Image Processing for the Food Industry

The application of image processing in the food industry has significantly improved quality control, defect detection, and automation. However, despite its advantages, several technical and operational challenges must be addressed to ensure reliable, scalable, and real-time implementation. These challenges arise due to the inherent variability of food products, environmental factors, and the stringent demands of high-speed production lines [11].

This section explores the primary challenges associated with image processing in the food industry and discusses potential solutions for overcoming these limitations.

### 6.1. Variability in Product Appearance

One of the most significant challenges in food quality inspection is the high variability in the appearance of food items. Unlike manufactured products, which have standardized dimensions and characteristics, food items such as fruits, vegetables, meat, and baked goods exhibit natural variations in:

- *Color:* Differences in ripeness, moisture content, and storage conditions affect color consistency.
- *Shape and Size:* Variability in natural products complicates segmentation and object recognition.
- *Texture:* Surface irregularities, bruises, and defects are inconsistent and non-uniform [11].

Variability in food products significantly affects image processing performance. Thresholding-based segmentation can fail when color variations within the same product category are too high, making it difficult to distinguish defects from natural appearance differences. Edge detection algorithms also face challenges when dealing with irregular shapes or natural surface deformations commonly found in fruits, vegetables, and baked goods [12]. Additionally, feature extraction becomes increasingly complex as statistical models must account for a wide range of visual variations.

To address these limitations, several strategies can be employed. Adaptive thresholding techniques adjust threshold values dynamically based on local pixel intensity distributions, improving segmentation under uneven lighting conditions. Shape-invariant feature extraction methods, which rely on geometric normalization, help reduce the impact of size and orientation differences on detection accuracy. Furthermore, multispectral and hyperspectral imaging, including infrared modalities, can reveal hidden defects and provide biochemical information that traditional RGB cameras may not capture. These approaches collectively enhance the robustness and reliability of image processing in food quality control.

### 6.2. Lighting Conditions and Environmental Variability

Lighting plays a crucial role in image processing accuracy. Variations in illumination caused by shadows, reflections, or ambient light changes can significantly impact image segmentation and feature extraction.

Lighting conditions have a substantial impact on image processing accuracy. Overexposure or underexposure can lead to incorrect defect classification, while reflections on moist surfaces—such as fresh fruits or meat—may generate false edges in edge detection algorithms. Non-uniform illumination across an inspection conveyor can further result in inconsistent detection performance, reducing overall reliability in automated quality control systems [3].

Several solutions can mitigate these issues. Controlled illumination setups, including uniform LED panels and diffuse lighting, help minimize reflections and provide stable, even lighting. Image normalization techniques—such as histogram equalization and adaptive contrast enhancement—can also compensate for lighting variations and enhance consistency. In addition, infrared and hyperspectral imaging reduce dependence on ambient lighting by capturing information from non-visible spectral ranges. By combining controlled lighting environments with advanced normalization methods, food inspection systems can maintain high accuracy even under challenging environmental conditions [3].

### 6.3. Real-Time Processing Requirements

Food production lines operate rapidly, requiring real-time image analysis to avoid bottlenecks and processing delays. Quality control must be instantaneous, as food items move through inspection points within milliseconds.

Real-time image processing presents several challenges in industrial food inspection systems. Advanced techniques such as deep learning and feature-based segmentation often require substantial computational power, making real-time deployment difficult. Hardware limitations can also impede performance, as high-speed conveyor belts demand cameras and processors capable of capturing and analyzing fast-moving objects with high precision [1]. Additionally, the system must deliver low-latency decisions to avoid production delays, requiring rapid classification and immediate action based on inspection results [2].

To overcome these challenges, various strategies can be implemented. Algorithmic optimization—particularly through the use of deterministic methods such as thresholding and morphological operations—can significantly improve processing speed by reducing computational complexity. Edge computing solutions, which rely on embedded vision processors, enable on-site decision-making and reduce dependence on cloud-based processing. Parallel processing approaches, including multi-threading and GPU acceleration, further decrease the time required to analyze each frame. By combining these optimizations with appropriate hardware enhancements, food manufacturers can achieve fast, reliable, and real-time defect detection even in high-speed production environments [2].

### 6.4. Contaminant Detection and False Positives

Natural food surface irregularities may sometimes be mistaken for defects, leading to false positive detections. Similarly, some contaminants (e.g., bacteria, pesticides) are not always visible, making it difficult to detect them using conventional imaging techniques.

Contaminant identification poses several challenges in automated food inspection systems. Foreign object detection often depends on contrast differences, which can fail when contaminants share similar colors or textures with the surrounding food material. Microbial contamination presents an even greater difficulty, as bacteria and fungi typically require specialized imaging techniques that go beyond standard visual inspection. Additionally, minimizing false positives is critical, since excessive rejection of products leads to unnecessary waste and increased production costs [1].

Several approaches can help address these challenges. X-ray and hyperspectral imaging enable the detection of foreign particles and internal defects by capturing information from non-visible spectral ranges. Advanced texture analysis techniques—such as wavelet transforms and frequency domain analysis—can distinguish natural surface variations from actual contaminants. Hybrid approaches that combine multiple image processing strategies, such as thresholding paired with machine learning classifiers, can further enhance detection accuracy while keeping computational costs manageable. By integrating specialized imaging modalities and multi-stage classification methods, food manufacturers can significantly improve contaminant identification while reducing false positives [1].

### 6.5. Scalability and Integration Challenges

Implementing image-processing-based quality control requires seamless integration with existing production lines. However, many legacy food manufacturing systems lack the infrastructure for advanced image analysis techniques.

Industrial deployment of automated image processing systems presents several practical challenges. Many existing food production lines rely on older hardware that may not be compatible with modern vision systems, creating integration difficulties. High-volume image processing also generates substantial data, requiring efficient storage and retrieval solutions to maintain workflow continuity. Additionally, successful adoption depends on the workforce's ability to operate, manage, and troubleshoot automated inspection technologies, making training and adaptation essential components of deployment.

Several strategies can help address these challenges. Modular and scalable system designs enable gradual integration, allowing food production facilities to adopt plug-and-play vision components without extensive infrastructure changes. Cloud-based data management, combined with edge AI processing, facilitates efficient handling, analysis, and storage of large datasets while supporting real-time decision-making. Furthermore, interactive operator training programs can prepare factory personnel to effectively use and maintain automated inspection systems, ensuring smooth implementation and long-term operational success.

Ensuring scalability and integration compatibility allows food manufacturers to transition smoothly into automated quality control without disrupting existing workflows [2].

While image processing has revolutionized food quality control, several technical and operational challenges must be addressed to ensure accuracy, efficiency, and scalability. Key obstacles include:

- Variability in product appearance, requiring adaptive segmentation and feature extraction techniques.
- Lighting inconsistencies can be mitigated using controlled illumination setups and image normalization methods.
- Real-time processing constraints necessitate optimized algorithms and parallel processing strategies.
- Contaminant detection challenges can be improved through advanced imaging modalities.
- Integration and scalability issues demand modular, flexible solutions for factory adaptation.
- By leveraging deterministic image processing techniques and optimized computational strategies, food manufacturers can overcome these challenges, ensuring efficient and reliable automated quality control in high-speed production environments [2][3][11].

The following sections of this thesis will explore practical implementations of these solutions, showcasing real-world applications and experimental results from automated food inspection systems.

## 7. Applications of Image Processing in Quality Control

The integration of image processing in quality control has not just changed but transformed modern manufacturing industries, enabling automated, high-speed, and highly accurate inspection processes. Image processing ensures product integrity, safety, and compliance with food production, pharmaceuticals, automotive, and electronics regulatory standards. By leveraging deterministic image processing techniques, manufacturers can enhance efficiency, reduce waste, and minimize human error, ultimately improving the overall quality of their products [2].

This section delves into the pivotal role of image-processing applications in quality control, specifically focusing on the food industry. The real-time detection of defects and the contamination analysis, both crucial for ensuring food safety, are at the heart of this exploration.

### 7.1. Defect Detection and Surface Quality Analysis

One of the primary applications of image processing in quality control is the detection of product defects and surface inconsistencies. Defects may include physical deformities, discoloration, cracks, or contamination that compromise product quality and consumer safety.

*Key Techniques Used:*

- Thresholding: Helps identify color inconsistencies in food products, such as spoiled fruits or overcooked baked goods.
- Edge Detection (Sobel, Canny Operators): Detects cracks, bruises, or irregularities on product surfaces.
- Morphological Processing: Enhances defect visibility by removing noise and refining object boundaries.

*Example Applications:*

- Fruit Sorting: Detecting bruises on apples, bananas, and citrus fruits.
- Eggshell Crack Detection: Identifying microfractures in eggs using high-resolution imaging.
- Bakery Product Analysis: Ensuring uniform shape, color, and texture in bread and pastry production.

By implementing real-time defect detection, manufacturers can proactively remove defective products before packaging, significantly reducing the likelihood of customer complaints and returns. This instills confidence in the quality of the products consumers receive.

### 7.2. Contaminant Detection and Food Safety Compliance

Food contamination poses a significant health risk, making automated contaminant detection a critical image processing application in food quality control. Unlike manual inspections, which are prone to human error, computer vision systems can detect contaminants more accurately and consistently.

*Key Techniques Used:*

- X-ray Imaging: Identifies foreign objects such as plastic, glass, or metal in food products.
- Hyperspectral Imaging Detects chemical contamination and spoilage by analyzing spectral variations.
- Blob Analysis: Identifies unwanted particles or foreign substances in processed foods [2].

*Example Applications:*

- Metal Fragment Detection in Packaged Foods: Ensuring that metal particles from processing equipment are not present in final products.
- Pesticide Residue Analysis in Fresh Produce: Using hyperspectral imaging to identify chemical contaminants.
- Microbial Contamination Assessment: Detecting early signs of mold, bacterial growth, or spoilage in dairy and meat products.

By integrating image-based contaminant detection, food manufacturers can ensure compliance with global food safety standards such as HACCP, FDA, and EFSA regulations. This prevents recalls and ensures that consumers can trust the safety and quality of the products they purchase.

### 7.3. Size, Shape, and Structural Integrity Analysis

Ensuring uniformity in size, shape, and structure is critical in food packaging, manufacturing, and logistics. Image processing enables high-speed measurements and classification, ensuring products meet predefined dimensional standards.

*Key Techniques Used:*

- Geometric Shape Matching: Ensures products adhere to ideal branding and consumer appeal shapes.
- Fourier Transform Analysis: Detects variations in shape that might be invisible to the human eye.
- Edge and Contour Detection: Verifies structural integrity and packaging consistency [1].

*Example Applications:*

- Automated Nut Sorting: Ensuring uniform size and shape of almonds, cashews, and walnuts.
- Pasta and Noodle Quality Control: Detecting broken or misshaped pieces in high-speed production lines.
- Biscuit and Cracker Inspection: Identifying misshapen or overbaked products.

Automated size and shape analysis offers manufacturers the benefits of ensuring product consistency, reducing waste, and improving customer satisfaction. This approach can be a game-changer in the food industry.

**7.4. Barcode and Label Verification**

Labeling errors can result in product misidentification, regulatory non-compliance, and logistical issues. Image processing enables automated barcode scanning and label verification, ensuring products are correctly labeled before distribution.

*Key Techniques Used:*

- Optical Character Recognition (OCR): Reads text on packaging labels to verify product details.
- Barcode and QR Code Scanning: This ensures that labels match the product's database records.
- Color and Logo Matching: Detects printing errors and packaging inconsistencies [2].

*Example Applications:*

- Expiration Date Verification: Ensuring that correct dates are printed on food packaging.
- Allergen Label Compliance: Detecting missing allergen information on packaging.
- QR Code Authentication: Confirming that QR codes on packaging are functional and scannable.

By integrating automated label verification, manufacturers can effectively prevent mislabeling issues and ensure strict compliance with food packaging regulations. This is a crucial aspect of quality control in the food industry.

### 7.5. Sorting and Automated Grading Systems

Image processing has revolutionized automated sorting and grading systems, allowing food manufacturers to categorize products based on predefined quality parameters.

*Key Techniques Used:*

- Color-Based Sorting: Uses thresholding algorithms to classify products based on color uniformity.
- Texture Analysis: Identifies surface smoothness and consistency.
- Multi-Spectral Imaging: Classifies food products based on moisture levels and freshness indicators.

*Example Applications:*

- Coffee Bean Grading: Sorting beans based on color, size, and defect presence.
- Meat Fat Content Analysis: Evaluating fat-to-protein ratios using infrared imaging.
- Automated Vegetable Sorting: Categorizing tomatoes, peppers, and potatoes based on ripeness and defects.

With real-time sorting and grading, image processing can significantly reduce manual labor costs, improve classification accuracy, and enhance operational efficiency. This is a key advantage for food producers.

### 7.6. Packaging Inspection and Seal Integrity Analysis

Faulty packaging can lead to contamination, leakage, and spoilage in food production. Image processing enables automated inspection of package integrity, ensuring proper sealing and compliance with quality standards.

*Key Techniques Used:*

- Edge Detection and Contour Analysis: Verifies that seals and package edges are intact.
- Infrared Imaging for Heat Seals: Detects improper sealing in vacuum-packed foods.
- Bubble and Leak Detection: Identifies air bubbles or seal gaps in food packaging [2].

*Example Applications:*

- Vacuum-Sealed Meat Inspection: Detecting leaks in plastic-sealed meat products.
- Beverage Bottle Cap Verification: Ensuring that caps are adequately sealed and aligned.
- Carton Package Integrity: Checking for structural defects in boxed products.

By integrating automated packaging inspection, manufacturers can ensure product freshness, prevent leaks, and reduce recalls.

Image processing applications in quality control span defect detection, contaminant analysis, product classification, barcode verification, automated sorting, and packaging inspection. These technologies enhance efficiency, improve product safety, and reduce reliance on manual labor.

By leveraging deterministic image processing techniques, manufacturers can achieve real-time quality assessment without the computational overhead of machine learning models [2].

This thesis will explore specific implementations and experimental results in the following sections, demonstrating how image-processing-driven quality control systems can be optimized for industrial-scale food production.

## 8. Evaluating Deterministic and Machine Learning Techniques for Food Quality Inspection

### 8.1. Deterministic Image Processing Methods

Deterministic image processing is grounded in rule-based algorithms that rely on predefined mathematical operations to analyze image features such as color, texture, edges, and shape. These methods are highly effective in applications with well-defined inspection criteria that do not require adaptive learning mechanisms. Key advantages of deterministic image processing include:

*Predictability and Consistency:* Deterministic algorithms apply explicit mathematical rules, ensuring that identical inputs always yield identical outputs. This consistency is crucial in regulated quality control environments where standardization and repeatability are mandatory.

*Low Computational Requirements:* These algorithms run efficiently on standard hardware and embedded systems, unlike ML models that typically require powerful GPUs or cloud-based infrastructures.

*No Need for Training Data:* Deterministic approaches do not rely on labeled datasets, eliminating the need for data collection, annotation, and model training.

*Ease of Implementation and Maintenance:* Deployment does not require hyperparameter tuning or ongoing retraining, making deterministic systems simpler to integrate and maintain in real-time industrial environments.

Several well-established deterministic techniques enable fast and accurate defect detection, contamination identification, and shape analysis:

*Thresholding (e.g., Otsu's Method):* Separates foreground objects from the background based on pixel intensities, often used to detect contaminants, spoilage spots, and surface discoloration.

*Edge Detection (Sobel, Canny):* Identifies intensity discontinuities to locate boundaries, cracks, or shape irregularities—crucial for assessing the uniformity of baked goods, fruits, and packaged items.

*Morphological Operations:* Clean and refine segmented regions by removing noise, filling gaps, and enhancing structural integrity. These methods are highly effective for identifying bruises, dents, and deformities.

Collectively, these techniques offer high-speed, transparent, and computationally efficient inspection capabilities suitable for real-time industrial use.

### 8.2. Machine Learning Techniques

Machine learning-based methods are increasingly used for complex quality control tasks that require adaptive pattern recognition and high-dimensional feature extraction. Unlike deterministic methods, ML systems learn from data and refine their decision-making based on experience, allowing them to handle variability and subtle defect characteristics that are difficult to define through explicit rules. Key characteristics of machine learning-based image processing include:

*Adaptability to Variability:* ML models excel at detecting subtle or unpredictable defects, spoilage indicators, and complex visual patterns.

*High Computational and Data Requirements:* Effective ML models typically require large and labeled datasets and high-performance hardware for both training and inference. Maintenance requires continuous updates, retraining, and dataset expansion.

*Risk of Black-Box Behavior:* Many ML models lack transparency in their decision-making, which can be problematic in regulated industries that require full traceability and explainability. ML-based approaches are most suitable for:

- highly variable product characteristics
- complex defect detection tasks
- large production facilities with computational resources

However, their challenges—cost, complexity, and data dependency—often limit adoption in small and mid-sized food manufacturing operations.

### 8.3. Deterministic vs. Machine Learning-Based Image Processing

Both deterministic and machine learning–based image processing techniques offer valuable capabilities for food quality control, but their suitability depends significantly on operational constraints, inspection complexity, and available resources. As summarized in Table 8.1, deterministic methods provide high consistency, low computational demand, and complete explainability, making them ideal for real-time and resource-limited environments. In contrast, machine learning approaches require extensive training data and significant computational power yet excel in detecting complex or highly variable defect patterns.

| Criteria | Deterministic Methods | Machine Learning Methods |
|---|---|---|
| Consistency | High predictability, fixed output | Output varies with data and model state |
| Computational Needs | Low; runs on embedded systems | High; requires GPUs/cloud |
| Data Requirements | No training data needed | Requires large labeled datasets |
| Explainability | Transparent and traceable | Often black-box and non-explainable |
| Implementation | Fast, low-cost, minimal maintenance | Complex; requires continuous updates |
| Ideal Use Case | Real-time, cost-sensitive applications | Complex or variable defect detection |

Table 8.1. Deterministic vs. Machine Learning-Based Image Processing.

Choosing the right image processing approach depends heavily on the specific needs, constraints, and operational conditions of a food production environment. Deterministic processing is especially well suited for real-time, low-latency production lines, for manufacturers operating with limited budgets, and for regulated settings that require fully transparent and traceable decision-making. In contrast, machine learning is more appropriate in situations where defects are highly variable or subtle, where multi-feature or multi-sensor analysis is necessary, or where large-scale producers have access to extensive datasets and substantial computational resources.

In conclusion, while machine learning provides strong adaptability and advanced pattern-recognition capabilities, deterministic image processing remains the most practical and cost-effective solution for many food quality control applications—particularly in cases where consistency, processing speed, and explainability are essential. For these reasons, this thesis focuses on deterministic methods for their reliability, efficiency, and scalability, while recognizing that future hybrid systems integrating deterministic techniques with selective machine learning components hold significant potential for enhancing food inspection performance.

# 9. Materials and Methods

## 9.1. Overview of the Experimental Setup

This study aims to evaluate the effectiveness of deterministic image processing techniques in automated food quality control systems. A comprehensive experimental setup was designed and implemented to achieve this, integrating hardware and software components that simulate real-world food production environments. The system was built to facilitate high-speed image acquisition, real-time processing, and defect classification, ensuring manufacturers can efficiently identify and remove defective products.

Given the high demand for food safety and quality assurance, implementing cost-effective and scalable image processing solutions has become essential for small-scale and industrial-level food manufacturers. The experimental system was developed with ease of integration in mind, allowing it to be deployed with minimal disruption to existing workflows. The experimental setup was designed to meet the following key requirements:

*Real-time processing:* The system must operate within the speed constraints of industrial production lines.

*Computational efficiency:* Deterministic image processing techniques must minimize computational overhead while maintaining high accuracy.

*High precision and consistency:* Unlike machine learning-based models that can vary in output, deterministic methods must ensure predictable and repeatable defect detection.

*Scalability:* The system should be adaptable to different food products and defect types, making it suitable for various industrial applications.

*Robust image acquisition techniques:* The system must handle variability in lighting conditions, food texture, and color inconsistencies while ensuring clear and sharp image quality.

The hardware and software components used in this study were divided into three main categories:

- *Hardware:* Smart glasses, high-resolution cameras, controlled lighting systems, and processing units.
- *Software:* Image processing algorithms, defect classification methods, and real-time analysis frameworks.
- *Data Collection and Validation:* Performance metrics, accuracy evaluations, and real-world testing methodologies.

By integrating these elements, the system ensures a comprehensive, automated, and efficient approach to food quality inspection without the reliance on complex machine learning algorithms.

**9.2 Hardware Components**

A well-structured hardware setup is essential for achieving high accuracy and efficiency in an image-processing-based quality control system. This section details the various hardware components used in the experimental setup.

*Smart Glasses for Hands-Free Inspection:* The Epson BT-350 smart glasses were used in this study to support hands-free operation during food inspection tasks. The device enabled inspectors to capture images in real time while interacting directly with food products, eliminating the need for handheld cameras. Equipped with a built-in high-resolution camera capable of capturing Full HD images, the glasses also feature augmented reality integration, allowing inspection results to be overlaid within the user's field of view. Wireless connectivity ensures seamless transmission of captured images to processing units. These capabilities improve mobility and convenience during manual quality control activities and reduce overall inspection time by streamlining the image acquisition process.

*Camera and Optical System:* The smart glasses provide a Full HD resolution of 1920 × 1080 pixels, delivering high-definition imagery suitable for detailed defect detection. The frame rate can be configured between 30 and 60 frames per second, ensuring smooth image capture even in high-speed production settings. Additional optical features include adjustable lens focus and exposure settings, allowing the device to adapt to dynamic inspection environments. The system also supports infrared and multispectral imaging, enabling the detection of non-visible defects such as moisture irregularities or hidden contamination.

*Lighting System:* Lighting plays a critical role in image processing-based quality control, as inconsistent illumination can lead to errors in segmentation and defect detection. In this study, an LED-based uniform illumination system was used to minimize shadow effects and ensure consistent brightness across different types of food products. Infrared and hyperspectral lighting options were also integrated to enhance the detection of chemical contaminants, microbial growth, and internal structural defects that are not visible under standard lighting conditions.

*Infrared and Hyperspectral Options:* Used to enhance the detection of chemical contamination, microbial growth, or internal structural defects.

*Processing Unit:* The computing hardware used in this system included a multi-core processor capable of handling real-time image analysis and a minimum of 8 GB of RAM to support high-speed data buffering. This configuration enabled the processing of images in real time using deterministic algorithms and facilitated rapid defect classification and rejection mechanisms necessary for efficient production line operation.

**9.3. Software Environment**

The software system was developed to process captured images, apply the necessary image processing algorithms, and deliver real-time feedback to quality control inspectors. The Unity Engine was used to support augmented reality–based visualization of defects and to provide an interactive interface that enhanced inspector engagement. C# served as the primary programming language for implementing the algorithms and system logic, while Azure's image processing libraries were integrated to support advanced analysis and cloud-enabled functionalities. Figure 9.1 shows the design of the database used in the system.

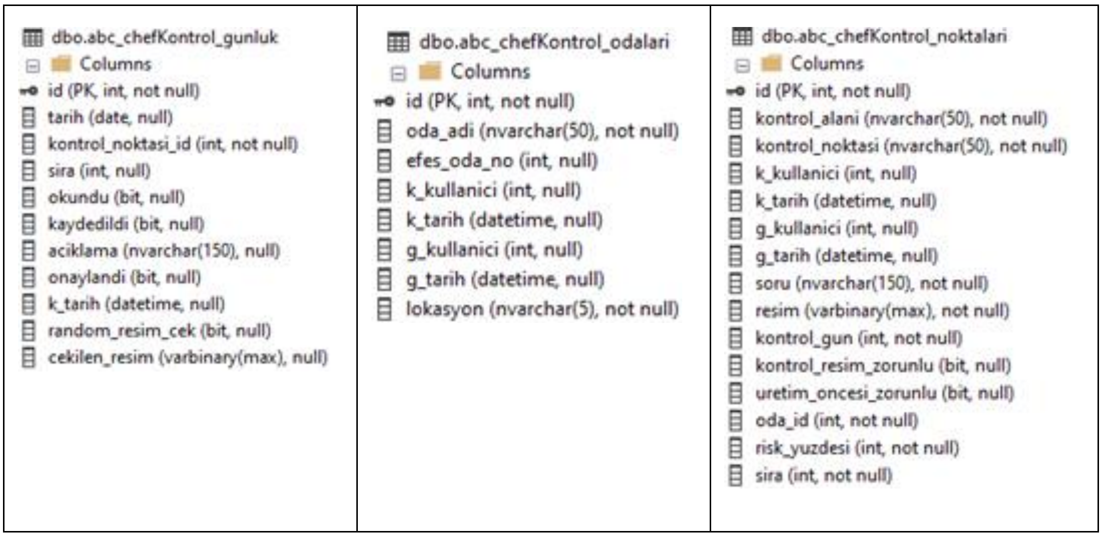


Figure 9.1. Design of the database.

### 9.4. User Interface Snapshots

The digital inspection system used in the quality control workflow consists of two main components: the mobile inspection interface and the desktop-based helper form. Together, these components ensure that inspection activities are standardized, traceable, and fully integrated across field and office environments.

The structure of the mobile inspection screen is presented in Figure 9.2. Each numbered section in the figure corresponds to specific interface functions, which are described below:

- ✓ **Control Area (1):** Displays the current inspection step, ensuring that the inspector clearly understands which control point is being evaluated.
- ✓ **Next Control Area (2):** Provides advance visibility of the upcoming control step, supporting a smooth and uninterrupted workflow.
- ✓ **Error Message Section (3):** Shows system-generated warnings such as missing inputs, mandatory actions, or validation errors.
- ✓ **Area-Specific Questions (4):** Presents the predefined inspection questions associated with the current control point.
- ✓ **Suitable/Not Suitable Buttons and Optional Description (5):** Enables the inspector to record the evaluation result and add explanatory notes if necessary.
- ✓ **Reference Image (6):** Displays a visual sample of the control area to guide the inspector and minimize misinterpretation.

This interface design enhances the reliability of the inspection process by combining textual guidance and visual reference elements.

Certain inspection steps require mandatory photo capture. The workflow for this functionality is shown in Figure 9.3. The area marked with **number 7** indicates the system's requirement for the inspector to take a photo before completing the record.

This enforcement ensures that visual evidence is collected for all critical control points, thereby strengthening traceability and supporting post-audit verification.

The configuration and management of inspection steps, including sequencing, question assignment, and image association, are carried out through a desktop helper form. An example of this form interface is provided in Figure 9.4. Through this form, administrators can:

- Define and order inspection steps,
- Add or modify inspection questions,
- Review uploaded photographs and previous inspection records,
- Create or update control templates for different locations.

By combining the mobile inspection interface with the desktop configuration tool, the system establishes a fully integrated and synchronized quality control environment. This integrated design ensures consistency, accelerates inspection processes, and enhances the accuracy and transparency of all recorded data.


Figure 9.2 Mobile Control Interface Layout


Figure 9.3 Mandatory Photo Capture Workflow in Mobile Interface

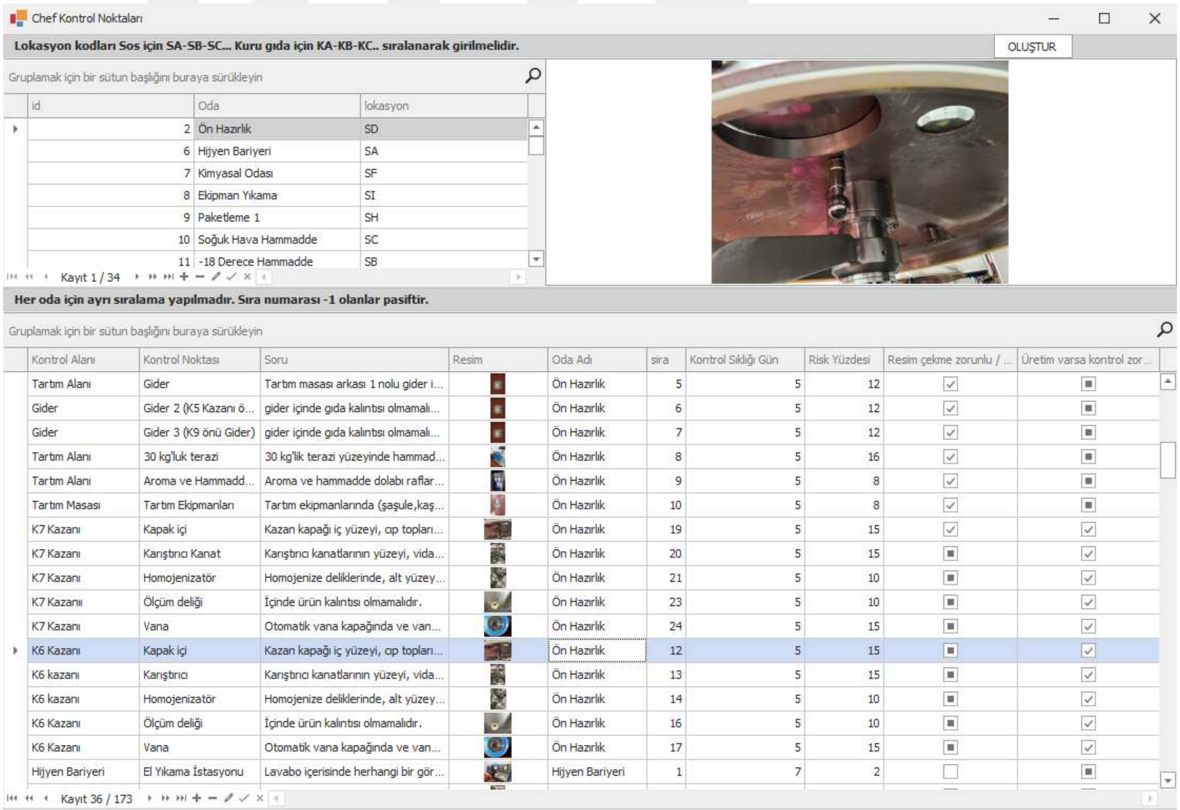


Figure 9.4 Desktop Helper Form for Control Configuration and Record Management

### 9.5. Workflow of the Inspection System

The Desktop Application is used by administrators to define and manage checkpoint data, including daily sequences and reference images. All updates are written directly to the MSSQL Database, which serves as the central repository for checkpoint definitions, reference images, captured images, and checkpoint statuses.

The system incorporates an API Layer consisting of two endpoints. The GET API allows the Unity Mobile Application to retrieve the daily checkpoint list and associated reference images from the MSSQL Database (as shown in Appendix 1). The POST API receives images and approval statuses submitted by the mobile application and stores them back into the database (as detailed in Appendix 2). This overall architecture is illustrated in Figure 9.5.

The Unity Mobile Application is used by field personnel to access assigned checkpoints, capture images, and submit approval or rejection decisions. A Scheduled Job operates as an automated background process that retrieves captured images from the MSSQL Database, sends them to the Azure API for compliance analysis, collects the returned results, and compiles them into a structured report. This final report is then distributed to relevant stakeholders via email. The system's workflow proceeds through the following steps:

*Phase 1- Checkpoint Configuration (Desktop Application):* Administrators configure checkpoints by defining their attributes, assigning daily sequences, and uploading reference images. These configurations are saved directly into the MSSQL Database.

*Phase 2- Daily Checkpoint Execution (Unity Mobile Application):* The mobile application fetches checkpoint data through a GET request. After the API retrieves and returns the checkpoint list and reference images, the application displays them to the user. Field personnel complete each checkpoint by performing the required task, capturing an image, and submitting the result through the POST API, which stores the data in the MSSQL Database (as shown in Appendix 3).

*Phase 3- Daily Image Analysis and Reporting (Scheduled Job):* A scheduled job is triggered to collect all images captured during the day. The job sends these images to the Azure API for analysis and receives the corresponding results (as shown in Appendix 4). It then compiles the findings into a report, optionally saving the analyzed data back into the MSSQL Database. Finally, the report is delivered to designated recipients via email.

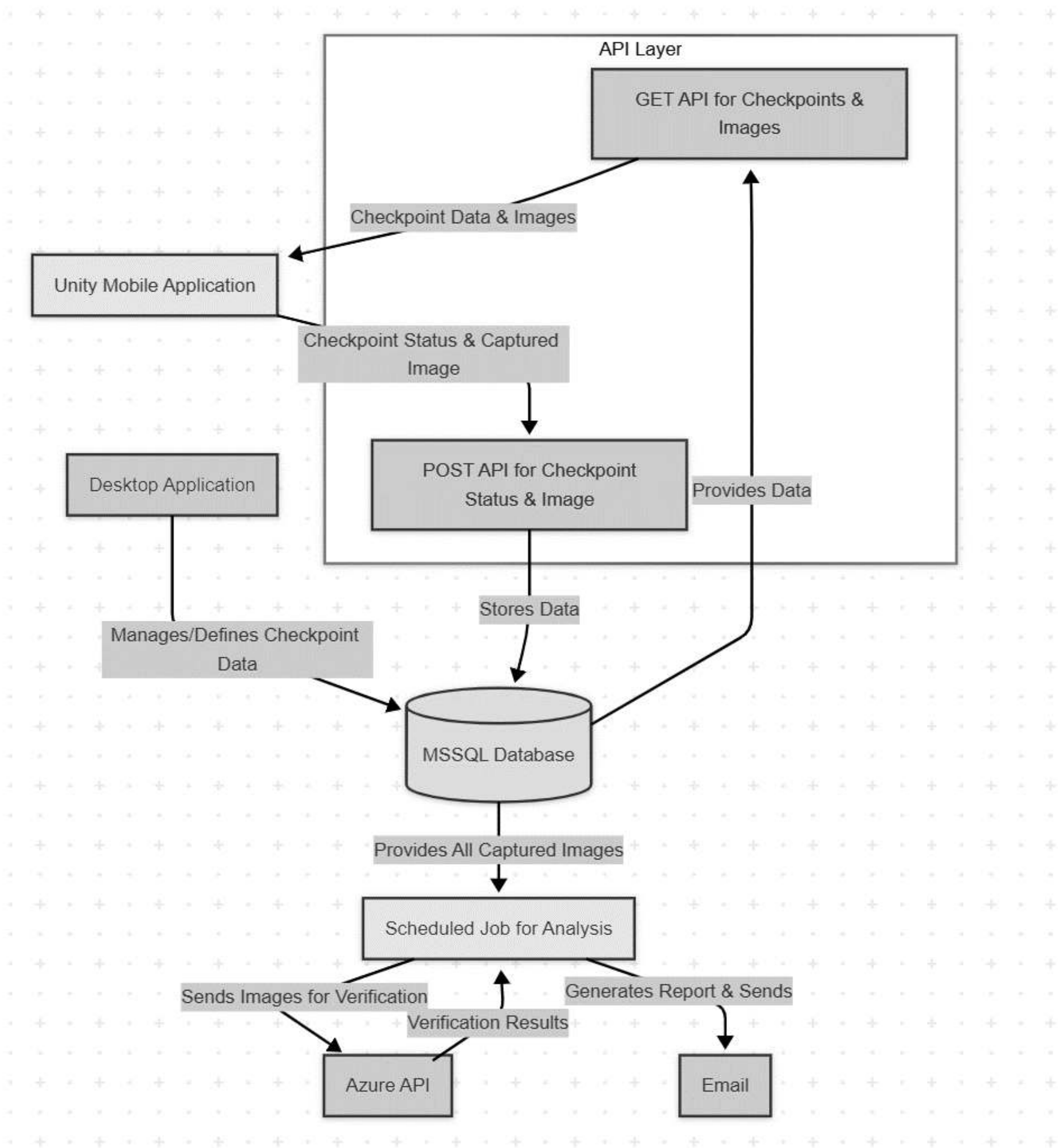


Figure 9.5. System architecture and data flow of the inspection workflow

### 9.6. Implementation of the Azure Custom Vision Method

In this study, the Azure Custom Vision service was utilized to automate visual inspection processes in the production area and to measure user accuracy rates.

The system enables the analysis of photographic data from specific control points on the production floor. Thus, manual inspection processes were supported by an AI-based verification mechanism, ensuring more objective and consistent quality control.

*1. Definition and Numbering of Control Areas:* Within the scope of the application, the production areas requiring visual control were identified and systematically numbered according to room, machine, and equipment categories.

Each control point was assigned a unique identifier (ID) to ensure traceability and precise mapping between visual data and physical equipment.

In total, the system covered 217 control points, distributed across two buildings, including 10 production rooms, 4 warehouses, corridors, and intermediate storage areas. For example, the mixer of the second machine in Room 2 was registered in the system as ID:81, while the third machine in Room 1 was defined as ID:45, and the first mixer in Room 1 as ID:42. This structured mapping ensured that photographs were correctly associated with their corresponding areas, facilitating consistent model learning and minimizing labeling errors.

*2. Preparation of Reference Images:* For each control point, photographs representing the correct and ideal operational condition of the equipment were captured. These reference images formed the core training dataset and were uploaded to the Azure Custom Vision platform.

During the upload process, each image was labeled with its corresponding ID, clearly linking the image to its respective control area. Since the quality of training data directly affects model performance, images were captured under different lighting conditions, angles, and production times to increase data diversity and robustness.

*3. Model Training and Performance Analysis:* A dedicated project was created on the Azure Custom Vision service, and the labeled reference images were used to train the model. As a result of the training, the model learned to recognize the correct position, shape, color, and structural characteristics of each piece of equipment.

Initial test results revealed that the third machine in Room 1 (ID:45) achieved higher accuracy compared to other machines.

This improvement was attributed to the balanced lighting conditions in that area, which allowed the model to better capture visual details. Conversely, the second machine in the same room (ID:43) exhibited relatively lower consistency in classification results. Further investigation indicated that low light conditions around the machine negatively affected detection accuracy.

To mitigate this issue, additional lighting was installed, and the images were retaken. After retraining the model with the improved dataset, a significant increase in accuracy was observed. These observations demonstrated that environmental factors, particularly lighting, played a crucial role in the model's overall reliability.

*4. Real-Time Inspection Process:* During real-time operations, the operator captures a current photograph of the relevant equipment and uploads it to the system.

The image is then sent to the Azure Custom Vision API, where it is compared with the previously stored "ideal state" reference image for the corresponding ID. The model produces a similarity score (%), which indicates how closely the current image matches the reference condition.

For instance, a similarity score of 91% for the mixer with ID:81 signifies that the equipment is positioned correctly, whereas values below 70% may suggest misalignment or potential anomalies. In some cases, surface reflections, dust accumulation, or other environmental factors temporarily affected model performance.

To address these issues, the model was retrained and image preprocessing techniques (e.g., brightness correction, contrast enhancement, and background normalization) were applied, resulting in improved accuracy.

*5. User Performance and Feedback Mechanism:* The similarity scores provided by Azure Custom Vision were used not only to measure system accuracy but also to evaluate operator performance. Each user's inspection results were logged, and consistency between repeated checks on the same equipment was analyzed.

This enabled the assessment of user attention levels and error tendencies as quantitative performance metrics. For example, the average accuracy rate of operators working in Room 1 was 88%, while the rate in Room 2 was 76% before environmental improvements.

After optimizing lighting conditions and standardizing camera angles, this figure increased to 90%, demonstrating a substantial improvement in both user and system performance.

The implementation of the Azure Custom Vision–based inspection system resulted in visual inspections that were:

- Objective, by minimizing subjective human bias;
- Repeatable, by standardizing analysis across different operators and times;
- Measurable, by quantitatively tracking user and model performance.

Through proper management of environmental variables (lighting, angle, reflection), the reliability of the model was significantly enhanced. Following the corrective actions and retraining processes, the system consistently achieved higher accuracy than traditional manual inspection methods.

Overall, this study demonstrates how AI-based image processing can be effectively integrated into industrial quality control workflows, providing a scalable and data-driven approach to operational monitoring.

As shown in Table 9.1, the initial accuracy rates ranged between 68% and 91%. After implementing environmental enhancements—such as improved lighting, fixed camera positions, and background normalization—and retraining the model, the average accuracy increased to 88%.

The most significant improvement was observed in Room 2, Mixer 2 (ID:57), where accuracy rose from 68% to 90% following lighting adjustments. These findings clearly indicate that environmental factors have a direct impact on the performance and stability of AI-based visual inspection models.

This study employed deterministic image processing techniques to support automated food inspection, using Otsu-based thresholding for binary segmentation, Sobel and Canny operators for edge detection, and morphological operations such as dilation and erosion to refine segmented regions and enhance defect visibility. All collected images and defect classifications were stored in a structured database, and system performance was evaluated through accuracy, processing speed, and false positive/negative rates. Several challenges emerged during implementation, including lighting variability, motion-induced blur, and compatibility issues with legacy systems; these were mitigated through adaptive thresholding, motion compensation filters, and custom API integrations. In summary, this chapter detailed the hardware, software, and experimental methods used in the research, setting the stage for quantitative performance results in the next chapter.

<table>
<tr><th>ID</th><th>Room Number</th><th>Machine / Equipment</th><th>Initial Accuracy (%)</th><th>Post-Improvement Accuracy (%)</th><th>Observed Issue</th><th>Applied Improvement</th></tr>
<tr><td rowspan="2">42</td><td>1</td><td>Mixer 1</td><td>86</td><td>90</td><td>Angle variation</td><td>Camera stabilization and fixed shooting angle</td></tr>
<tr><td colspan="6">Reduced camera angle deviation improved model stability.</td></tr>
<tr><td rowspan="2">43</td><td>1</td><td>Machine 2</td><td>74</td><td>89</td><td>Low light conditions</td><td>Additional lighting and model retraining</td></tr>
<tr><td colspan="6">15% accuracy improvement after lighting enhancement.</td></tr>
<tr><td rowspan="2">45</td><td>1</td><td>Machine 3</td><td>91</td><td>93</td><td>No major issue</td><td>Increased data diversity</td></tr>
<tr><td colspan="6">High accuracy achieved from the initial training stage.</td></tr>
<tr><td rowspan="2">56</td><td>2</td><td>Filling Unit 1</td><td>79</td><td>88</td><td>Reflection / glare</td><td>Contrast and exposure adjustment</td></tr>
<tr><td colspan="6">Reflection effects reduced through image preprocessing.</td></tr>
<tr><td rowspan="2">57</td><td>2</td><td>Mixer 2</td><td>68</td><td>90</td><td>Low light and shadows</td><td>Extra lighting and new image set</td></tr>
<tr><td colspan="6">Significant improvement after illumination adjustment.</td></tr>
<tr><td rowspan="2">58</td><td>2</td><td>Pumping Unit 3</td><td>83</td><td>87</td><td>Partial blurriness</td><td>Tripod usage and reshooting</td></tr>
<tr><td colspan="6">Image clarity increased, enhancing overall consistency.</td></tr>
<tr><td rowspan="2">73</td><td>3</td><td>Filling Nozzle 1</td><td>76</td><td>85</td><td>Variable camera angle</td><td>Standardized capture position</td></tr>
<tr><td colspan="6">Fixed camera points defined for operators.</td></tr>
<tr><td rowspan="2">81</td><td>2</td><td>Machine Mixer 2</td><td>80</td><td>91</td><td>Low light and angle issue</td><td>Lighting correction and model retraining</td></tr>
<tr><td colspan="6">Model consistency increased by 11%.</td></tr>
<tr><td rowspan="2">88</td><td>3</td><td>Packaging Line 4</td><td>84</td><td>88</td><td>Partial object visibility</td><td>Image cropping and updated labeling</td></tr>
<tr><td colspan="6">Reduced false-positive detections.</td></tr>
<tr><td rowspan="2">92</td><td>4</td><td>Weighing Unit 1</td><td>78</td><td>90</td><td>Background color variation</td><td>Background normalization</td></tr>
<tr><td colspan="6">Eliminated background bias, improved model accuracy.</td></tr>
</table>

Table 9.1. Azure Custom Vision Results and Accuracy Comparison.

## 10. Tests and User-Based Evaluation

This chapter presents a comprehensive evaluation of the deterministic image processing system through both controlled technical tests and operator-based usability assessments conducted under realistic production conditions. The objective is to establish a robust performance baseline by examining the system's accuracy, processing speed, and real-time responsiveness in detecting product defects, contamination, hygiene-related irregularities, and labeling inconsistencies. By simulating diverse operational environments—including controlled and variable lighting, high-speed conveyor scenarios, and mixed-quality product batches—the testing framework demonstrates how deterministic methods perform across the full spectrum of quality control requirements in modern food manufacturing. In addition to these technical evaluations, a user-based assessment was conducted with production operators to measure system usability, ergonomic impacts, and overall operator acceptance. This combined approach provides a holistic understanding of system performance by capturing not only quantitative inspection outcomes but also the human factors that influence the successful integration of digital inspection technologies into daily operational workflows.

### 10.1. Introduction to Test Framework

This phase of the study involved testing the developed deterministic image processing system within a controlled environment to establish a baseline for performance [13][14]. The goal was to assess the system's ability to detect and report defects or contamination in food products using thresholding and edge detection techniques [10][15][16]. Additionally, the scope of the evaluation extended beyond product integrity to include critical hygiene and labeling factors—emphasizing a comprehensive view of quality control in food manufacturing [17][18][19].

The system was tested under the following three core conditions:

*Uniform Lighting Conditions:* To evaluate global thresholding and edge detection under consistent illumination.

*Variable Lighting Conditions:* To test the robustness of adaptive thresholding in fluctuating light settings [10][20][21].

*High-Speed Production Simulation:* To assess the system's real-time inspection and classification accuracy on a conveyor-belt simulation [5][22][23][24].

A dataset of 500 food product samples was created:

200 defect-free samples [25]

150 samples with structural defects (cracks, deformities) [26][27][28]

150 samples with contamination (dirt, foreign objects, discoloration) [29]

Evaluation criteria included:

- Accuracy of defect and contamination detection
- Processing speed per image
- Human error reduction [8]
- Operator usability feedback
- Compatibility with broader quality control requirements including hygiene and labeling issues [20][30][31][32]

The system achieved a 92% defect detection accuracy, outperforming manual inspection methods (average 75%). It accurately detected:

- Surface contamination and discoloration via adaptive thresholding [33]
- Structural deformities such as cracks and irregularities via edge detection (Canny, Sobel) [10][12][16][34][35][36]

False positives were limited to 4.3%, and false negatives to 3.7%, minimizing unnecessary product rejections and enhancing efficiency [37][38].

Importantly, beyond physical defects [16] the system framework also supports detecting hygiene violations (e.g., unclean equipment surfaces) [20][39] and safety-critical issues such as open machinery panels or foreign objects in food zones—underscoring the broader scope of inspection compared to traditional methods.

The system maintained stable performance, while human inspectors showed fluctuating accuracy between 70–80%, particularly under fatigue [40][41][42].

- Manual inspections showed a false positive rate of 11.6%, significantly higher than the automated system.
- The system also detected 23% more defects, including hygiene-related anomalies and labeling misalignments that human inspectors often overlooked.

## 10.2. Processing Speed, Real-Time Capabilities and Human Error Reduction

This section evaluates the system's performance in terms of processing speed, real-time adaptability, and overall contribution to operational efficiency. In modern food production environments, rapid inspection and consistent decision-making are essential to avoid bottlenecks, reduce labor dependency, and maintain regulatory compliance. Deterministic image processing offers significant advantages in this context by enabling fast, predictable, and resource-efficient analysis. The following subsections detail how the system performs under industrial conditions, its ability to sustain high throughput, and its impact on production efficiency and human error reduction.

*Processing Speed Analysis:* The system demonstrated strong performance with an average image processing time of 0.5 seconds, meeting industrial throughput requirements [43]. In contrast, manual inspection required 3–5 seconds per item, creating bottlenecks in high-volume production environments [5][44].

*Real-Time Adaptability:* Capable of processing up to 120 items per minute, the system outperformed manual inspection rates of 30–40 items per minute [45][46]. This efficiency was achieved through parallelized, multi-threaded image analysis, which prevented latency even when handling products with complex textures or detailed labeling elements [5][31].

*Impact on Production Efficiency:* Real-time detection reduced overall quality control downtime by approximately 35% [47][48]. Furthermore, automated monitoring of label alignment and carton printing accuracy prevented labeling-related errors that could lead to shipment issues and traceability problems [40][49][50].

*Reduction of Human Error:* Automation significantly lowered human error rates from an average of approximately 20% to below 5% [51]. This reduction minimized judgment-based inconsistencies and improved regulatory compliance related to hygiene and labeling [22][52]. Operators also reported reduced fatigue due to fewer repetitive visual inspection tasks, while objective cleanliness verification—covering surfaces such as storage units, drain covers, and equipment—further reduced subjectivity in hygiene assessments [20][53][54][55].

### 10.3. Operator Feedback and System Usability

This section presents a unified evaluation of operator feedback and system usability following the transition from manual, paper-based inspections to a fully digital quality and hygiene control process supported by Smart Glasses integrated with an Azure-based visual recognition system. Historically, operators conducted inspections by manually recording observations on paper and later transferring them into digital formats, a workflow that was time-consuming, prone to inconsistency, and susceptible to human error. The newly implemented system streamlines this process by projecting inspection criteria directly into the operator's field of vision and enabling hands-free interaction through voice commands or touch controls, with all observations automatically captured in real time [56].

To assess the effectiveness of this digital workflow, a user satisfaction survey (as shown in Appendix 5) was conducted with 10 operators who performed quality control using the smart glasses. The survey consisted of ten questions categorized under general experience, performance, ergonomics, and overall satisfaction, rated on a five-point Likert scale (1 = strongly disagree, 5 = strongly agree) [57]. Results showed overwhelmingly positive feedback, with an average satisfaction score of 4.6 out of 5 (as shown in Appendix 6). Operators stated that the interface was intuitive (90%), visual recognition accuracy was "very successful," inspection times were reduced (80%), and the device was ergonomically suitable for extended use [58][59][60]. All participants expressed willingness to adopt the system permanently.

The transition from manual to digital inspections significantly improved operational efficiency. Manual inspections required operators to visually inspect areas, write notes, and later perform digital entry—leading to time loss, data inconsistencies, and elevated error risk. The smart glasses eliminated these inefficiencies by enabling automatic data collection, real-time validation, and hands-free operation, which not only improved workflow continuity but also enhanced workplace safety by maintaining continuous visual awareness of the production environment [61]. The system also reduced subjectivity in hygiene evaluations, providing objective verification for elements such as storage units, drain covers, and equipment surfaces [20][53][54].

The advantages of the new system are further highlighted by a direct comparison between the traditional paper-based method and the smart glasses-supported method in Table 10.1. This comparison illustrates substantial improvements in speed, accuracy, ergonomics, and data management, validating the operational value of the smart glasses system.

| Evaluation Criteria | Traditional Method (Paper-Based) | Smart Glass Method |
| --- | --- | --- |
| Data Collection | Manual observation and handwritten notes | Visual + Voice/Touch input |
| Time Efficiency | 12–15 min per inspection | 5–7 min per inspection |
| Accuracy Rate | Dependent on observer | High (via visual recognition) |
| Data Archiving | Paper storage, difficult access | Automatically stored digitally |
| Error Risk | High, due to manual input | Reduced through automated validation |
| User Ergonomics | Hands occupied with pen and paper | Hands-free, natural motion control |
| Overall Satisfaction (1–5) | 3.1 average | 4.6 average |

Table 10.1. Comparison of Traditional and Smart Glass Quality Control Methods.

When considered alongside existing approaches, deterministic image processing presents several advantages for industrial quality control. Unlike machine learning systems, deterministic methods provide consistent outputs without retraining, require lower computational resources, and offer greater transparency for audit processes—critical for hygiene and safety verification [4][5]. These systems can also be pre-programmed to detect critical safety conditions, such as open access hatches or missing hygiene barriers, without reliance on probabilistic inference.

Statistical validation confirmed the robustness of the system: a 95% confidence interval verified detection accuracy, standard deviation analysis showed reduced performance variance compared to manual inspection, and a t-test demonstrated statistically significant improvement ($p < 0.01$) [14][62]. However, certain challenges were observed, including sensitivity to lighting fluctuations [10][20] and difficulty in segmenting highly irregular product surfaces such as cracked eggshells or heavily textured coatings [63][64]. Similar segmentation challenges appeared when assessing hygiene-critical areas like air conditioners and drainage structures, suggesting the need for enhanced preprocessing and feature extraction in future iterations.

In conclusion, the deterministic image processing system combined with smart glasses provides a powerful, scalable solution for holistic quality control in the food industry. It not only surpasses manual inspections in accuracy, speed, and consistency but also extends quality assurance to hygiene monitoring, workplace safety verification, and label and packaging accuracy. By integrating both product-level and environmental oversight, the system lays the foundation for a comprehensive smart manufacturing ecosystem, with future developments likely to incorporate automated reporting, visual archiving, and machine-learning-based anomaly detection for enhanced performance.

## 11. Evaluation, Insights, and Industry Implications

### 11.1. Interpretation of Key Findings

This study demonstrates that deterministic image processing is an effective and reliable tool for food quality control. The system achieved a 92% detection accuracy, successfully identifying surface contamination, structural deformities, and discoloration across a broad range of food products [20][32][40][52]. Importantly, the system's capabilities extended beyond product defects, contributing to hygiene monitoring and label verification—areas traditionally assessed manually. This versatility highlights the potential of deterministic vision systems to support multiple layers of quality assurance within modern production facilities.

Several strengths became evident during evaluation [80]. The high detection accuracy greatly exceeded the average performance of manual inspections, which typically ranged between 70–80%. The system also significantly reduced human error by eliminating subjective variability and fatigue-prone decision-making [22][52][65]. Its processing capacity of up to 120 items per minute [5][31] enabled seamless operation on high-speed production lines, supporting real-time decision-making. Furthermore, the system's potential to monitor hygiene-sensitive surfaces such as machinery housings, drain covers, and packaging workstations broadened its contribution to food safety and compliance [20][54][66].

Despite these advantages, several factors influenced system performance. Variations in lighting and background noise occasionally disrupted segmentation, though adaptive thresholding mitigated most errors [10][20][67]. Additionally, highly textured products, cluttered environments, or irregular label designs sometimes required additional preprocessing to maintain consistent accuracy.

### 11.2. Implications for the Food Industry

The results carry meaningful implications for food production environments. Automating visual inspection workflows reduces labor dependency and minimizes the delays and bottlenecks caused by manual inspection times. Processing each image in approximately 0.5 seconds helps maintain continuous production flow and improves throughput [68][20][54][69]. Beyond product assessment, the system supports facility-wide hygiene monitoring, allowing producers to evaluate the cleanliness of infrastructure such as air-handling units, shelving, and vacuum systems—key components of compliance audits [70].

In terms of workforce roles, inspectors can shift from repetitive visual checks to supervisory positions focused on system monitoring and exception handling [71]. This not only improves job satisfaction and safety but also increases consistency in inspection outcomes. Adoption of deterministic systems, however, may require upfront training and adaptation, particularly in legacy facilities accustomed to manual workflows.

### 11.3. Comparison with Machine Learning Approaches

Compared with machine learning–based inspection, deterministic image processing offers several practical advantages in manufacturing settings [72][73]. It operates with lower computational requirements and does not depend on large datasets, retraining, or GPU-based inference [4] [5]. This makes deterministic methods faster to deploy and easier to integrate into existing production lines. The deterministic approach also provides transparent, predictable results that support regulatory audits and traceability—critical in food safety.

However, deterministic systems are less adaptable to evolving defect patterns and may not detect subtle or internal defects that require spectral analysis or deep learning models [20] [68]. Machine learning methods retain strengths in defect variability and complex pattern recognition, although at the cost of higher infrastructure and maintenance requirements [74].

### 11.4. Challenges and Limitations

Several limitations emerged during testing. Lighting fluctuations and reflections caused occasional false detections, despite adaptive thresholding reducing most inconsistencies [10][20][75]. Products with rough, glossy, or highly irregular surfaces—such as cracked shells or textured baked goods—sometimes challenged edge-based segmentation methods [63][64][70][76][77]. Similar issues occurred when inspecting hygiene-critical zones with complex geometries or cluttered backgrounds, such as door handles, drain areas, or equipment enclosures [78]. Finally, large-scale deployment across multiple product groups may require additional calibration to accommodate product diversity, packaging variations, and different environmental conditions [49][79][80][81].

### 11.5. Comparison with Existing Literature

The findings align with previous studies emphasizing the reliability of thresholding and edge detection for identifying defects and the cost-efficiency of deterministic systems compared with deep learning approaches [5][10]. This study also expands the literature by demonstrating practical applications beyond product evaluation. Integrating smart-glass technology (Epson BT-350) enabled hands-free inspection, real-time guidance, and automatic documentation. The research further incorporated hygiene monitoring, safety checks, and label verification—areas rarely examined together—creating a comprehensive framework for smart, interconnected manufacturing.

## 12. Conclusion and Future Work

This thesis demonstrated that deterministic image processing methods provide an effective, practical, and scalable solution for automated quality control in the food industry. By employing rule-based techniques such as thresholding, edge detection, and morphological operations, the proposed system achieved consistent and repeatable defect detection without the need for complex machine learning models or large training datasets. The integration of Epson BT-350 smart glasses and a custom Unity-based mobile interface enabled real-time visual inspection, seamless data capture, and automated reporting through Azure Custom Vision. Experimental results showed that the system significantly reduced inspection time, minimized human error, and improved overall operational efficiency compared with manual inspection practices. Moreover, user evaluations confirmed that the system enhanced workflow clarity, reduced cognitive load, and increased confidence in inspection accuracy. These findings validate deterministic image processing as a viable and cost-effective alternative for food manufacturers seeking to modernize their inspection processes without substantial computational or financial investment.

Although the proposed system provides strong performance in controlled and semi-structured environments, several avenues for future research may further enhance its capabilities and applicability. First, integrating multispectral or hyperspectral imaging could improve the detection of internal defects or chemical contaminants not visible in RGB images. Second, hybrid approaches—combining deterministic algorithms with lightweight machine learning modules—may provide increased robustness in highly variable production environments. Third, adapting the system for full-scale industrial deployment would require addressing environmental variability, conveyor speed synchronization, continuous lighting control, and long-term maintenance strategies. Finally, future work may include expanding the system to cover additional quality control modules such as allergen labeling verification, workplace safety monitoring, or predictive maintenance analytics. These enhancements would contribute to a more comprehensive, intelligent inspection ecosystem aligned with Industry 4.0 standards.

# REFERENCES


[1] Pitas, I. (2000). Digital Image Processing: Algorithms and Applications. New York: Wiley-Interscience, pp. 1–432. From: Wiley / Google Books.

[2] Cubero, S.; Aleixos, N.; Moltó, E.; Gómez-Sanchis, J.; Blasco, J. (2011). Advances in Machine Vision Applications for Automatic Inspection and Quality Evaluation of Fruits and Vegetables, Food and Bioprocess Technology, 4(4), pp. 487–504, doi:10.1007/s11947-010-0411-8. From: IVIA / FAO / SemanticScholar.

[3] Vibhute, A.; Bodhe, S. K. (2012). Applications of Image Processing in Agriculture: A Survey, International Journal of Computer Applications, 52(2), pp. 34–40. From: IJCA PDF.

[4] Huang, B.; Ma, S.; Wang, P.; Wang, H.; Yang, J.; Guo, X.; Zhang, W.; Wang, H. (2018). Research and Implementation of Machine Vision Technologies for Empty Bottle Inspection Systems, Engineering Science and Technology, an International Journal, 21(1), pp. 159–169, doi:10.1016/j.jestch.2018.01.004.

[5] Babić, M.; Farahani, M. A.; Wuest, T. (2021). Image-Based Quality Inspection in Smart Manufacturing Systems: A Literature Review, Procedia CIRP, 103, pp. 262–267, doi:10.1016/j.procir.2021.10.042.

[6] Şanver, U.; Yavuz, E.; Eyüpoğlu, C. (2017). An Image Processing Application to Detect Faulty Bottle Packaging, in 2017 International Conference EIConRus, doi:10.1109/EIConRus.2017.7910722.

[7] Zhou, X.; Wang, Y.; Xiao, C.; Zhu, Q.; Lu, X.; Zhang, H.; Ge, J.; Zhao, H. (2019). Automated Visual Inspection of Glass Bottle Bottom with Saliency Detection and Template Matching, IEEE Transactions on Instrumentation and Measurement, 68(11), pp. 4253–4267, doi:10.1109/TIM.2018.2886977.

[8] Maraveas, C.; Kalitsios, G.; Kotzabasaki, M.-I.; Giannopoulos, D.-V.; Dimitropoulos, K.; Vatsanidou, A. (2025). Real-Time Freshness Prediction for Apples and Lettuces Using Imaging Recognition and Advanced Algorithms in a User-Friendly Mobile Application, Smart Agricultural Technology, 12, 101129, doi:10.1016/j.atech.2025.101129.

[9] He, K.; Zhang, X.; Ren, S.; Sun, J. (2016). Deep Residual Learning for Image Recognition, in Proc. IEEE CVPR, pp. 770–778, doi:10.1109/CVPR.2016.90. From: CVPR PDF.

[10] Sahoo, P. K.; Soltani, S.; Wong, A. K. C. (1988). A Survey of Thresholding Techniques, Computer Vision, Graphics, and Image Processing, 41(2), pp. 233–260, doi:10.1016/0734-189X(88)90022-9.

[11] Brosnan, T.; Sun, D.-W. (2004). Improving Quality Inspection of Food Products by Computer Vision—A Review, Journal of Food Engineering, 61(1), pp. 3–16, doi:10.1016/S0260-8774(03)00183-3.

[12] Umbaugh, S. E. (2010). Digital Image Processing and Analysis: Human and Computer Vision Applications with CVIPtools (2nd ed.). Boca Raton: CRC Press, pp. 1–977, doi:10.1201/9781439802069.

[13] Dutta, S.; Pal, S. K.; Mukhopadhyay, S.; Sen, R. (2013). Application of Digital Image Processing in Tool Condition Monitoring: A Review, CIRP Journal of Manufacturing Science and Technology, 6(3), pp. 212–232, doi:10.1016/j.cirpj.2013.02.005.

[14] Zhao, Y.; Sun, Y.; Peng, S.; Zhou, H. (2006). Ultrasound-Based Detection of Glass Fragments in Bottled Beverages, Food Research International, 39(5), pp. 620–628, doi:10.1016/j.foodres.2006.01.010. From: ScienceDirect.

[15] Davies, E. R. (2000). Image Processing for the Food Industry. Singapore: World Scientific, pp. 1–289. From: Google Books.

[16] Burger, W.; Burge, M. J. (2008). Digital Image Processing: An Algorithmic Introduction Using Java. London: Springer, pp. 1–565, doi:10.1007/978-1-84628-968-2.

[17] Music, J.; Babić, Z.; Zovko, M.; Stojković, I.; Papić, V. (2023). Image-Based Sensor for Liquid Level Monitoring During Industrial Bottling, Sensors, 23(16), 7126, doi:10.3390/s23167126. From: miho / Vision-Tec.

[18] Cruz, S.; Ribeiro, M.; Araújo, R. (2021). Real-Time Quality Control of Heat-Sealed Bottles Using Infrared Imaging and Machine Learning, Journal of Imaging, 7(2), 24, doi:10.3390/jimaging7020024. From: MDPI.

[19] Microsoft Learn (2025). Prepare Images for Product Recognition — Modify Images for Shelf Analysis, (documentation). From: Microsoft Learn.

[20] Hwang, C.; Ko, S.; Lee, H.; Kim, M. S. (2021). Development of Fluorescence Imaging Technique to Detect Fruit Residues on Food-Processing Equipment Surfaces, Applied Sciences, 11(1), 458, doi:10.3390/app11010458.

[21] Guillot, V. (2023). Infrared Thermography for Seal Defects Detection on Packaged Products: Unbalanced Machine Learning Classification With Iterative Digital Image Restoration, ELCVIA Electronic Letters on Computer Vision and Image Analysis, 22(1), pp. 35–51, doi:10.5565/rev/elcvia.1567. From: ELCVIA.

[22] Li, W.; Xu, C.; Chen, L. (2025). Hyperspectral Imaging for Foreign Matter Detection in Foods: A Review, Foods, 14(17), 3026, doi:10.3390/foods14173026. From: MDPI.

[23] Lin, C.-Y.; Hsu, C.-Y.; Lin, P.-C.; Hsu, J.-T.; Su, H.-J.; Lin, C.-W.; Yang, P.-H.; Wu, D.-C. (2025). Smartphone-Based Deep Learning System for Detecting Pork Cut/Origin and Ractopamine, Sensors, 25(9), 2698, doi:10.3390/s25092698.

[24] Kazmi, M.; Hafeez, A.; Rauf, H. T.; Ghafoor, A.; Bukhari, S. A. C.; Tanveer, M.; Irtaza, A. (2022). Machine-Vision-Based Plastic Bottle Inspection for Quality Assurance, Engineering Proceedings (MDPI), 20(1), 9, doi:10.3390/engproc2022020009.

[25] Shetty, B.; Madhushree, S. M.; Muddukrishna, B. S.; Shenoy, R.; Kirankumar, H.; Joshi, M.; Pai, G. K. (2024). Machine Vision Based Quality Inspection of Pharmaceutical Bottle Packaging, Research Journal of Pharmacy and Technology, 17(10), doi:10.52711/0974-360X.2024.00789.

[26] Liu, G.; Zhang, S.; Wang, L.; Li, X.; Li, G. (2025). Research on Mechanical Automatic Food Packaging Defect Detection Model Based on Improved YOLOv5 Algorithm, PLOS ONE, 20(4), e0321971, doi:10.1371/journal.pone.0321971.

[27] Chen, B.; Li, C.; Yuan, P.; Yin, Y.; Li, X.; Li, G. (2024). Research on Defect Detection of Bottle Cap Interior Based on Low-Angle and Large-Divergence-Angle Vision System, PLOS ONE, 19(5), e0303744, doi:10.1371/journal.pone.0303744.

[28] Sridevi, S.; Karthikeyan, P.; Arun Prakash, C.; Jaganathan, A.; Mani, A. (2016). Bottle Cap Inspection Based on Machine Vision, IJERT — NCARMS 2016 (Vol. 4, Issue 26), Article ID: 10.17577/IJERTCONV4IS26006.

[29] Farhangi, O.; Sheidaee, E.; Kisalaei, A. (2024). Machine Vision for Detecting Defects in Liquid Bottles, Cloud Computing and Data Science, 5(2), pp. 242–254, doi:10.37256/ccds.5220244756. From: ResearchGate.

[30] Peter, S.; Rösch, P.; Popp, J. (2021). Cultivation of Chlorella vulgaris on Dairy Waste Using Vision Monitoring, Bioresource Technology, 341, 125892, doi:10.1016/j.biortech.2021.125892.

[31] Desai, J. (2021). A Low-Cost, Cloud-Based Automated AI Device for Object Detection, ICT Express, 7(4), pp. 408–413, doi:10.1016/j.icte.2021.07.004.

[32] Hosozawa, K.; Wijaya, R. H.; Seya, H. (2018). Recognition of Expiration Dates Written on Food Packages with Open-Source OCR, International Journal of Computer Theory and Engineering, 10(6), pp. 178–183.

[33] Andriiashen, V.; van Liere, R.; van Leeuwen, T.; Batenburg, K. J. (2021). Unsupervised Foreign Object Detection Based on Dual-Energy X-ray Absorptiometry in the Food Industry, arXiv preprint, arXiv:2104.05326, pp. 1–15. From: arXiv.org.

[34] Shimonomura, K.; Chang, T.; Murata, T. (2021). Detection of Foreign Bodies in Soft Foods with a Camera-Based Tactile Image Sensor, Frontiers in Robotics and AI, 8, 774080, pp. 1–13, doi:10.3389/frobt.2021.774080.

[35] Pan, H.; Zhang, X.; Wang, J.; Liu, Y. (2024). Surface Defect Detection of Ceramic Discs Based on Improved YOLOv5s, Heliyon, 10, e25979, doi:10.1016/j.heliyon.2024.e25979.

[36] Sharma, S.; Krupa, K. V.; Gandhi, R.; Jain, A.; Shah, N. (2015). Empty and Filled Bottle Inspection System, ICTACT Journal on Image and Video Processing, 6(2), pp. 1122–1126, doi:10.21917/ijivp.2015.0163.

[37] Black, M.; Guzman, L.; Sibbique, A.; Sierra, K.; Tashiguano, V.; Garner, L.; Mackinnon, N.; Sokolov, S.; Vasefi, F.; Qin, J.; Chan, D.-E.; Baek, I.; Chao, K.; Kim, M.-S.; Morey, A. (2025). Enhancing Poultry Food Safety: Advanced Detection of Visible and Invisible Fecal Contamination on Chicken Carcasses Using Multispectral Fluorescence Imaging and Machine Learning to Mitigate Salmonella Risks, Journal of Food Protection, 88(10), e10063, doi:10.1016/j.jfp.2025.100613.

[38] Chen, D.; Zhang, J.; Jiao, Z.; Lei, H. (2024). Multi-Scale Surface Defect Detection Method for Bottled Products Based on Variable Receptive Fields and Gather–Distribute Feature Fusion Mechanism, Computers & Electrical Engineering, 116, 109148, doi:10.1016/j.compeleceng.2024.109148. From: ScienceDirect.

[39] Sueker, M.; Tafur, J.; Lucas, M.; Khankan, R.; Peruski, A.; Caraveo, G.; Ram, S.; Petrovic, V.; Nallala, J.; Aalam, B.; Roy, S. (2021). Handheld Multispectral Fluorescence Imaging System to Detect and Disinfect Surface Contamination, Frontiers in Sensors, 2, 736725, doi:10.3389/fsens.2021.736725.

[40] Zhao, Y.-X.; Ren, Z.; Zhang, L.; Wang, S. (2023). Cylindrical Label Defect Detection Based on Machine Vision, Proceedings of SPIE, 12916, 12916E, doi:10.1117/12.3002191.

[41] Gromova, K.; Elangovan, V. (2022). Automatic Extraction of Medication Information from Cylindrically Distorted Pill Bottle Labels, Machine Learning and Knowledge Extraction, 4(4), pp. 852–864, doi:10.3390/make4040043.

[42] Zhang, L.; Xu, H. (2021). Research on Cylindrical Labels Unfolding Algorithm Based on Geometric Correction, in Proceedings of the International Conference on Machine Vision and Image Processing (MVIP 2021).

[43] Kim, H.; Lee, S.; Park, J.; Kim, E.; Jeong, H.; Kim, S.; Choi, J.; Park, S. (2023). Recognition of Adherent Polychaetes on Oysters and Scallops Using Microsoft Azure Custom Vision, Electronic Research Archive (ERA), 31(6), pp. 3601–3619, doi:10.3934/era.2023088.

[44] Microsoft ISE Blog (2019). Food Classification with Custom Vision Service, (blog post). From: Microsoft ISE Blog.

[45] Sönmez, M.-E.; Altınsoy, B.; Yılmaz-Öztürk, B.; Gümüş, N.-E.; Eczacıoğlu, N. (2023). Deep Learning-Based Classification of Microalgae Using Light and Scanning Electron Microscopy Images, Micron, 172, 103506, doi:10.1016/j.micron.2023.103506.

[46] Pithadiya, K. J.; Modi, C. K.; Chauhan, J. D. (2010). Machine Vision Based Liquid Level Inspection System Using ISEF Edge Detection Technique, in ICWET 2010 — International Conference & Workshop on Emerging Trends in Technology (Mumbai, India), pp. 601–605, doi:10.1145/1741906.1742044.

[47] Xiao, Z.; Wang, J.; Han, L.; Guo, S.; Cui, Q. (2022). Application of Machine Vision System in Food Detection, Frontiers in Nutrition, 9, 888245, pp. 1–15, doi:10.3389/fnut.2022.888245.

[48] Dave, R.; Hadia, S. (2015). Liquid Level and Cap Closure United Inspection Using Image Processing. International Journal for Innovative Research in Science & Technology (IJIRST), 1(12), pp. 62–68. From: Semantic Scholar / Academia.

[49] Scazzoli, D.; Bartezzaghi, G.; Uysal, D.; Magarini, M.; Marcon, M. (2019). Usage of Hough Transform for Expiry Date Extraction via Optical Character Recognition, in 2019 Advances in Science and Engineering Technology International Conferences (ASET), pp. 1–6, doi:10.1109/ICASET.2019.8714306.

[50] Grumeza, T.; Niță, C. I.; Stoichescu, D. (2024). Integration of LLM in Expiration Date Scanning for Visually Impaired People (EasyOCR + Live Feed), Scalable Computing: Practice and Experience, 25(6), pp. 5722–5733, doi:10.12694/scpe.v25i6.4967.

[51] Kim, K.; Kim, H.; Chun, J.; Kang, M.; Hong, M.; Min, B. (2021). Real-Time Anomaly Detection in Packaged Food X-ray Images, Computer Modeling in Engineering & Sciences (CMES), 67(2), pp. 2547–2568, doi:10.32604/cmes.2021.014642.

[52] Kurniawan, H.; Arief, M. A. A.; Lohumi, S.; Kim, M. S.; Baek, I.; Cho, B.-K. (2024). Dual Imaging Technique for a Real-Time Inspection System of Foreign Object Detection in Fresh-Cut Vegetables, Current Research in Food Science, 9, 100802, pp. 1–12, doi:10.1016/j.crfs.2024.100802.

[53] Malesa, M.; Rajkiewicz, P. (2021). Quality Control of PET Bottles Caps with Dedicated Image Calibration and Deep Neural Networks, Sensors, 21(2), 501, doi:10.3390/s21020501.

[54] Tomita, D.; Iwamoto, K.; Matsuyama, T.; Ohta, M. (2025). Detection of Chips on the Threaded Part of Cosmetic Glass Bottles, Journal of Imaging, 11(3), 77, doi:10.3390/jimaging11030077.

[55] Everard, C. D.; Fagan, C. C.; O'Donnell, C. P. (2016). Assessment of a Handheld Fluorescence Imaging Device for Detection of Food Residues on Food-Contact Surfaces, Food Control, 66, pp. 1–9, doi:10.1016/j.foodcont.2016.01.019. From: ScienceDirect.

[56] Microsoft TechCommunity (2021). A Visual Guide to Azure Percept, (community article). From: Microsoft TechCommunity.

[57] Peng, H.; Bayon, J.; Recas, J.; Guijarro, M. (2025). Efficient Expiration Date Recognition in Food Packages for Mobile Applications, Algorithms, 18(5), 286, doi:10.3390/a18050286. From: MDPI.

[58] Payne, K.; O'Bryan, C. A.; Marcy, J. A.; Crandall, P. G. (2023). Detection and Prevention of Foreign Material in Food: A Review, Heliyon, 9(9), e19574, pp. 1–14, doi:10.1016/j.heliyon.2023.e19574.

[59] Chen, I.-C.; Chi, H.-Y.; Ku, Y.-C. (2025). Deep Learning for the Detection of Good Hygienic Practices Control Measures for Food Handlers, Food Control, 171, 111041, doi:10.1016/j.foodcont.2024.111041.

[60] Zhong, R.; Shafait, F.; Mian, A. (2020). Multi-View Hand Hygiene Recognition with Deep Neural Networks, Journal of Imaging, 6(11), 120, doi:10.3390/jimaging6110120. From: MDPI.

[61] Li, K.; Meng, F.; Huang, Z.; Wang, Q. (2019). A Correction Algorithm of QR Code on Cylindrical Surface, Journal of Physics: Conference Series, 1237(2), 022006, doi:10.1088/1742-6596/1237/2/022006.

[62] Thota, M.; Kollias, S.; Swainson, M.; Leontidis, G. (2020). Multi-Source Domain Adaptation for Quality Control in Retail Food Packaging, Computers in Industry, 123, 103293, doi:10.1016/j.compind.2020.103293.

[63] Wu, H.; Luo, Z.; Sun, F.; Li, X.; Zhao, Y. (2024). An Improvement Method for Improving the Surface Defect Detection of Industrial Products Based on Contour Matching Algorithms, Sensors, 24(12), 3932, doi:10.3390/s24123932.

[64] Zhu, X.; Liu, Z.; Zhang, X.; Sui, T.; Li, M. (2022). A Very Fast Image Stitching Algorithm for PET Bottle Caps, Journal of Imaging, 8(10), 275, doi:10.3390/jimaging8100275.

[65] Caballero-Ramírez, D.; Tortorella, G.; García-Alcaraz, J.; Jiménez-Macías, E.; Limón-Romero, J.; Báez-López, Y.; Tlapa, D. (2025). Deep Learning-Based Detection of Wine Bottle Capsules for Contamination Prevention, Results in Engineering, 27, 105681, pp. 1–12, doi:10.1016/j.rineng.2025.105681.

[66] Balakreshnan, B.; Richards, G.; Nanda, G.; Mao, H.; Athinarayanan, R.; Zaccaria, J. (2020). PPE Compliance Detection Using Artificial Intelligence in Learning Factories, Procedia Manufacturing, 45, pp. 277–282, doi:10.1016/j.promfg.2020.04.017.

[67] KEYENCE (2020). Bottle Cap Inspection for Food & Beverage Packaging, (industry application page). From: KEYENCE.

[68] Kang, Z.; Li, W.; Mujumdar, A. S.; Yu, D. (2022). Advances in Machine Learning and Hyperspectral Imaging for Food Quality and Safety, Food Engineering Reviews, 14, pp. 176–199, doi:10.1007/s12393-021-09298-5. From: Engilico (HSI seal inspection).

[69] Cognex (2021). Tamper & Safety Seal Inspection, (industry application page). From: Cognex.

[70] Ramalingam, B.; Liu, Y.; Krishnan, R. (2022). Optimal Selective Floor Cleaning Using Deep Learning for Autonomous Robots, Scientific Reports, 12, 15645, doi:10.1038/s41598-022-19249-7. From: Nature.

[71] Cheng, J.; Sun, Z.; Li, H. (2025). Real-Time Warehouse Monitoring with Ceiling Cameras and Knowledge-Graph World Models, Machines, 9(4), 153, doi:10.3390/machines9040153. From: MDPI.

[72] Borugadda, P. K.; Kalluri, H. K.; Garikapati, S.; Vemuri, S. (2025). A Comprehensive Analysis of Artificial Intelligence in Food Processing and Safety, Journal of Future Foods, 5, 100155, doi:10.1016/j.jfutfo.2025.07.002.

[73] Tahir, G. A.; Loo, C. K. (2021). Explainable Deep Learning Ensemble for Food Image Analysis on Edge Devices, Computers in Biology and Medicine, 139, 104972, doi:10.1016/j.compbiomed.2021.104972. From: PubMed.

[74] Roșca, C.-M.; Stancu, A. (2025). Innovative AIoT Solutions for PET Waste Collection in the Circular Economy Towards a Sustainable Future, Applied Sciences, 15(13), 7353, doi:10.3390/app15137353.

[75] Rahman, N. N. S. A.; Saad, M. N.; Yusoff, N. I. N. (2019). A Review of Vision-Based Defect Detection Using Image Processing Techniques for Beverage Manufacturing Industry, Jurnal Teknologi, 81(5), pp. 111–124.

[76] Ashino, M.; Takeuchi, Y. (2020). Expiry-Date Recognition System Using Combination of Deep Neural Networks for Visually Impaired, in Computers Helping People with Special Needs (ICCHP 2020), Lecture Notes in Computer Science, vol. 12376, Springer, doi:10.1007/978-3-030-58796-3_58. From: SpringerLink.

[77] Claypo, N.; Jaiyen, S.; Hanskunatai, A. (2023). Inspection System for Glass Bottle Defect Classification Based on Deep Neural Network, International Journal of Advanced Computer Science and Applications, 14(7), pp. 340–348, doi:10.14569/IJACSA.2023.0140738.

[78] Zhang, J.; Li, C.; Rahaman, M. M.; Yao, Y.; Ma, P.; Zhang, J.; Zhao, X.; Jiang, T.; Grzegorzek, M. (2022). A Comprehensive Review of Image Analysis Methods for Microorganism Counting: From Classical Image Processing to Deep Learning Approaches, Artificial Intelligence Review, 55, pp. 2875–2944, doi:10.1007/s10462-021-10082-4.

[79] Charlebois, S.; Latif, N.; Ilahi, I.; Sarker, B.; Music, J.; Vezeau, J. (2024). Digital Traceability in Agri-Food Supply Chains: A Comparative Analysis of OECD Member Countries, Foods, 13(7), 1075, doi:10.3390/foods13071075.

[80] Lema, D.-G.; Pedrayes, O.-D.; Usamentiaga, R.; García, D.-F.; Alonso, Á. (2021). Cost-Performance Evaluation of a Recognition Service of Livestock Activity Using Aerial Images, Remote Sensing, 13(12), 2318, doi:10.3390/rs13122318.

[80] Pan, Z.; Wang, L.; Li, K.; Zhang, C.; Zhang, X.; Liu, Z. (2024). Developing a Portable Fluorescence Imaging Device for Rapid Fish Freshness Detection, Sensors, 24(5), 1401, doi:10.3390/s24051401.

[81] Chen, C.; et al. (2025). A Vision-Based Method for Detecting the Position of Stacked Boxes on Pallets (STEGNet), Sensors, 25(8), 2623, doi:10.3390/s25082623. From: MDPI.

# Appendix 1 ChefWebApi get checkpoints with comment script

```
using ChefWebData.Entities.Entity;
using ChefWebData.Helpers.Helper;
using System;
using System.Collections.Generic;
using System.Linq;
using System.Web;
using System.Web.Script.Serialization;
using System.Web.UI;
using System.Web.UI.WebControls;
namespace Chef.WebData
{
  public partial class chefKontrol_liste : System.Web.UI.Page
  {
    public string Message = "";
    protected void Page_Load(object sender, EventArgs e)
    {
      //--------------------------------------------------
      using (PanelModel pn_model = new PanelModel())
      {
        DateTime dt = DateTime.Now.Date;
        DateTime old_dt = Convert.ToDateTime("2000-01-01 00:00:00.000");
                      // To show the next checkpoints ordered
        var lst = pn_model.abc_chefKontrol_gunluk.Where(w => w.tarih == dt &&
w.k_tarih == old_dt).OrderBy(o => o.sira).ToList();
        if (lst.Count > 0)
        {
          var sec = lst.FirstOrDefault();
                              // current checkpoint read
          sec.okundu = true;
          pn_model.SaveChanges();
          var oda_bilgi = pn_model.abc_chefKontrol_noktalari.Where(w => w.id ==
sec.kontrol_noktasi_id).FirstOrDefault();
          abc_chefKontrol_gunluk sonraki = new abc_chefKontrol_gunluk();
                              // To show the next checkpoint
          if (lst.Count > 1)
          {
            sonraki = lst.Where(w => w.sira == sec.sira + 1).FirstOrDefault();
          }
          var sonraki_oda = sonraki != null ?
pn_model.abc_chefKontrol_noktalari.Where(w => w.id ==
sonraki.kontrol_noktasi_id).FirstOrDefault() : null;
                              // We defined the object and sent it to json
          kontrol_bilgi kntrol_nok = new kontrol_bilgi
          {
            id = oda_bilgi.id,
            kontrol_noktasi = "Sıradaki kontrol: " + Environment.NewLine +
oda_bilgi.kontrol_alani + " " + oda_bilgi.kontrol_noktasi +
            Environment.NewLine + (sonraki_oda != null ? "Sonraki kontrol: " +
Environment.NewLine + sonraki_oda.kontrol_alani + " " + sonraki_oda.kontrol_noktasi :
""),
            soru = oda_bilgi.soru,
            resim = oda_bilgi.resim,
            okundu = sec.okundu,
            random_resim_cek = sec.random_resim_cek
          };
          JavaScriptSerializer j = new JavaScriptSerializer();
          Message = j.Serialize(kntrol_nok);
        }
        else
        {   // end of the controls
          var lst_biten = pn_model.abc_chefKontrol_gunluk.Where(w => w.tarih ==
dt).ToList();
          var onayli = lst_biten.Where(w => w.onaylandi == true).ToList();
          var onaysiz = lst_biten.Where(w => w.onaylandi == false).ToList();
          Message = "Kontrol tamamlandı. " + onayli.Count.ToString() + " adet kontrol
noktası onaylandı. " + onaysiz.Count.ToString() + "adet kontrol noktası
onaylanmadı.";
        }
      }
    }
              // required object
    class kontrol_bilgi
    {
      public int id { get; set; }
```

```
        public string kontrol_noktasi { get; set; }
        public string soru { get; set; }
        public byte[] resim { get; set; }
        public bool okundu { get; set; }
        public bool random_resim_cek { get; set; }
    }
  }
}
```

## Appendix 2 ChefWebApi post with comment script

```
using Microsoft.AspNetCore.Authorization;
using Microsoft.AspNetCore.Mvc;
using Newtonsoft.Json;
using System;
using System.Collections.Generic;
using System.Globalization;
using System.IO;
using System.Linq;
using System.Net.Http;
using System.Text.Json;
using System.Threading.Tasks;
using ChefWebData.Entities;
using ChefWebData.Entities.PanelEntities;
using ChefWebApi.functions;
namespace ChefWebApi.Controllers
{
  [ApiController]
  [Route("[controller]")]
  [AllowAnonymous]
  public class ChefControlResimApiController : ControllerBase
  {
    [HttpPost]
    public async Task<IActionResult> Upload([FromBody] dynamic _image)//unity script
running
    {
       //Deserialize Object
      var ob = (JsonElement)_image;
      var jsonText = ob.GetRawText();
      var dynamicObject = JsonConvert.DeserializeObject<point_obj>(jsonText)!;
                      //set json to variables
      var kontrol_noktasi_id = dynamicObject.kontrol_noktasi_id;
      var random_resim_cek = dynamicObject.random_resim_cek;
      var cekilen_resim = dynamicObject.cekilen_resim;
      var onay = dynamicObject.onay;
      var aciklama = dynamicObject.aciklama;
      response res = new response();
       //saving to msssql database with entity framework
      if (kontrol_noktasi_id > 0)
      {
        DateTime dt = DateTime.Now.Date;
        using (var db = new PanelModel())
        {
          var guncellenecek = db.abc_chefKontrol_gunluk.Where(w =>
w.kontrol_noktasi_id == kontrol_noktasi_id && w.tarih == dt).FirstOrDefault();
          guncellenecek.onaylandi = onay;
          guncellenecek.aciklama = aciklama;
          guncellenecek.cekilen_resim = cekilen_resim;
          guncellenecek.k_tarih = DateTime.Now;
          guncellenecek.kaydedildi = true;
          guncellenecek.okundu = true;
          var input = await db.SaveChangesAsync();
          res.mesaj = "id " + kontrol_noktasi_id.ToString()+" Kaydedildi.";
          res.status = 1;
        }
      }
      else
      {
        res.mesaj = "Kayıt yapılmadı.";
        res.status = 0;
      }
      return new ObjectResult(res);
    }
  }
   //required object types
  public class rsm
  {
    public int id { get; set; }
    public byte[] resim { get; set; }
  }
  public class point_obj
  {
    public int kontrol_noktasi_id;
    public bool random_resim_cek;
    public byte[] cekilen_resim;
```

```
    public bool onay;
    public string aciklama;
  }
}
```

## Appendix 3 Unity Scripts with comment script

```
using System.Collections;
using System.Collections.Generic;
using UnityEditor;
using UnityEngine;
using UnityEngine.UI;
using UnityEngine.SceneManagement;
using UnityEngine.Networking;
using System;
using System.Text;
public class MainCnvsScript : MonoBehaviour
{
   //declaration variables and objects
  public GameObject onay_canvas;
  public GameObject capture_obj;
  public Text msg_text;
  public Text capture_msg_text;
  public Text kontrol_text;
  public Image Kontrol_resim;
  public Image cekilen_resim;
  public RawImage Kontrol_resim_raw;
  public InputField onay_aciklama;
  public Text onay_mesaj;
  public Text onay_baslik;
  public static List<point_obj> point_list = new List<point_obj>();
  public static point_obj current_point;
  public static kayit_obj kaydedilecek;
  point_obj yeni = new point_obj("Sunucuya Bağlanılamadı", 404, "", 1);
  resp res = new resp { status = 0, mesaj = "" };
   // Start is called before the first frame update
  void Start()
  {
    onay_canvas.SetActive(false); // set visible false. Buttons for suitable or not
suitable and optional description
    StartCoroutine(get_KontrolNoktasi()); // getting the control area via api
  }
   // Update is called once per frame
  void Update()
  {
    if (Input.GetKey("escape")) // press escape to quit
    {
      Application.Quit();
    }
  }
  public void TakePhoto() // take photo function for compulsory to take a picture
  {
    TakePicture(512);
  }
  IEnumerator get_KontrolNoktasi()// getting the control area via api
  {
    Kontrol_resim.enabled = true;
    onay_aciklama.text = "";
    onay_baslik.text = "";
    onay_mesaj.text = "";
    onay_canvas.SetActive(false);
           //clearing last control area properties
    List<IMultipartFormSection> formData = new List<IMultipartFormSection>();
    UnityWebRequest www =
UnityWebRequest.Post("http://YourUrlAdress/GetKontrol_liste.aspx", "");
    yield return www.SendWebRequest();
    if (www.result != UnityWebRequest.Result.Success)
    {
      Debug.Log(www.error);
      msg_text.text = "Sunucuya Bağlanılamadı!";
       // request return null // show message; Cannot connect api
    }
    else
    {
      if (www.downloadHandler.text != "")//request not null
      {
        Debug.Log(www.downloadHandler.text);
        try
        {
          current_point = JsonUtility.FromJson<point_obj>(www.downloadHandler.text);
                                    //json parsed. control area  showing
```

```
        }
        catch (Exception)
        {
                             //show error message
          kontrol_text.text = www.downloadHandler.text;
          current_point = null;
          Kontrol_resim.enabled = false;
        }
        if (current_point == null)
        {
        }
        else
        {
          foreach (var item in point_list)
          {
            Debug.Log(item.kontrol_noktasi + " " + item.okundu);
          }
           // control area properties showing
          kontrol_text.text = current_point.kontrol_noktasi;
          onay_baslik.text = current_point.soru;
          capture_obj.SetActive(false);
          Texture2D tex = new Texture2D(2, 2);
          tex.LoadImage(current_point.resim);
          tex.Apply();
          Kontrol_resim.sprite = Sprite.Create(tex, new Rect(0, 0, tex.width,
tex.height), new Vector2(0.5f, 0.5f));
          if (current_point.okundu)
          {
            onay_canvas.SetActive(true);//Buttons for suitable or not suitable and
optional description showing
          }
        }
      }
      else
      {
        Debug.Log(www.result + " " + www.downloadHandler.text);
        msg_text.text = "Sunucuda hata oluştu!";//error messages
      }
    }
  }
  public void onay_click()//suitable button
  {
    if (current_point.random_resim_cek) //If taking a photo is necessary, a photo
will be taken.
    {
      if (current_point.cekilen_resim == null)
      {
        if (capture_obj.activeSelf)
        {
          TakePhoto();
        }
        else
        {
          capture_obj.SetActive(true);
        }
      }
      else
      {
        Onayla_new();
         //suitable flag, variables and photo(optional) are sent to the API
      }
    }
    else
    {
      Onayla_new();//suitable flag,variables and photo(optional) are sent to the API
    }
  }
  public void red_click()
   //not suitable button
  {
    if (current_point.cekilen_resim == null)
    {
      if (capture_obj.activeSelf)
      {
        TakePhoto();
         //Photographs are required because they are marked as not suitable.
      }
```

```
      else
      {
        capture_obj.SetActive(true);
      }
    }
    else
    {
      Onayla_new(false);
       //not suitable flag,variables and photo are sent to the API
    }
  }
  public void Onayla_new(bool onay = true)
  {
    kaydedilecek = get_kayitObj(onay);
    string jsn = kaydedilecek.SaveToString();//saving photo and send to api
    StartCoroutine(Post("http://YourUrlAdress/ResimApi", jsn));
  }
  public resp parseRespJson(string jsn) // convert photo to json
  {
    resp rs = JsonUtility.FromJson<resp>(jsn);
    var ikili = jsn.Split(',');
    foreach (var item in ikili)
    {
      var it = item.Split('\"');
      bool kont = false;
      bool m_kont = false;
      foreach (var i in it)
      {
        if (i == "" || i == ":" || i == "{" || i == "}")
        {
          continue;
        }
        if (i == "status")
        {
          kont = true;
        }
        else if (kont)
        {
          var spl = i.Split(':');
          try
          {
            int idx = spl.Length - 1;
            rs.status = Convert.ToInt32(spl[idx]);
          }
          catch (Exception ex)
          {
            rs.status = 0;
            var a = ex;
          }
          kont = !kont;
        }
        if (i == "mesaj")
        {
          m_kont = true;
        }
        else if (m_kont)
        {
          rs.mesaj = i;
          m_kont = !m_kont;
        }
      }
    }
    return rs;
  }
   IEnumerator Post(string url, string bodyJsonString)//post to api
  {
    var request = new UnityWebRequest(url, "POST");
    byte[] bodyRaw = Encoding.UTF8.GetBytes(bodyJsonString);
    request.uploadHandler = (UploadHandler)new UploadHandlerRaw(bodyRaw);
    request.downloadHandler = (DownloadHandler)new DownloadHandlerBuffer();
    request.SetRequestHeader("Content-Type", "application/json");
    yield return request.SendWebRequest();
    if (request.downloadHandler.text != "")
    {
      try
      {
        res = parseRespJson(request.downloadHandler.text);
```

```
        onay_mesaj.text = res.mesaj;
        if (res.status == 1)
        {
          StartCoroutine(get_KontrolNoktasi());
        }
      }
      catch (Exception)
      {
        onay_mesaj.text = "Sunucuda hata oluştu.";
        Debug.Log(request.downloadHandler.text);
      }
    }
    else
    {
      onay_mesaj.text = "Sunucuya bağlanılamadı!" + request.responseCode;
    }
    Debug.Log("Status Code: " + request.responseCode);
    Debug.Log("res: " + request.result.ToString());
  }
  private void TakePicture(int maxSize)// take photo function
  {
    NativeCamera.Permission permission = NativeCamera.TakePicture((path) =>
    {
      Debug.Log("Image path: " + path);
      if (path != null)
      {
         // Create a Texture2D from the captured image
        Texture2D texture = NativeCamera.LoadImageAtPath(path, maxSize);
        if (texture == null)
        {
          Debug.Log("Couldn't load texture from " + path);
          return;
        }
         // Assign texture to a temporary quad and destroy it after 5 seconds
        GameObject quad = GameObject.CreatePrimitive(PrimitiveType.Quad);
        quad.transform.position = Camera.main.transform.position +
Camera.main.transform.forward * 2.5f;
        quad.transform.forward = Camera.main.transform.forward;
        quad.transform.localScale = new Vector3(1f, texture.height /
(float)texture.width, 1f);
        Material material = quad.GetComponent<Renderer>().material;
        if (!material.shader.isSupported) // happens when Standard shader is not
included in the build
          material.shader = Shader.Find("Legacy Shaders/Diffuse");
        var readTexture = duplicateTexture(texture);
        current_point.cekilen_resim = readTexture.EncodeToJPG();
        msg_text.text = "uzunluk "+current_point.cekilen_resim.Length.ToString();
        cekilen_resim.sprite = Sprite.Create(texture, new Rect(0, 0, texture.width,
texture.height), new Vector2(0.5f, 0.5f));
        Destroy(quad, 5f);
        capture_msg_text.text = "Resim Başarıyla Yüklendi.";
      }
    }, maxSize);
    Debug.Log("Permission result: " + permission);
  }
  Texture2D duplicateTexture(Texture2D source)
  {
    RenderTexture renderTex = RenderTexture.GetTemporary(
          source.width,
          source.height,
          0,
          RenderTextureFormat.Default,
          RenderTextureReadWrite.Linear);
    Graphics.Blit(source, renderTex);
    RenderTexture previous = RenderTexture.active;
    RenderTexture.active = renderTex;
    Texture2D readableText = new Texture2D(source.width, source.height);
    readableText.ReadPixels(new Rect(0, 0, renderTex.width, renderTex.height), 0, 0);
    readableText.Apply();
    RenderTexture.active = previous;
    RenderTexture.ReleaseTemporary(renderTex);
    return readableText;
  }
    // declaration objects
  public class point_obj
  {
    public string kontrol_noktasi;
```

```
    public int id;
    public string soru;
    public bool okundu;
    public bool kaydedildi;
    public int sira;
    public byte[] resim;
    public bool random_resim_cek;
    public byte[] cekilen_resim;
    public point_obj(string _kontrol_noktasi, int _id, string _soru, int _sira, bool
_okundu = false, bool _random_resim_cek = false, bool _kaydedildi = false, byte[]
_resim = null)
    {
      kontrol_noktasi = _kontrol_noktasi;
      id = _id;
      soru = _soru;
      resim = _resim;
      okundu = _okundu;
      kaydedildi = _kaydedildi;
      sira = _sira;
      random_resim_cek = _random_resim_cek;
    }
    public string SaveToString()
    {
      return JsonUtility.ToJson(this);
    }
  }
    // declaration objects
  public class kayit_obj
  {
    public int kontrol_noktasi_id;
    public bool random_resim_cek;
    public byte[] cekilen_resim;
    public bool onay;
    public string aciklama;
    public string SaveToString()
    {
      return JsonUtility.ToJson(this);
    }
  }
   //set variables to object
  private kayit_obj get_kayitObj(bool _onay = true)
  {
    kayit_obj kay = new kayit_obj
    {
      kontrol_noktasi_id = current_point.id,
      random_resim_cek = current_point.random_resim_cek,
      cekilen_resim = current_point.cekilen_resim,
      onay = _onay,
      aciklama = onay_aciklama.text
    };
    return kay;
  }
  public class resp
  {
    public int status { get; set; }
    public string mesaj { get; set; }
  }
}
```

## Appendix 4 Azure image processing demo script

```
using System;
using System.IO;
using System.Threading.Tasks;
using Microsoft.Azure.CognitiveServices.Vision.CustomVision.Prediction;
using Microsoft.Azure.CognitiveServices.Vision.CustomVision.Prediction.Models;
// try link
/*https://learn.microsoft.com/tr-tr/azure/ai-services/Custom-Vision-
Service/quickstarts/image-classification?tabs=linux%2Cvisual-
studio&pivots=programming-language-csharp */
namespace CustomVisionPredictionExample
{
  class Program
  {
    private static string predictionEndpoint = "https://<your-prediction-
resource>.cognitiveservices.azure.com/";
    private static string predictionKey = "<your-prediction-key>";
    private static Guid projectId = Guid.Parse("<your-project-id>");
    private static string publishedModelName = "<your-iteration-name>"; // Genelde
'Iteration1'

    static async Task Main(string[] args)
    {
      var predictionClient = new CustomVisionPredictionClient(
        new ApiKeyServiceClientCredentials(predictionKey))
      {
        Endpoint = predictionEndpoint
      };
      string imagePath = @"C:\your\local\image.jpg";
      using (var imageStream = File.OpenRead(imagePath))
      {
        var result = await predictionClient.ClassifyImageAsync(projectId,
publishedModelName, imageStream);
        Console.WriteLine("Tahmin Sonuçları:");
        foreach (var prediction in result.Predictions)
        {
          Console.WriteLine($"{prediction.TagName}: {prediction.Probability:P1}");
        }
      }
    }
  }
}
```

# Appendix 5 Quality & Hygiene Control Experience Survey

**AR Glasses Quality & Hygiene Control Experience Survey**

## 1 General Experience

**1.** How easy did you find the process of scanning the environment using AR glasses?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**2.** How clear and understandable was the application interface (screen, commands, menus)?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**3.** Does the application adequately cover all quality and hygiene control criteria?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

---

## 2 Performance and Efficiency

**4.** How would you rate the scanning accuracy of the AR glasses (object recognition, area detection, etc.)?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**5.** How does the inspection time with AR glasses compare to traditional methods?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**6.** Did the AR glasses save you time in reporting and data collection?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

---

## 3 Ergonomics and User Comfort

**7.** Did the weight or ergonomics of the glasses cause you any discomfort?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**8.** How smoothly did the voice command or touch control system operate?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

---

## 4 Overall Satisfaction

**9.** Overall, how satisfied are you with the quality and hygiene control experience using AR glasses?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

**10.** Would you like to use this system regularly in quality control processes?
Worst ☐ 1 ☐ 2 ☐ 3 ☐ 4 ☐ 5 Best

## Appendix 6 Survey Results (10 Employees – 10 Questions)

| Employee | Q1 | Q2 | Q3 | Q4 | Q5 | Q6 | Q7 | Q8 | Q9 | Q10 | Average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| E1 | 5 | 5 | 5 | 4 | 5 | 5 | 4 | 5 | 4 | 5 | 4.7 |
| E2 | 4 | 5 | 5 | 4 | 4 | 5 | 5 | 5 | 4 | 5 | 4.6 |
| E3 | 5 | 4 | 5 | 4 | 5 | 4 | 5 | 5 | 5 | 4 | 4.6 |
| E4 | 5 | 5 | 4 | 5 | 5 | 5 | 4 | 5 | 5 | 4 | 4.7 |
| E5 | 4 | 5 | 4 | 4 | 5 | 5 | 4 | 4 | 5 | 5 | 4.5 |
| E6 | 5 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 5 | 5 | 4.9 |
| E7 | 4 | 4 | 5 | 4 | 5 | 5 | 4 | 5 | 4 | 5 | 4.5 |
| E8 | 5 | 4 | 5 | 5 | 4 | 5 | 5 | 4 | 5 | 4 | 4.6 |
| E9 | 5 | 5 | 4 | 4 | 5 | 5 | 5 | 5 | 4 | 5 | 4.7 |
| E10 | 4 | 5 | 5 | 5 | 5 | 4 | 5 | 5 | 4 | 5 | 4.7 |