FINAL PROJECT - TI23485

APPLICATION OF SMART INSPECTION WITH STATISTICAL PROCESS CONTROL IN VISUAL QUALITY INSPECTION OF TEMPEH

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Surabaya

2026

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APPROVAL SHEET

APPLICATION OF SMART INSPECTION WITH STATISTICAL PROCESS CONTROL IN VISUAL QUALITY INSPECTION OF TEMPEH

UNDERGRADUATE THESIS

Submitted as a requisite

To acquire of Bachelor of Engineering at

Undergraduate study program of Industrial Engineering

Department of Industrial and Systems Engineering

Faculty of Industrial Technology and Systems Engineering

Institut Teknologi Sepuluh Nopember

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Hereby declare that the final project with the title of "APPLICATION OF SMART INSPECTION WITH STATISTICAL PROCESS CONTROL IN VISUAL QUALITY INSPECTION OF TEMPEH" is the result of my own work, is original. and is written by following the rules of scientific writing.

If in the future there is any discrepancy with this statement, then I am willing to accept sanctions in accordance with provisions they apply at Institut Teknologi Sepuluh Nopember.

Surabaya, 20 January 2026

Acknowledge
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ABSTRACT

APPLICATION OF SMART INSPECTION WITH STATISTICAL PROCESS CONTROL IN VISUAL QUALITY INSPECTION OF TEMPE

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Abstract

Tempeh, a traditional Indonesian fermented soybean food, is widely consumed and valued for its nutritional and cultural significance. However, quality inspection in small and medium enterprises (SMEs) is still largely performed manually, leading to inconsistency, subjectivity, and inefficiency. Despite the importance of quality inspection, there has been little research on developing affordable, AI-based visual inspection frameworks tailored for traditional food SMEs. This study aims to address that gap by proposing a low-cost AI-assisted visual inspection system for Tempe, capable of detecting defects based on texture, granule distribution, color, and mycelium coverage. The methodology involves controlled image capture, AI prompt optimization, and the application of statistical process control (SPC) tools such as Xbar S-Chart, NP-Chart, and C-Chart to evaluate and monitor product quality. Data are collected from self-documented photos with 40 replications to ensure statistical reliability. Controlled image capture and standardized AI prompts were used to classify defects based on texture, granule dispersion, color, and mycelium coverage. SPC charts (Xbar-S Chart, NP-Chart and C-Chart) monitored process stability, while ANOVA confirmed that variations in defect detection were statistically significant, validating the responsiveness of the AI system. By optimizing lighting arrangements, specifically using a smartphone flashlight positioned centrally above the sample, shadows were minimized, enabling consistent detection. Overall, AI assisted inspection offers SMEs a reliable, affordable, and scalable solution to enhance product quality, minimize financial losses, and strengthen competitiveness in the tempeh industry.

Keywords: Artificial intelligence, quality control, defect detection, statistical process control, low-cost inspection.

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ABSTRAK

PENERAPAN KECERDASAN BUATAN DENGAN PENGENDALIAN PROSES STATISTIK DALAM INSPEKSI KUALITAS VISUAL TEMPE

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Abstrak

Tempe, sebagai makanan tradisional Indonesia berbahan dasar kedelai fermentasi, merupakan produk yang banyak dikonsumsi serta memiliki nilai gizi dan budaya yang tinggi. Namun demikian, proses inspeksi kualitas pada usaha kecil dan menengah (UKM) masih dilakukan secara manual, sehingga menimbulkan ketidak konsistenan, subjektivitas, dan inefisiensi. Meskipun inspeksi kualitas memiliki peran penting, penelitian mengenai pengembangan kerangka inspeksi visual berbasis kecerdasan buatan (AI) yang terjangkau dan sesuai dengan kebutuhan UKM pangan tradisional masih sangat terbatas. Penelitian ini bertujuan untuk mengisi kesenjangan tersebut dengan mengusulkan sistem inspeksi visual berbantuan AI berbiaya rendah untuk tempe, yang mampu mendeteksi cacat berdasarkan tekstur, distribusi granula, warna, dan cakupan miselium. Metodologi penelitian meliputi pengambilan citra secara terkontrol, optimasi perintah (prompt) AI, serta penerapan alat Statistical Process Control (SPC) seperti Xbar-S Chart, NP-Chart, dan C-Chart untuk mengevaluasi dan memantau kualitas produk. Data diperoleh dari foto terdokumentasi sendiri dengan 40 kali replikasi guna memastikan reliabilitas statistik. Pengambilan citra terkontrol dan perintah AI yang terstandarisasi digunakan untuk mengklasifikasikan cacat berdasarkan tekstur, sebaran granula, warna, dan cakupan miselium. Diagram SPC (Xbar S-Chart, NP-Chart, dan C-Chart) digunakan untuk memantau stabilitas proses, sementara uji ANOVA mengonfirmasi bahwa variasi dalam deteksi cacat signifikan secara statistik, sehingga memvalidasi responsivitas sistem AI. Dengan mengoptimalkan pengaturan pencahayaan, khususnya menggunakan lampu kilat (flashlight) smartphone yang diposisikan secara sentral di atas sampel, bayangan dapat diminimalkan sehingga deteksi menjadi konsisten. Secara keseluruhan, inspeksi berbantuan AI menawarkan bagi UKM solusi yang andal, terjangkau, dan dapat diskalakan untuk meningkatkan kualitas produk, meminimalkan kerugian finansial, serta memperkuat daya saing dalam industri tempe.

Kata Kunci: *Artificial Intelligence(AI)*, pengendalian kualitas, deteksi cacat, produk, pengendalian proses statistik, inspeksi berbiaya rendah.

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PREFACE

Praise be to Allah Subhanahu wa Ta'ala for His abundant blessings and grace, which have enabled the author to complete this undergraduate thesis as a requirement for obtaining the Bachelor of Science degree in Biology at the Faculty of Industrial Technology and Systems Engineering, Institut Teknologi Sepuluh Nopember, Surabaya. The author would like to express sincere gratitude to:

1. Mrs. Retno Widyaningrum, S.T., M.T., M.B.A., Ph.D., as the advisor and Mr. Yudha Prastyawan, S.T., M.T., as the Co-Advisor, for their continuous guidance, invaluable knowledge, constructive suggestions, and support throughout the completion of this final project.
2. Mrs. Anny Maryani, S.T., M.T., and Mr. Satrio Samudro Aji Basuki, S.T., M.T., M.B.A., as the thesis examiners, for their valuable knowledge, insightful criticism, and constructive suggestions that greatly contributed to the improvement of this thesis.
3. The author's beloved parents, Mr. Mohammad Taufik Hidayat and Mrs. Wiwiek Sisyati, as well as the author's siblings, Dhiya Fathimah and Mohammad Zaki Arkan, for their endless prayers, unwavering support, encouragement, and motivation throughout the author's academic journey from beginning to completion.
4. The author's research colleagues and loved ones, Yasmin Nur Shabrina, Corien Fakhirah Rahmadian, Nurul Khorina Ilmi, and Salmaa Azzah together with all colleagues and members of the academic community of the Department of Industrial and Systems Engineering, for their assistance, encouragement, and motivation during the completion of this final project.

This final project represents the author's best effort as a contribution to the advancement of scientific knowledge. Constructive comments and suggestions are sincerely welcomed to improve the quality and usefulness of this work.

Sincerely,

Aisyah

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TABLE OF CONTENT

LIST OF FIGURE

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LIST OF TABLE

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CHAPTER I
INTRODUCTION

1.1 Background

Indonesia has long been known for both its rich cultural heritage and its profusion of food production. Although the quality of Indonesian food has declined because of its advantageous location at the crossroads of international trade between China, India, and Middle East (Santosa, 2023), a number of foods from Indonesia, including sate, nasi goreng, and rendang, have become more well-known over time. It has shown that a great way to demonstrate a people's traditions and culture is through ethnic cuisine. Historically, people have used the fermentation process to extend the shelf life of food since the prehistoric period, and this knowledge has been transmitted as it reflects the social, technological, and economic circumstances of the area where the foods are produced (Santosa, 2023). Since then, fermentation techniques have gained popularity, both in and outside of Indonesia, and product like Tempeh is considered as comfort food among locals. This can be proven by the consumption of Tempeh in some cities of Indonesia as can be seen below,

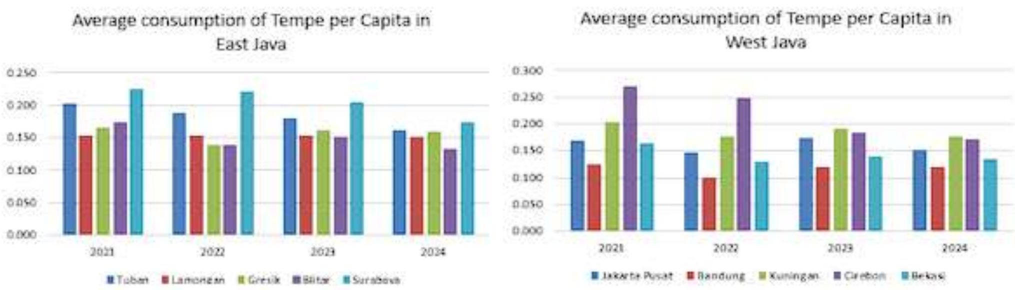

Figure 1.1 Average Tempeh Consumption in Indonesia

Source: *Badan Pusat Statistik*

The consumption rate both in East Java and West Java has steady value between 0.100-0.300 with the earliest from 2021, and the latest is from 2024.

Tempeh is an Indonesian culinary product made from fermented soybeans. For hundreds of years, it has been an essential component of Indonesian cuisine. Rhizopus species, which produce white mycelia that cover and bind soybean grains together to create a compact cake, are involved in the fermentation of Tempeh. This item is frequently referred to as "vegan meat" and is generally acknowledged as a very nutrient-dense, healthful diet that contains about 90% protein, and is a good source of vitamins and minerals (Ahnan et al,2021). Despite its popularity, there has not been proper automated process of making it, because of the complicated process and it still needs manual work to achieve the best quality. To produce tempeh properly, soybeans is washed to remove dirt, pebbles. Remove the skins and the black eye to avoid a harsh taste and preserve texture. As excess heat or moisture can hinder Rhizopus oryzae growth, the beans must be dry. Finally, maintaining the right fermentation temperature is crucial for optimal fungal development (UNS, 2020). The manual labor performed by human hands may have an impact on the hygienic conditions and quality of tempeh products. Workers' perspiration during the fermentation process and the potential for bacterial contamination from talking or sneezing are two effects of hygiene (Ahnan et al, 2021).

Figure 1.2 Manual production of Tempeh

Source: *Kampung Tempe*

Defect detection used to rely on expert examination, but this method was unreliable because of its high subjectivity, which frequently produced conflicting results. Furthermore, manual inspection is inadequate for many contemporary needs since it cannot conduct real-time analysis. Conventional methods for detecting surface flaws have been around for a while. When the defect and backdrop have a sharp contrast, these traditional image processing techniques work well. These techniques are usually divided into three divisions according to the properties of the product: texture-based, color-based, and shape-based (Saberironaghi, 2023).

Figure 1.3 Quality Parameter of Tempeh

Source: Kompas.com

Manufacturers began using technologies like X-ray imaging and machine vision systems to improve the precision and effectiveness of these examinations. Even while these techniques improved detection rates, their flexibility and adaptation to various product kinds and flaws remained limited (Kaplan, 2024). Manufacturing defect identification is being revolutionized by artificial intelligence (AI), which makes automated, faster, and more accurate inspection possible. AI examines data using machine learning to find trends and spot abnormalities, enhancing product quality and cutting down on waste (Kaplan, 2024).

The ability of a machine or computer program to simulate cognitive processes like learning and problem-solving that are connected to the human mind is known as artificial intelligence, or AI. Artificial intelligence (AI) systems are frequently faster and more accurate than humans in analyzing complex data, identifying patterns, and making judgments. Without explicit programming, these systems may learn and grow from experience thanks to deep learning and machine learning. AI aims to create software that can reason with input and explain with output, enabling a higher degree of automation across a range of industries, including manufacturing (Kaplan, 2024). Artificial intelligence (AI) systems can analyze hundreds or even thousands of photos in a fraction of the time that a human inspector would need which would increase accuracy and efficacy. Furthermore, unlike human inspectors, AI systems can work continually without becoming tired, which boosts productivity. Because faulty items can be quickly identified and removed from the production line, the use of AI also helps to reduce waste.

Manufacturing defect identification is being revolutionized by artificial intelligence (AI), which makes automated, faster, and more accurate inspection possible. AI examines data using machine learning to find trends and spot abnormalities, enhancing product quality and cutting down on waste. The transition from manual and conventional techniques to AI-powered systems improves productivity and facilitates wider uses in process optimization, inventory management, and predictive maintenance. AI's influence on manufacturing is predicted to increase much more as it develops (Leberruyer, 2023). Despite technological developments, more than 65% of firms continue to use manual inspection techniques, resulting in 40% of product recalls. This reliance leads to enormous financial losses, with manufacturers globally losing an estimated $1.3 trillion each year owing to quality failures (Leberruyer, 2023).

Small and Medium Enterprises have drawn attention because of their labor-intensive production methods and potential to create jobs, particularly in economies with a labor surplus. Many have therefore demanded that policies be put in place to assist these businesses.

Figure 1.4 Tempeh storage in *Kampung Tempe*

Source: *Kampung Tempe*

Labor intensity alone, however, is insufficient to maintain employment; long-term viability, or the capacity to endure in the market, is just as important. For SMEs competing freely in the market, sustained profitability is essential. Small firms with higher production costs face constant pressure to maintain profitability. These costs depend on production methods (e.g., capital intensity) and input prices (Seth, 1995). Hence, this study aims to improves the inspection system of SMEs that still have financial and technological concerns to remain in competitive market, with less expensive and quicker solutions that do not sacrifice product quality.

1.2 Problem Statement

1) How could the extensive use of inorganic fillers to reduce manufacturing costs be undermining customer trust and harming the reputation of SMEs in the local food industry?
2) What is the impact on product safety and quality when SMEs, due to a lack of inexpensive alternatives, are forced to rely on error-prone manual inspection that fails to detect such contaminants?
3) How can SMEs efficiently identify dangerous foreign contaminants in their products when automated inspection methods are prohibitively expensive?
4) How can the defect rate identified through Statistical Process Control (SPC) be combined with the proposed inspection systems' error rate to measure financial losses and support the adoption of AI-based quality control?

1.3 Limitations and Assumptions

1.3.1 Limitations

1) The research focuses on detecting visual defects such as texture, color, and shape using Artificial Intelligence (AI) Gemini by Google.
2) Case studies limited to Small and Medium Enterprises (SMEs).
3) Data collection is limited into images taken in the morning when Tempeh is still fresh.

1.3.2 Assumptions

1) To detect the quality of Tempeh, additional light is added from bedside lamp.
2) To detect defects, the light is adjusted with only natural lights without any additional light.
3) The parameter for defects is color, mycelium percentage, and whether there is any cracked form in the Tempeh.

1.4 Research Goal

1) To improve inspection quality through automated inspection.
2) To map inspection needs that can be solved using AI.
3) To reduce reliance on manual inspection methods that are prone to subjectivity.
4) To conduct trials for more accurate AI usage procedures.
5) To ensure the solution remains scalable for resource-limited SMEs.

1.5 Research Benefit

1) Eliminates any initial financial barrier, as it requires absolutely no investment in expensive hardware licenses.
2) The expected results will be designed with the user in mind, featuring an intuitive, step-by-step procedure that is easy for anyone to follow.

3) The ongoing operational expenses will be kept to an absolute minimum, making this an exceptionally low-cost procedure for SMEs.
4) Straightforward and simple framework that can be mastered quickly, minimizing both training time and the potential for errors.
5) There will be no need to use any sophisticated software or machinery, as the entire task is accomplished without any complicated tools.

1.6 Writing System

To provide a clearer understanding of this study, the materials presented in this undergraduate thesis are organized into several sub-chapter as outlined below,

CHAPTER I INTRODUCTION

This section explains the background of Tempeh as a traditional food, the challenges SMEs face with manual inspection, and the research gap. It outlines the problem statement, objectives, and benefits of developing an affordable AI based inspection system.

CHAPTER II LITERATURE REVIEW

The review covers SMEs' role in food production, quality control tools, and previous studies on AI inspection in agriculture. It compares traditional image processing with AI assisted methods and provides the theoretical basis for SPC and intelligent inspection.

CHAPTER III METHODOLOGY

This section describes the research design, data collection using controlled Tempeh images, and AI prompt engineering for defect detection. It explains the use of SPC tools (Xbar-S chart, NP-Chart, C-Chart) and simple instruments such as smartphone camera and Minitab.

CHAPTER IV RESULT AND DISCUSSION

Findings from control charts show stable quality with deviations in certain weeks. AI inspection detects these variations consistently, reduces human bias, and enables real-time monitoring. The discussion highlights improved accuracy, cost efficiency, and benefits for SMEs.

CHAPTER VI CONCLUSION & RECOMMENDATION

The study concludes that AI assisted inspection with SPC provides a practical, low-cost solution for SMEs, improving product quality and competitiveness. Limitations are noted, and future work is suggested to expand datasets and integrate more advanced tools.

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CHAPTER II
LITERATURE REVIEW

2.1 Previous Study

The table below shows previous research that has been done for this topic:

Table 2.1 Previous Study

Writer	Title	Year	Content
Anifowose, Oluwaseun & Ghasemi, Matina & Olaleye, Banji	Total Quality Management and Small and Medium-Sized Enterprises' (SMEs) Performance: Mediating Role of Innovation Speed	2022	This study focuses on investigating the role of innovation speed in mediating the relationship between total quality management and small and medium-sized enterprise performance. Cross-sectional data from 484 Nigerian small and medium-sized manufacturing enterprises were collected using judgmental sampling, which was targeted at the owners and managers of small-scale manufacturing enterprises within Nigeria. The obtained data were evaluated using both descriptive and inferential statistical techniques. Hence, the heuristic model for the relationship was subjected to a string of tests using the partial least squares structural equation modeling technique.
Juan Carlos Miranda et al.	Fruit sizing using AI: A review of methods and challenges	2023	Fruit size at harvest is an economically important variable for high-quality table fruit production in orchards and vineyards. In addition, knowing the number and size of the fruit on the tree is essential in the framework of precise production, harvest, and postharvest management. A prerequisite for analysis of fruit in a real-world environment is the detection and segmentation from background signal. In the last five years, deep learning convolutional neural network have become the standard method for automatic fruit detection, achieving F1-scores higher than 90 %, as well as real-time processing speeds. At the same time, different methods have been developed for, mainly, fruit size and, more rarely, fruit maturity estimation from 2D images and 3D point clouds. These sizing methods are focused on a few species like grape, apple, citrus, and mango, resulting in mean absolute error values of less than 4 mm in apple fruit. This review provides an overview of the most recent methodologies developed for in-field fruit

Writer	Title	Year	Content
			detection/counting and sizing as well as few upcoming examples of maturity estimation.
Vibhute, Kshitiy	Artificial Intelligence Based Grading System for Mango Fruit- A Review	2022	In mango-processing industries and during export of mango accurate grading and classification is an essential post-harvest unit operation. However, these processes are carried out manually which are tedious and leads to some errors and low accuracy that directly effects its quality. Thus, substituting the traditional labor-intensive technique by automated technologies based on artificial intelligence will not only increase operation efficiency but also optimize accuracy, labor saving, and appropriate handling of fruits. Also, premium quality fruits can be sorted separately for export. The main objective of this article is to study methodology which utilizes digital fuzzy image processing for grading mangoes and development of effective algorithm for segregating mangoes with greater accuracy as compared to manual grading. Also, this study focusses on computer vision-based grading technique which uses image processing and extraction of feature based on grading parameter by combining artificial intelligence and many more grading systems based on different parameter. This study will help farmers to evaluate mango quality before export and procure profitable income.

2.2 Background Theory

2.2.1 Small and Medium Enterprises

Micro, Small, and Medium Enterprises (SMEs) are a vital component of Indonesia's economy, contributing over 7,034.1 trillion Rupiah, or around 61% of the nation's GDP in 2020. They make up 99.99% of all businesses in the country and provide employment for more than 96% of the workforce. There are approximately 63.4 million micro enterprises, 783.1 thousand small enterprises, and 60.7 thousand medium enterprises, with these figures continuing to grow over time. Due to their vast presence, the performance and sustainability of SMEs are crucial for Indonesia's economic growth and stability. Most are concentrated in Java, with the largest share in the food and beverage sector (37.5%), followed by woodwork and crafts, and then clothing (Soetopo, 2025).

Data from the center for statistics (BPS) shows that only 25.92% of businesses in Indonesia use digital technology in their operations, with 75% of these located on the island of Java. Most are traditional businesses that rely primarily on messaging services and social media for their activities. Despite over 53% of the population having internet access, the adoption of internet-based technologies among businesses remains relatively low (Soetopo, 2025). With such reality, it is essential for survival and growth of SMEs. Digital tools can help them streamline operations, reach wider markets, and compete more effectively, even with limited resources. The use of affordable innovations, such as artificial intelligence (AI), offers a particularly promising opportunity. AI-powered solutions can automate repetitive tasks, improve customer targeting, forecast demand, and even enhance product quality—all at relatively low costs compared to traditional method (Soetopo, 2025).

2.2.2 Control Chart

Good quality refers to products whose specifications meet the standards set by the company. Quality control aims to minimize or eliminate products that fail to meet these standards. Commonly, seven key tools are used in quality control: flow charts, check sheets, histograms, control charts, scatter diagrams, fishbone diagrams, and Pareto diagrams (Sengoz, 2018).

Despite these measures, deviations in quality still occur and need to be addressed, often stemming from human factors, methods, or machinery. Implementing quality control allows companies to identify the root causes of issues, thereby preventing major problems in the future. Factors influencing quality control include the capabilities of the production process, the accuracy of specifications, the level of non-conformance detected, and the available quality budget. To address quality issues effectively, businesses often rely on tools such as histograms, Pareto charts, fishbone diagrams, and scatter diagrams, check sheets, stratification, and control charts. One of 7 tools of quality used in this research is control chart, which is a graphical tool based on the normal distribution curve. On the y-axis, it displays a specific quality characteristic of a product or process, measured in appropriate units. The x-axis represents either time intervals or sample numbers. The chart includes a center line indicating the average value of the measured characteristic or its nominal value. The upper limit marks the upper control limit (UCL), while the lower limit represents the lower control limit (LCL). Data points are plotted in sequence, and the resulting pattern on the chart is then analyzed to interpret process performance.

1. Standard deviation control chart (Xbar S-chart)
   A standard deviation control chart monitors process variation by using standard deviation values, making it more detailed than charts based only on averages. It is especially useful for large or varying sample sizes, as it shows the overall spread of data from the mean and provides a broader view of process stability. Unlike range charts, which highlight differences between individual measurements, standard deviation charts display the general distribution pattern. This means two samples can have the same range but very different standard deviations, leading to different interpretations.
2. Control chart for number of nonconforming units (NP-Chart)
   An np-control chart is a type of control chart used to track the number of nonconforming items. Unlike p-control charts, it does not calculate proportions because the total production quantity remains constant for each day, shift, or production run. This eliminates the need for repeated division to find a proportion. Examples include counting defective skirts produced in a single day or the number of faulty yarn cones in one shift when the production volume is the same each time.
3. Control Chart for nonconformities (C-Chart)
   A c-control chart is used to monitor the number of nonconformities per fixed unit. In this case, the focus is on counting defects, with the unit of measurement kept constant for all collected data. Since the basis of comparison remains the same, there is no need for repeated division when calculating values. For example, in textiles, this could involve recording the number of imperfections—such as thick spots, thin spots, or neps—per 1 kilometer of yarn.

2.2.3 Implementation process of OpenAI

Generative AI systems like ChatGPT and Gemini are among the most outstanding innovations of OpenAI, an artificial intelligence (AI) company that creates and provides a wide range of technological services. ChatGPT is a flexible tool for a range of applications since it is a sophisticated language model that is made to comprehend and produce text that is appropriate for its environment, while **Gemini** is capable of accurately and efficiently handling complicated tasks, and they introduced the first model to outperform human experts in the Massive Multitask Language Understanding (MMLU) benchmark. Beyond basic communication, technology can help with more difficult tasks including analyzing photographs, extracting important information from complicated documents, creating reports, and even helping with creative writing. These features demonstrate how useful and revolutionary this technology is in today's digital worlds (Afandi and Kurnia, 2023).

Artificial intelligence (AI) is a machine that has capacity to mimic aspects of human intelligence, such as learning, reasoning, problem-solving, and decision-making. In contrast to computer systems, artificial intelligence (AI) can modify its responses in response to patterns in new input rather than only carrying out pre-programmed instructions. Because of its adaptability, AI can get better over time, increasing its precision and efficiency in a variety of usage. The impact of artificial intelligence (AI) is evident in many different fields, such as healthcare systems that use AI for patient monitoring and diagnosis, educational platforms use AI for individualized learning experiences, and the automobile sector uses AI for safety optimization and autonomous driving (Afandi and Kurnia, 2023).

Prompt engineering has become a crucial strategy to optimize the performance of AI models such as ChatGPT. In order to direct the AI system to provide precise, pertinent, and context-sensitive responses, prompt engineering entails meticulously planning and organizing instructions, or prompts. AI outputs are heavily reliant on the input they receive, therefore iterative experimentation and modification are frequently necessary to get the best results. Prompt engineering ensures that the technology is more in line with user intentions and needs by enhancing human-AI communication, which closes the gap between raw computational power and meaningful human-centered applications (Mesko, 2023).

2.2.4 Intelligent inspection

Technologies like computer vision (CV) and machine learning (ML) are transforming inspection processes by enhancing the precision and effectiveness of damage identification. Deep learning (DL) makes it possible to detect flaws in images that could go unnoticed during standard visual inspections, assisting experts in more accurately labeling and categorizing them. These CV-based techniques are used in AI-assisted visual inspection to evaluate and decipher digital images, enabling systems to be trained to identify characteristics like cracks, surface deterioration, or irregular patterns. Early problem detection allows for the implementation of preventative maintenance before problems escalate and need expensive repairs or present a safety risk. AI-assisted inspection also speeds up operations and makes digital record-keeping easier, guaranteeing that inspection results can be reviewed and verified later. In addition to improving decision-making, the integration of AI and human knowledge reinforces long-term quality control and preservation initiatives (Mishra, 2024).

The described approach can be extended in several ways, such by including more specific details, improving the algorithms, using insights from related issues, or changing the way outcomes are monitored and interpreted. Its adaptability comes from combining advanced AI approaches with human input. In many fields, dependable, effective inspection with little maintenance is crucial. AI-based inspection is a useful approach to speed up procedures and cut down on development time because of its automated systems, simplicity of setup, and capacity to record expert knowledge. It is sufficient to gather and categorize actual data during operations rather than depending on predetermined error lists. As a result, a more accurate knowledge base is produced that may be used for future work that is comparable (Trampert, 2025).

2.2.5 Quality control

Quality Control (QC) is the process of establishing quality specification, to ensure that the products comply with those specification, and continuously enhancing overall product quality. The overall QC process keeps evolving in response to the dynamic nature of manufacturing environments. Methods like Design of Experiments (DoE), Failure Mode and Effects Analysis (FMEA), Quality Function Deployment (QFD), and Acceptance Sampling each provide distinct frameworks for product inspection. Although these techniques have proven highly effective in quality control, modern production lines now present the possibility of inspecting 100% of products. Advances in sensor networks and artificial intelligence have made continuous product quality assessment a practical reality (Sundaram, 2023). Inspectors usually maintain quality control by first reading blueprints and specifications, then monitoring operations to ensure that they meet production standards, recommending changes to the assembly or production process, and finally inspecting, testing, or measuring materials or products being produced (Verma, 2020).

Quality control involves visual inspection, where research on the topic has been ongoing since the early 20th century to identify factors influencing accuracy. A consistent finding across studies is the limitation of human inspectors, with defect detection errors often falling between 20% and 30% (See, 2015). Despite the extensive body of work in this area, there remain three aspects of visual inspection that have yet to be fully explored. there are four-step visual inspection operation that consists of presenting the product for inspection, examine and analyze the product for possible flaws/defects, assess the flaws/defects and determine if it falls out of the desired specifications, and to accept or reject the item based on the decision (Sundaram, 2023).

2.2.6 Comparison with inspection system using image processing

Color distribution, texture patterns, regional forms, edge consistency, and object-based classification are some of the features that may be evaluated and extracted from images. Advanced applications in these systems, such as large-scale picture comparison for matching or random visual inspections, often need great processing resources. Image segmentation is strongly related to image analysis, in contrast to image enhancement or restoration, which concentrate on enhancing visual quality. In order to better process images in the stages of display, recognition, or classification, segmentation acts as a prelude by breaking it up into useful sections (Peker, 2023).

Image processing is a computational approach that relies heavily on programming code, commonly implemented in software such as MATLAB. MATLAB's Image Processing Toolbox provides a wide range of functions and operations, including opening image files, decomposing images into RGB color channels, performing segmentation to isolate regions of interest, conducting image analysis for feature extraction, and applying enhancement techniques to improve visual quality. The process generally begins with image acquisition, where the captured picture must be taken from an optimal angle to ensure that the subject is clearly visible and well-defined. Once obtained, the image is typically represented in RGB format and later converted into a grayscale image for further analysis, since grayscale simplifies processing by reducing computational complexity without losing essential structural information. However, during each conversion step—from RGB to grayscale or other transformations—various types of noise may be introduced, such as Gaussian noise, salt-and-pepper noise, or speckle noise. These disturbances can degrade the accuracy of subsequent analysis. To address this issue, adaptive filtering methods are commonly employed, as they are capable of dynamically adjusting their parameters based on local image characteristics, resulting in more effective noise suppression while preserving critical details such as edges and textures (Patel, 2013).

According to Dalila Say, the precision of defect detection can be greatly increased by using AI techniques to analyze inspection images, which would increase the process's overall efficiency. AI systems become more dependable in spotting even minute anomalies by improving algorithms through enhanced feature extraction, training data, and adaptive learning strategies. Furthermore, using cutting-edge imaging technologies like CT scans or infrared thermography improves the capacity to precisely identify and categorize flaws. When combined, these enhancements provide a more reliable and efficient inspection process, which minimizes human error and increases product dependability (Say, 2025).

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CHAPTER III
METHODOLOGY

3.1 Methods

Below is the flowchart of this study that contains all the steps from problem identification stage until the conclusion and recommendation stage,

Figure 3.1 Flowchart of Thesis

3.2 Research Sequences

3.2.1 Problem Identification

The research approach began with the identification of real-world challenges encountered in the community. This fundamental stage was critical for identifying relevant and important problems that might be addressed through methodical study. Following that, a problem statement was developed to offer a focused and structured basis for the research. The issue statement not only influenced the development of research questions, but also determined the direction of data collecting and analysis.

To achieve the research's objective, a thorough examination of relevant literature was conducted. This required reviewing scholarly literature, earlier studies, and other trustworthy sources that provided theoretical insights relevant to the problem. These references helped to reinforce the research framework and ensured that the study was based on existing information.

The principle of product quality was used as a primary analytical technique to determine whether the Tempe under observation has a good quality. This term incorporates various quality parameters, including texture, appearance (granules), color, and ratio of mycelium with the soybeans all of which are important indicators of a product's quality.

Furthermore, the principle of automation was incorporated into this research to help with the quality inspection process. Automation, in this context, refers to the use of technology, primarily artificial intelligence, to analyze product qualities faster and cheaper with more consistent and accuracy than manual approaches.

The problem-solving strategy used in this research included the strategic formulation of prompts aimed at improving the performance and reliability of AI responses. To improve the accuracy of AI-generated assessments, prompts were created using precise and contextually relevant language based on past research findings.

Data was gathered through direct observation of Temphe, assisted by a smartphone camera. This technology permitted a real-time recording of visual data, which was then processed to establish the product's quality attributes. The use of simple instruments like smartphone cameras reflects the research's emphasis on an accessible and less expensive technical alternatives.

3.2.2 Data Collection

An organized data collecting methodology is essential for accurately assessing product quality and ensuring consistency across multiple samples. The data collection process focuses on four primary visual and structural metrics that are important indications of product quality such as texture, granule structure, color, and the area covered by mycelium. These characteristics were chosen because of their immediate impact on consumer perception and the potential to reveal underlying quality flaws.

To control for variability and assure statistical significance, ten replications of each product sample were done. This repetition enables the analysis to capture a representative set of potential flaws or variances. Furthermore, attempts were taken to standardize external conditions during data collecting, particularly the product's placement and lighting arrangement. Controlled illumination is required in image-based analysis to avoid distortion of color and texture data, which could result in inaccurate AI outputs. These criteria help to verify that the input data has high integrity and consistency between samples.

3.2.3 Quality Testing with the help of AI

The use of AI into the quality assurance workflow constitutes a considerable shift from traditional inspection methods, providing more accuracy, speed, and consistency. In this work, Gemini AI (a generative AI tool) was used to help with visual quality testing of product samples.

To make this possible, four distinct Gemini accounts were created. Each account was set up to handle a set of ten product photos, which were preprocessed using the settings specified in the data collecting step. Such is an example of how the process of successful prompts in Gemini,

Table 3.1 Example of Result obtained from Gemini

Image	Visual	Texture	Granule	Color	Mycelium Coverage (%)	Scalability to Sell
	Symmetrical	Quite Dense	Apparent	Brown	65	Unprofitable
	Asymmetrical	Less Dense	Very Apparent	Brown	55	Unprofitable
	Symmetrical	Quite Dense	Apparent	Brown	65	Unprofitable
	Asymmetrical	Quite Dense	Apparent	Brown	65	Unprofitable
	Asymmetrical	Dense	Less Apparent	Brown	75	Unprofitable
	Asymmetrical	Less Dense	Apparent	Brown	55	Unprofitable

Image	Visual	Texture	Granule	Color	Mycelium Coverage (%)	Scalability to Sell
	Asymmetrical	Dense	Less Apparent	Brown	75	Unprofitable
	Asymmetrical	Less Dense	Very Apparent	Brown	55	Unprofitable
	Symmetrical	Dense	Less Apparent	Brown	75	Unprofitable
	Symmetrical	Less Dense	Apparent	Brown	55	Unprofitable

The AI system was given instructions on visual quality criteria, such as identifying surface irregularities, estimating granule distribution, and detecting discoloration or mycelium concentration.

Before complete implementation, a trial testing phase was carried out to fine-tune prompt structures and evaluate the AI's capacity to detect and classify quality issues correctly. This trial phase ensured that the AI provided consistent and objective results. AI-assisted testing helps to standardize the quality evaluation process by decreasing subjective variability, which frequently occurs by human inspectors such as inconsistent visual judgement caused by different perceptions of people that inspected them, and color related quality attributes can be judged differently under inconsistent setups.

3.2.4 Result and Discussion

Following AI-based inspection, the output data—categorized as pass/fail and classified with defect indicators—was gathered and arranged for statistical analysis. Several forms of attribute control charts were used to process this information. These included variable charts which consist of Xbar S-chart and attribute charts which consist of NP-chart (number of nonconforming units), and C-chart (Number of nonconformities units). These charts were chosen because they can be used with categorical (binary) data such as pass/fail outcomes. These charts allowed for visual tracking of process stability over time and emphasized any out-of-control points, suggesting abnormal variance due to identifiable reasons. This visualization assists quality managers in identifying specific stages where remedial action may be required.

The attribute charts were then examined using statistical process control methods to find trends, variances, and potential areas for improvement. Such is an example of data processing using **minitab**:

Table 3.2 Example of table used in Minitab to process data

No	Batch	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
1	1	70	70	70	80	80	70	80	50
2	1	70	70	60	80	70	70	70	55
3	1	70	60	70	80	70	70	70	65
4	1	70	60	70	80	70	60	70	55
5	1	70	70	70	70	70	70	60	70
6	1	70	70	70	70	70	70	70	75
7	1	70	70	70	70	70	60	70	70
8	1	70	70	70	70	70	70	70	65
9	1	70	80	70	70	70	70	60	55
10	1	70	70	70	70	70	70	70	65
11	2	70	70	60	60	70	80	60	65
12	2	70	70	60	80	70	70	60	65
13	2	70	70	80	70	70	70	80	70
14	2	70	70	80	70	70	70	80	65
15	2	70	60	80	70	70	70	80	55
16	2	70	70	80	70	60	80	60	50
17	2	70	70	70	70	70	70	70	55
18	2	70	70	70	70	70	70	70	55
19	2	70	70	70	60	70	80	70	65
20	2	70	70	70	70	70	80	70	65
21	3	70	70	70	70	70	80	80	70
22	3	70	80	70	60	60	80	70	70
23	3	70	80	70	70	60	80	70	65
24	3	70	70	70	70	80	70	70	65
25	3	70	70	70	70	80	70	70	55
26	3	70	70	70	80	80	60	80	50
27	3	70	70	70	70	80	60	70	50
28	3	70	70	60	70	70	80	70	55
29	3	70	70	80	70	70	70	70	55
30	3	70	70	80	70	80	70	70	65
31	4	70	70	70	70	80	70	60	50
32	4	70	70	70	70	70	70	60	50
33	4	70	70	70	70	70	70	70	65
34	4	70	60	60	70	60	60	70	65
35	4	70	60	80	80	70	80	60	70
36	4	70	70	70	80	70	80	70	55
37	4	70	70	70	80	60	70	70	60
38	4	70	60	70	70	70	70	80	65

No	Batch	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8
39	4	70	70	70	70	70	70	80	70
40	4	70	80	70	60	70	60	70	70

Using this table in **Minitab,** below is the result of Xbar S-chart,

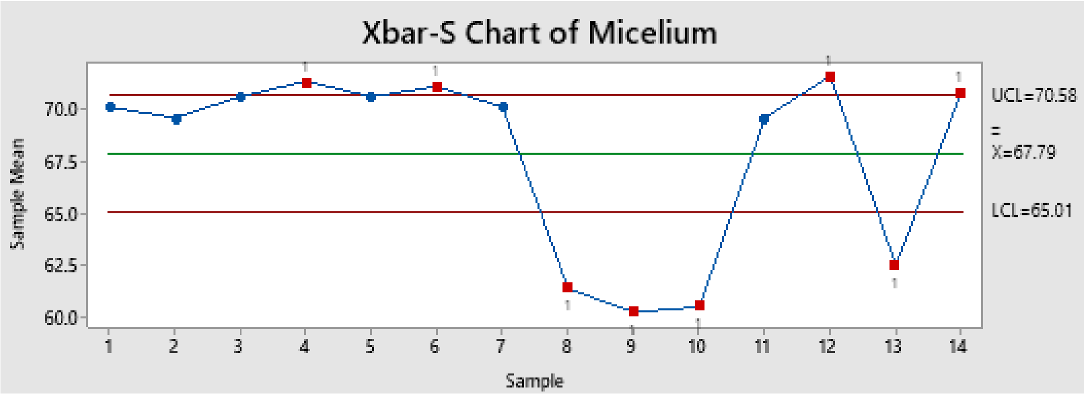

Figure 3.2 Chart obtained from Minitab

The chart shown contains value from ratio of mycelium in a Tempe sample. This stage involves calculating process capability and applying the seven quality tools such as control chart and root cause analysis to get a thorough understanding of the product.

A standardized but adaptable process was created for SMEs looking to adopt AI-assisted quality control based on the findings. The process describes easy procedures for taking high-quality photos, responding to AI prompts, and understanding the outcomes. The focus was on making sure the process is still feasible and scalable, regardless of the kind of product or size of the company.

The process was specifically created to be simple enough for non-technical individuals to understand and follow. Important elements include prompt templates for regular assessment, recommendations for managing AI accounts, and instructions for lighting setup. The resulting process is a practical structure that SMEs can use without having to make costly training or hardware investments.

3.2.5 Conclusion and Recommendation

Based on the thorough evaluation performed in earlier stages, a less complicated quality control framework designed for SMEs producing varied product lines would be introduced. Recognizing the resource constraints that small and medium-sized businesses often experience, the recommended approach prioritizes practicality, affordability, and ease of implementation. This approach integrates minimal manual labor for inspections and a flexible AI-powered analysis.

The final objective was to ensure that even small and medium-sized enterprises with limited resources could implement advanced quality assurance processes without the need for specialist equipment or personnel which are prone to subjectivity. The suggested model allows for data-driven decision-making and lays the framework for future digital transformation of quality management systems.

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CHAPTER IV
RESULT AND DISCUSSION

4.1 Data Collection

After collecting the data for 16 weeks with each week using 40 samples with the parameter of the pictures need to be taken in the morning because the product is still fresh. The criteria for a good Tempeh is if the mycelium growth reaches ≥80% with white color and smooth edges indicate good quality, while Tempeh that has bad quality was indicated by mycelium growth ≤ 60% with green to brown color and uneven edges. The data collected reached 560 samples which is adequate to be analyzed further with control charts such as NP-Chart, C-chart. Xbar-Schart.

Table 4.1 Data collection process

No	Process	Explanation
1		The initial setup of data collection process is using bedside lamp with tempeh sample in the center of the base and the image were captured right above the samples.
2		The result of good quality sample of tempeh with mycelium coverage over 80% with yellow to white color.
3		The result of defective sample of tempeh with mycelium coverage under 60% with brown to black color.

According to the screening of the visual quality, below is the percentages of how much the Tempeh is good to be eaten or not,

Table 4.2 Mycellium coverage percentage of Tempe Samples

Week	Batch				Week	Batch			
	1	2	3	4		1	2	3	4
Week 1	70	70	70	70	Week 8	50	65	70	50
	70	70	70	70		55	65	70	50
	70	70	70	70		65	70	65	65
	70	70	70	70		55	65	65	65
	70	70	70	70		70	55	55	70
	70	70	70	70		75	50	50	55
	70	70	70	70		70	55	50	60
	70	70	70	70		65	55	55	65
	70	70	70	70		55	65	55	70
	70	70	70	70		65	65	65	70
Week 2	70	70	70	70	Week 9	55	55	65	55
	70	70	80	70		60	65	65	55
	60	70	80	70		60	55	70	65
	60	70	70	60		65	70	55	65
	70	70	70	60		55	55	60	70
	70	70	70	70		75	50	65	70
	70	70	70	70		65	50	55	60
	80	70	70	60		70	55	50	55
	70	70	70	70		55	55	70	60
	70	70	70	80		60	50	65	55
Week 3	70	60	70	70	Week 10	55	55	70	50
	60	60	70	70		60	55	55	70
	70	80	70	70		65	65	60	65
	70	80	70	60		55	50	65	70
	70	80	70	80		50	50	55	65
	70	80	70	70		65	65	65	65
	70	70	70	70		55	55	55	55
	70	70	60	70		65	75	70	50
	70	70	80	70		65	65	55	65
	70	70	80	70		65	70	50	60
Week 4	80	60	70	70	Week 11	80	70	70	70
	80	80	60	70		80	70	60	70
	80	70	70	70		80	70	80	70
	80	70	70	70		70	70	80	70
	70	70	70	80		70	60	70	60
	70	70	80	80		70	70	70	60
	70	70	70	80		70	70	70	70
	70	70	70	70		70	60	70	60
	70	60	70	70		60	70	70	60
	70	70	70	60		70	70	70	70
Week 5	80	70	70	80	Week 12	70	80	60	80
	70	70	60	70		70	70	60	80
	70	70	60	70		70	70	80	80
	70	70	80	60		70	70	80	60
	70	70	80	70		70	70	80	70
	70	60	80	70		70	80	60	80
	70	70	80	60		60	80	70	80
	70	70	70	70		70	70	70	80
	70	70	70	70		70	70	60	70
	70	70	80	70		70	70	70	70

Week	Batch				Week	Batch			
	1	2	3	4		1	2	3	4
Week 6	70	80	80	70	Week 13	60	70	65	65
	70	70	80	70		65	65	55	65
	70	70	80	70		55	65	65	65
	60	70	70	60		65	55	65	55
	70	70	70	80		55	50	65	50
	70	80	60	80		70	55	55	50
	60	70	60	70		75	65	65	65
	70	70	80	70		70	65	65	70
	70	80	70	70		65	70	70	65
	70	80	70	60		55	70	55	60
Week 7	80	60	80	60	Week 14	70	60	70	60
	70	60	70	60		60	80	70	70
	70	80	70	70		80	70	80	70
	70	80	70	70		80	70	70	70
	60	80	70	60		70	70	70	70
	70	60	80	70		80	80	70	70
	70	70	70	70		80	80	70	60
	70	70	70	80		80	70	70	70
	60	70	70	80		80	70	60	60
	70	70	70	70		70	60	80	60

Gemini and ChatGPT differ in how they are distributed, accessed, and perceived by users. Gemini is more well recognized since it is directly incorporated into Google Search, allowing millions of people to encounter it naturally during their daily information-seeking activity. This integration provides Gemini with great exposure, quick accessibility, and excellent acceptance, as customers perceive it as an extension of their existing process rather than a separate product. GPT, on the other hand, is generally accessed through dedicated platforms or integrations like Microsoft Copilot, which makes its distribution more focused on people that actively seek AI services.

4.2 Data Adequacy Test

The criteria used according to Mr. Fauzi from *Kampung Tempe* in Tenggilis, for quality checking is represented by mold uniformity for taste, the richer mold uniformity the higher quality taste. To determine the minimum sample to use, data adequacy test by comparing the amount of tempeh production in one week (N) which is according to production Mr. Fauzi, they produce 1120 block of tempeh per week and the amount of sample taken with the help of camera to take pictures (n) represented by the formula below,

$$n = \frac{N}{1 + N * e^2}$$

With e or margin of error equal to 5% (0.05), the minimum sample for the data to be valid:

$$n = \frac{1120}{1 + 1120 * 0.05^2} = 294{,}7 \ \approx 295$$

According to the calculation, the data needed to be deemed adequate is 295 samples, while the data that have been collected reached 560 samples, hence the data is adequate.

4.3 Control Chart

The Artificial Intelligence Based Grading System for Mango Fruit review by Vibhute (2022) emphasizes the difficulty to apply image processing methods to agricultural items. According to the review, grading mangoes with AI is a complicated procedure that includes pre-processing, segmentation, feature extraction, classification, and validation. Because mistakes in early stages like segmentation or noise removal can lead to inaccurate feature extraction and misclassification, each step needs to be carefully adjusted. Hence, image processing is "quite difficult" due to this layered structure, especially when handling the innate variety in fruit appearance.

In order to standardize pictures and prevent illumination, orientation, and setting from skewing the analysis, the paper highlights the importance of pre-processing. After that, segmentation separates the mango from its surrounds, frequently utilizing edge detection or thresholding techniques. Mangoes are categorized into quality classes using machine learning models after the fruit is segmented and features including color, texture, and shape are assessed. Lastly, validation refines accuracy by comparing AI outputs with ground truth data. According to Vibhute, the interdependence of these steps makes the procedure difficult because even small mistakes may significantly reduce grading reliability.

Tempeh inspection is directly related to this layered method. Tempeh is naturally variable, just like mangoes, although it results from biological fermentation processes rather than varietal variations. The pipeline outlined by Vibhute can be modified to include pre-processing tempeh images by controlling the background and lighting, separating the tempeh block from packaging, extracting characteristics like texture firmness, discoloration, and mold uniformity, and then categorizing goods into quality groups according to the criteria that related to the taste and quality of Tempeh. The challenge is making sure that every step is resilient enough to deal with biological fluctuation, which is frequently more unpredictable than fruit ripening.

Over the course of sixteen weeks, systematic data collection was carried out to monitor and evaluate the observed variables. The accumulated dataset provides a comprehensive basis for analyzing process stability and performance trends. To visualize these findings, control charts have been constructed, serving as statistical tools that highlight variations within the process and distinguish between common-cause fluctuations and potential special-cause deviations, as can be seen below

- Standard deviation control chart (Xbar S-chart),
  A standard deviation control chart monitors process variation by using standard deviation values, making it more detailed than charts based only on averages. Using the help of Minitab software, the result can be seen below,

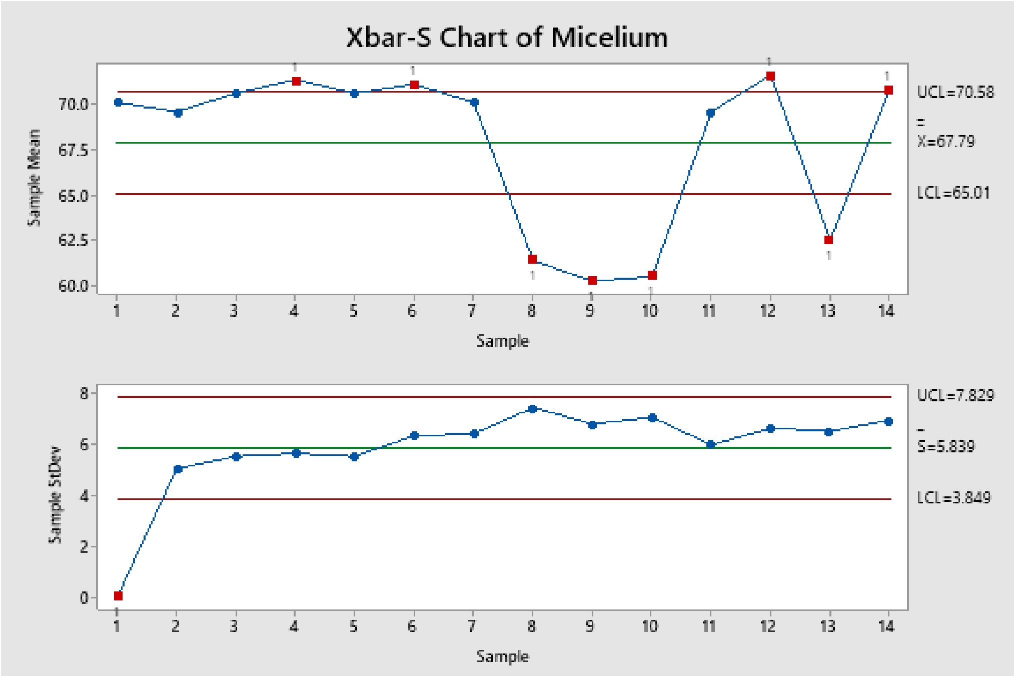

Figure 4.1 X-bar S-Chart according to Mycelium Coverage

The results shows that the process average is constant most of the time, but Weeks 8-10 indicate a possible specific factor (raw material or ambient variables) influencing product weight with average Mycelium Weight 67.79 g, and control limit, UCL is 70.58 g, LCL is 65.01 g. Most points are within limits, but Weeks 8–10 show a significant drop in mean weight near the LCL, suggesting a temporary deterioration in product consistency. For S-Chart, the average standard deviation is 5.839, with all points within limits. AI-assisted inspection detects these subtle variations in week 8-10 in texture and coverage more consistently than manual inspection.

- Control chart for number of nonconforming units (NP-Chart)
  An np-control chart is a type of control chart used to track the number of nonconforming items. Unlike p-control charts, it does not calculate proportions because the total production quantity remains constant for each day, shift, or production run. Using the help of Minitab software, the result can be seen below,

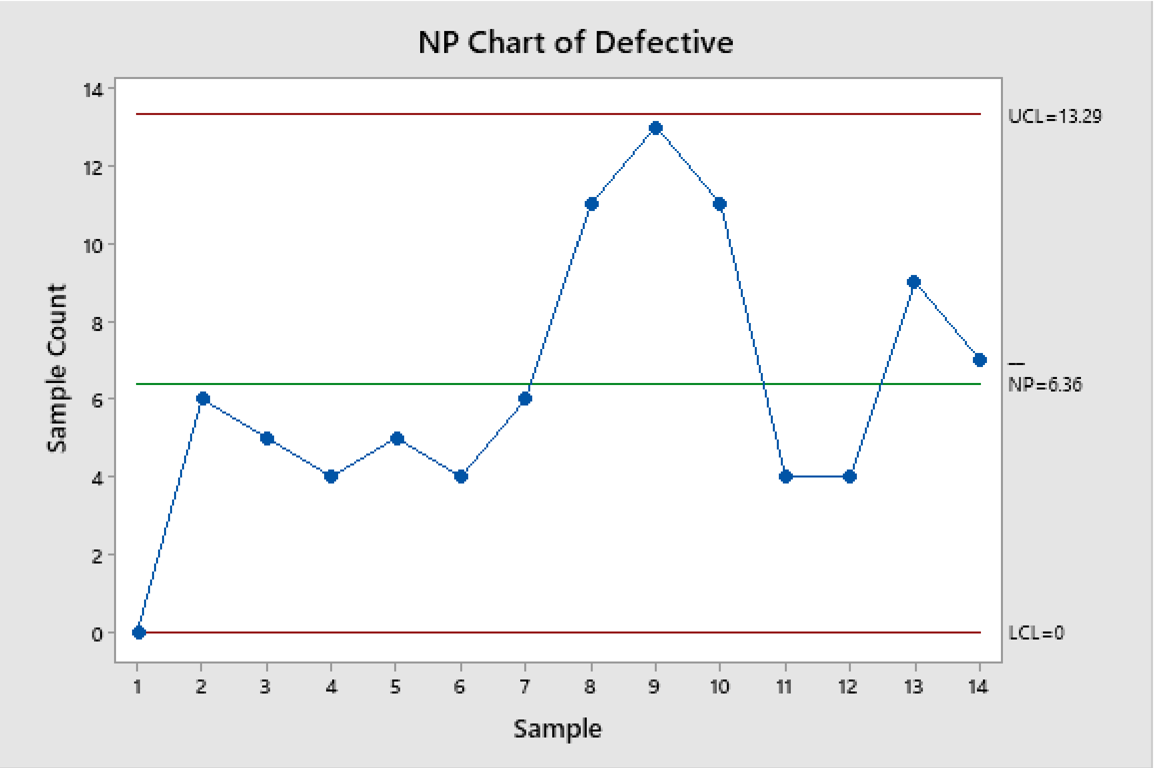

Figure 4.2 NP-Chart of Defective according to Mycelium Coverage

The results shows that the defect count is statistically controlled, but the surge in Weeks 8-9 coincides with a decline in mycelium weight from the X-S chart, suggesting a common underlying cause, with average Number Defective (NP) is 6.36 per batch of 40 units, and control limits, UCL is 13.29, LCL is 0. All points are within limits.

- Control chart of nonconformities units (C Chart)
  A c-control chart is used to monitor the number of nonconformities per fixed unit. Using the help of Minitab software, the result can be seen below,

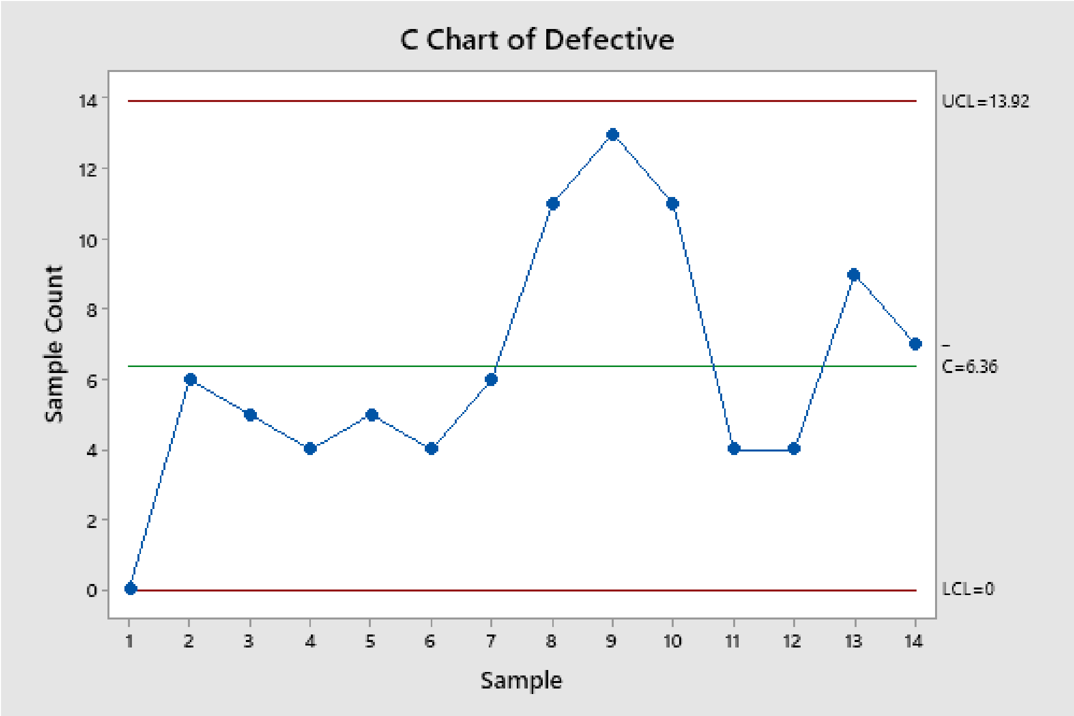

Figure 4.3 C-Chart of Defective According to Mycelium Coverage

The results shows that the number of defects per batch is stable, but the increase in Weeks 8 9 is consistent with other findings, with average defects per Batch (C) is 6.36, and control limits, UCL is 13.92, LCL is 0.

From the control chart, It can be concluded that the tempeh's quality analysis is shown statistically consistent throughout a 14-week period, with no points outside the control limits in any chart, showing the lack of uncontrolled special cause variation, which means the method produces consistent, reliable results.

Based on the ANOVA test conducted on the tempeh quality inspection data, the factor Week was found to have a statistically significant effect on classification results, with a P-Value = 0.000 and F-Value = 20.82. This indicates that there are meaningful differences across weeks in inspection outcomes, which may be caused by procedural variations such as lighting conditions, fermentation environment, or changes in the AI prompt used. In contrast, the factor Sample did not show a significant effect (P-Value = 0.747), meaning that variation among individual tempeh samples was not the main source of fluctuation in inspection results.

Table 4.3 ANOVA result for sensitivity analysis

Source	**DF**	**Adj SS**	**Adj MS**	**F-Values**	**P-Values**
Sample	39	1228	31.49	0.84	0.747
Week	13	10170	782.27	20.82	0.000
Error	507	19054	37.58		
Total	559	30451			

These findings suggest that the AI-based inspection system is highly sensitive to weekly and procedural variables. Therefore, standardization in image capture, lighting setup, and prompt usage is required to ensure consistent classification results across different weeks. Inconsistencies in procedure can increase the error rate, both in the form of false negatives (defective products passing as acceptable) and false positives (good products rejected), which directly impacts system accuracy and potential financial losses.

The student groups in the CIM course have also conducted visual inspection studies utilizing AI-based methods and MATLAB, with each group selecting a different type of object as the inspection target. For example, one group examined watermelon cubes by tasking the AI system with estimating cube dimensions and identifying visual attributes such as color characteristics. In general, the outcomes of these projects were mostly qualitative in nature, focusing on classification and categorical assessment rather than detailed defect quantification or precise numerical evaluation. This research takes it further by using SPC analysis to monitor defect rates over time and detect process drift. By combining defect classification with SPC charts, SMEs can identify when fermentation conditions deviate from acceptable ranges, which can be repurposed into other product such as Tempeh Chips. This approach extends beyond descriptive categorization, linking inspection results to actionable process improvements and economic outcomes.

4.4 Financial Benefit

4.4.1 Expenditure

This subsection presents the capital expenditure (CAPEX), operational expenditure (OPEX), and return on investment (ROI) analysis for the proposed inspection tools, highlighting both the initial costs of development and the ongoing expenses, as well as the financial benefits gained through improved quality control, The OPEX needed is only from operator’ wage which is Rp. 500,000 IDR, and CAPEX is listed below,

Table 4.4 CAPEX of tools design

No	Item Description	Cost
1.	0.8 mm galvanized plate	250,000
2.	3x3 cm iron angle bar	125,000
3.	Bolts and fastener	50,000
4.	3x3 cm hollow iron bar	135,000
5.	Black paint, varnish, epoxy, sandpaper, thinner	500,000
6.	Food-grade conveyor belt	465,000
7.	HP sprocket	40,000
8.	Gear and chain	300,000
9.	Lathe work for 4 conveyor belt holes	1,000,000
10.	Bearings (4 pieces)	220,000
11.	Welding and assembly services	1,500,000

According to the table above, the total CAPEX is IDR 4,485,000 for investment in automation.

4.4.2 Economic Benefit

Prior to the introduction of AI, tempeh quality checking relied solely on manual inspection process. At this stage, the error rate was roughly 20%, demonstrating the limitations of inspection procedures. Fatigue played a role in this error, where repeatedly inspecting large batches made it easy to overlook minor problems in texture or granule dispersion. Lighting conditions offered an additional element of unpredictability. Shadows and brightness in the production area made it difficult to detect changes in color or mycelium coverage, resulting in categorization errors. As a result, defective products were sometimes allowed through (false negatives), while acceptable products were occasionally rejected (false positives), which in return could affect the customer’s trust.

The monthly production rate of tempeh is 1,120 unit with 20% error rate, there are 224 product that was misclassified in the manual inspection process due to inconsistent lighting and high subjectivity, as illustrated below,

Table 4.5 20% Error rate Loss

Component	Value (IDR)	Explanation
Weekly Production	1,120 units	Weekly Production
Unit price (Tempeh)	5,000	Price of one Tempe
False Positives	100 units	Acceptable products were rejected
False Negatives	124 units	Defective products were allowed through
Loss from False Positives	500,000	100 x 5,000
Loss from False Negatives	620,000	124 x 5,000

According to the table above, the total loss from false positives and false negatives using manual quality inspection is IDR 1,140,000.

Optimizing the lighting arrangement during image collecting is crucial to reduce error rate in AI-based inspection. Using flashlight from phone in the middle of the Tempeh sample is one effective strategy. This arrangement guarantees consistent lighting throughout the surface, minimizing shadows and glare that could impede the AI's capacity to identify texture, granule dispersion, color, and mycelium coverage.

Figure 4.4 Proposed Data Collection Setup

Using the data collection setup above as a shape for automation could reduce the error rate up to 5% due to standardized setup and image take with consistent lighting as illustrated in the table below,

Table 4.6 5% Error rate Loss

Component	Value (IDR)	Explanation
Weekly Production	1,120 units	Weekly Production
Unit price (Tempeh)	5,000	Price of one Tempe
False Positives	26 units	Acceptable products were rejected
False Negatives	30 units	Defective products were allowed through
Loss from False Positives	130,000	26 x 5,000
Loss from False Negatives	150,000	30 x 5,000

According to the table above, the total loss from false positives and false negatives using automation and AI in quality inspection is IDR 280,000 which is significantly lower that manual quality inspection method.

4.4.3 Cost Benefit Ratio

The Cost–Benefit Ratio (CBR) is a key economic indicator used to evaluate whether an investment is financially justified. By comparing the total benefits gained against the costs incurred, CBR provides a clear measure of efficiency and feasibility. To calculate CBR, the annual benefit before and after using AI in quality inspection needs to be calculated, as illustrated below,

Table 4.7 Annual Benefit Calculation

Component	Value (IDR)	Explanation
Monthly Production	4,480 units	Monthly Production
Unit price (Tempeh)	5,000	Price of one Tempe
Loss before using AI (20%)	4,480,000	896 units x 5,000
Loss after using AI (5%)	1,120,000	224 units x 5,000
Monthly Benefit	3,360,000	4,480,000 – 1,120,000
Annual Benefit	40,320,000	Monthly Benefit x 12 Months

The equipment for the automation is expected to last 5 years, which means the annual CAPEX allocation is IDR 897,000 that is obtained by dividing IDR 4,485,000 to 5 years of lifetime, while the annual OPEX obtained from operator’s wages is IDR 6,000,000, then the Cost-Benefit Ratio is,

$$CBR = \frac{40{,}320{,}000}{6{,}897{,}000} = 5.84$$

The result is 5.84, which means for every IDR 1 spent in quality control, the SME can get IDR 5.84 benefit in return, which means the investment in automation and using AI is feasible to be adapted to quality inspection for SME.

4.5 Propose Design

4.5.1 Tools Design

To standardize the image-capture process, a more regulated system is required because the old manual method introduced various restrictions that compromised data quality. Inconsistent angles, distances, lighting, and object placement are common outcomes of manual image capturing, which causes a great deal of variation across photos. When the photos are utilized as input for AI models that are extremely sensitive to visual differences, such discrepancies can interfere with the analysis process. The model may generate erratic or erroneous predictions even with slight variations in camera angle or lighting.

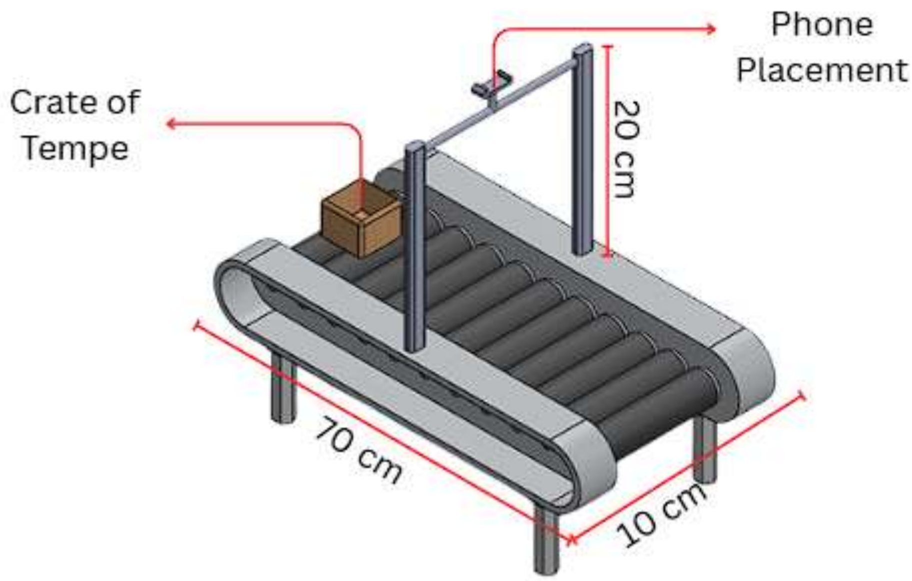

Figure 4.5 Proposed tools design for Automation

The phone positioning mechanism in the proposed tool design is purposefully built rotatable, allowing flexible camera angle modification to accommodate different box sizes and inspection requirements. The phone is positioned directly above the conveyor path on a vertical support pole. This approach allows a picture to be shot at the ideal time as each crate travels along the rollers and arrives at the center point, which is exactly beneath the phone mount. The phone may be positioned diagonally or perpendicularly to the crate surface thanks to its rotating feature, which improves sight and lessens glare and shadow interference. regardless of orientation or content, this guarantees uniform image capture for each crate. Depending on whether motion sensors or timed intervals are integrated into the system, this configuration allows for both automated and manual operation. Overall, the design guarantees precise, consistent recording or examination of every crate as it moves through the scanning area.

4.5.2 Standard Operating Procedure for Proposed tools design

It is crucial to standardize the inspection process by implementing a clear SOP for SMEs to lessen bias from the AI. The diversity in input data can be reduced by establishing consistent image capture procedures, such as camera distance, and prompt utilization,

- Procedure
  1) Place the Tempeh sample on the conveyor belt with a plain background when the sample is still fresh in the morning and position a phone centrally above the sample on the phone holder on the tool to ensure consistent angle.
  2) Capture one clear photo per sample while saving the file on specific album.
  3) Open Gemini AI on the smartphone or laptop if any and upload the captured Tempe image.
  4) Input the standardized prompt: "Analyze this Tempeh image and evaluate visual quality based on texture, granule dispersion (too much disperse is defective), color (yellow or brown is defective), and mycelium coverage (coverage under 60% is defective). Classify the sample as 'Defective' or 'Acceptable' and provide a brief explanation."

5) Copy Gemini’s output into the inspection log, note the classification and explanation, and store the image together with the AI output for traceability.

This standardization minimizes the possibility of misclassification caused on by inconsistent conditions by ensuring that the AI system receives reliable and uniform visual input. Additionally, an SOP gives operators useful guidelines that make the inspection process repeatable and less reliant on personal judgment. In this way, SMEs can improve productivity and quality control while obtaining more objective and accurate results from AI-based inspection.

4.6 Opportunity to Implement AI as Quality Inspection for SMEs

Ten SMEs in Malang and SMKN 7 Surabaya, which represent a variety of food goods, were interviewed to facilitate the adoption of AI-based quality evaluation. Tempeh Pomodoro, Kopikawi, fresh oyster mushrooms, veggies, assorted nuts, *sambal pecel*, and instant ginger are among the products of both SMEs and SMKN 7 Surabaya. This review was conducted to guarantee that the AI assessment encompasses a broad range of product attributes, processing techniques, and quality requirements.

Figure 4.6 Meeting with SMEs from Malang and SMKN 7 Surabaya

Understanding the present quality control procedures, difficulties, and expectations of each SME was made possible by the insights obtained from these interviews. These results served as the basis for evaluating the AI system's, more especially, Gemini's capability to carry out digital quality inspection.

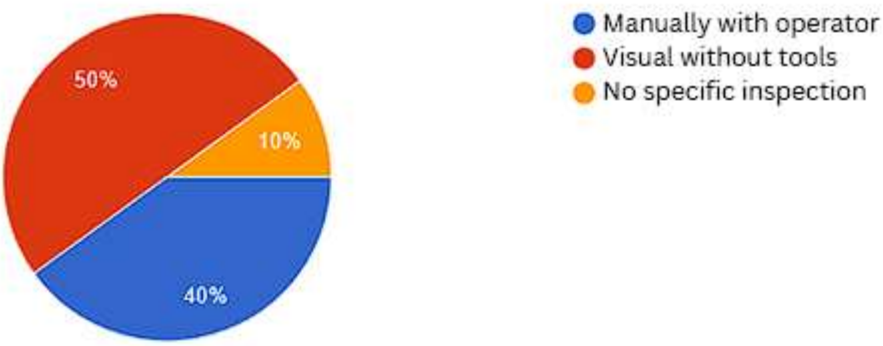

Figure 4.7 Result from how the respondents dealing with quality inspection

This data shows how the respondents conducted quality inspection where 50% of them are still visually doing it without tools, 40% by manual with operator and 10% with no specific inspection. This data shows that the quality inspection system of most SME is still underdeveloped as there still some that do not have specific inspection system, and the process are still highly manual and subjective.

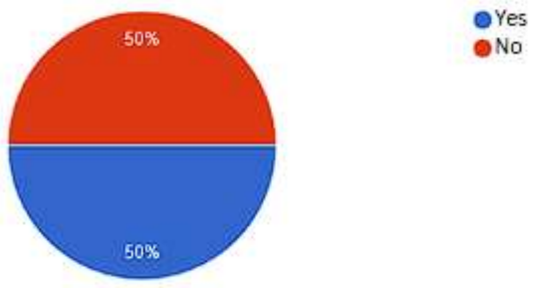

Figure 4.8 Result from whether the respondent has a specific training for quality inspection

This data shows that half of the respondents reported having received special training for quality inspection, while the other half had not. This split indicates a significant gap in capacity-building across SMEs. While some respondents are equipped with structured knowledge and inspection protocols, others rely on informal or experimental methods.

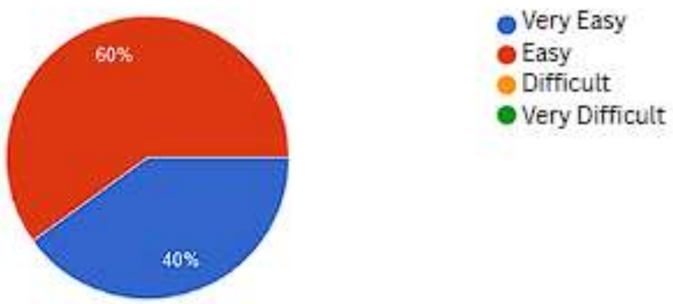

Figure 4.9 Result from how the AI Usability was easy

This data shows a highly positive perception of AI usability in the inspection process. All respondents found AI either “easy” with 60% percentage or “very easy” with 40% percentage to use, with no one reporting difficulty. This indicates strong initial acceptance and low resistance to adoption among SMEs and vocational users.

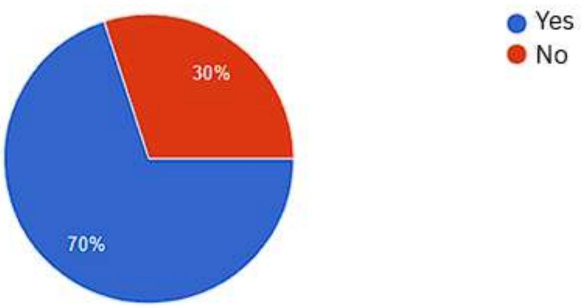

Figure 4.10 Result from whether AI can reduce defective in quality inspection

This data shows that most respondents (70%) believe that AI can help reduce defective or damaged products, while 30% remain unconvinced. This indicates a generally optimistic view of AI's potential to improve quality control, especially among SMEs. The positive perception suggests readiness for adoption, though the presence of skepticism highlights the need for further demonstration of AI's reliability and tangible impact in real-world inspection scenarios.

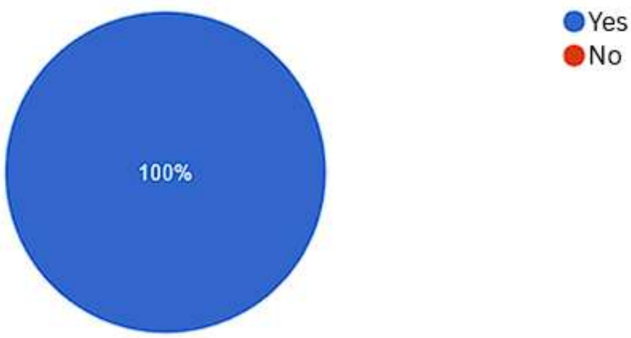

Figure 4.11 Result from how AI can help improve productivity

This data shows that all respondents unanimously agreed that AI can help improve work efficiency, indicating strong confidence in its practical value. This 100% positive response reflects a high level of openness among SMEs and vocational users toward adopting AI tools in operational workflows. It suggests that AI is not only perceived as usable but also as a strategic asset for streamlining tasks, reducing manual effort, and enhancing productivity.

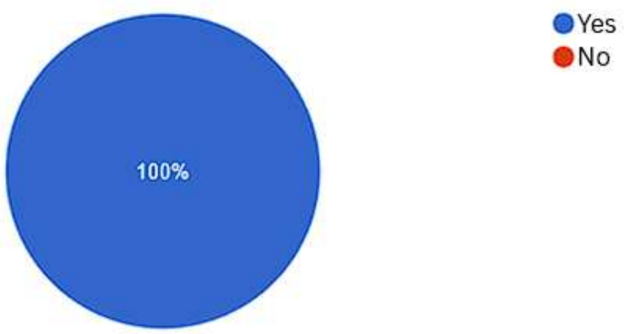

Figure 4.12 Result from how AI can reduce quality inspection cost

This data shows that all respondents unanimously agreed that AI can help reduce inspection costs, indicating strong confidence in its economic value. This 100% positive response reflects a clear perception that AI not only enhances accuracy but also offers financial efficiency for SMEs. It reinforces the case for adopting AI-based inspection systems as a cost-saving solution, especially in resource-constrained environments where manual methods are labor-intensive and inconsistent.

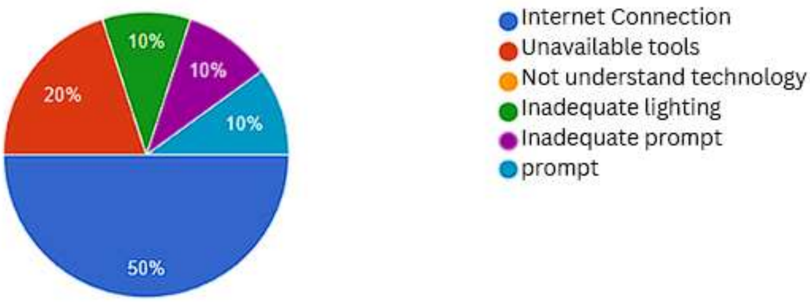

Figure 4.13 Result from the difficulty of using AI as quality inspection tools

This data shows that for 50% of the respondents, the most significant obstacle to implementing AI for quality inspection is internet connectivity. 20% of respondents were lacking in available devices, 10% of respondents have limited technological understanding, 10% of respondents considered poor photo lighting, and 10% of respondents has difficulty selecting appropriate prompts.

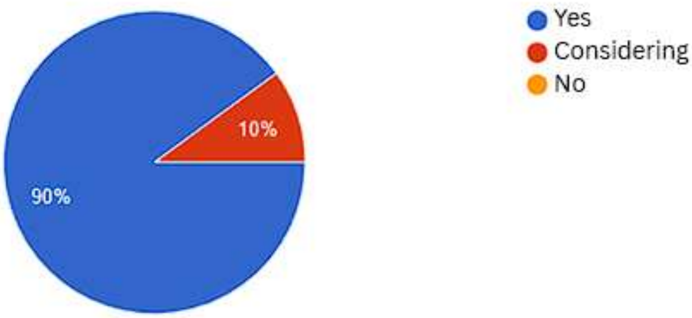

Figure 4.14 Result from whether the respondents are interested in using AI as quality inspection tools

This data shows that there are strong enthusiasm for continued AI use in quality inspection, with 90% of respondents expressing clear interest and the remaining 10% still considering it. Notably, none rejected the idea outright. This indicates a high level of acceptance and perceived value of AI among users, suggesting that with proper support and infrastructure, adoption could become widespread. The data also highlights an opportunity to engage the undecided group through targeted demonstrations and training.

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CHAPTER V
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

According to the result and discussion from this undergraduate thesis, these are the conclusions that can be taken,

1) The findings confirm that reliance on low-quality practices such as inorganic fillers undermine consumer confidence and damages SME reputation. By adopting AI-based inspection, SMEs can strengthen product authenticity and ensure consistent quality, thereby restoring trust and safeguarding brand image.
2) Manual inspection methods, constrained by subjectivity and human error, fail to reliably detect contaminants and defects. The AI-system system reduces bias, improves detection accuracy, and ensures that product safety and quality are maintained even in resource limited environments.
3) Automated inspection method is quite expensive for SMEs. The proposed framework, using smartphones and low-cost tools demonstrates that visual defects can be identified efficiently without requiring complex technology. Furthermore, the ANOVA sensitivity analysis confirms that variations in defect detection are statistically significant, showing that the AI system is responsive to changes in quality parameters such as texture, granule dispersion, and mycelium coverage. This statistical validation strengthens the reliability of the AI-assisted inspection, ensuring that improvements in defect reduction are consistent.
4) Integrating defect and inspection error rates demonstrates the economic value of AI adoption. CBR and ROI analyses shows that SMEs can achieve substantial returns through reduced losses and higher net revenue.

5.2 Recommendation

Recommendations for a better research and scoping,

1) Future research should consider expanding the inspection scope beyond visual parameters. While this study focuses on color, mycelium coverage, and structural defects, additional quality indicators such as moisture content, fermentation temperature, and microbial safety could be incorporated to create a more comprehensive quality control system.
2) Future research can conduct a pilot testing across multiple SMEs with more varying production volumes, equipment conditions, and worker skill levels to help validate the scalability and adaptability of the proposed inspection framework in different operational contexts.
3) Future research should focus on expanding the dataset used for inspection by Collecting more diverse images that covers different fermentation stages, defect types, soybean varieties, and lighting conditions will help the AI system generalize better and reduce the likelihood of misclassification.
4) Periodic adjustments to the Gemini prompt are recommended to maintain accurate and unbiased tempeh quality classification and adapt to changes in production conditions, lighting, and product characteristics.

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ATTACHMENTS

Format Standar Operasional Prosedur Inspeksi – Inspeksi Kualitas Produk

1. Tujuan

Untuk memberi panduan dalam melakukan aktifitas inspeksi kualitas produk sebelum masuk pasar

2. Alat dan Bahan
    - Handphone
    - Konveyor mini
    - Produk (Tempe)
3. Unit Kerja Terkait
    - Bagian inspeksi kualitas
4. Dokumen yang digunakan
    - File gambar
    - Log inspeksi
5. Prosedur pelaksanaan
    - Prosedur#1

      Letakkan sampel tempe di atas konveyor dengan latar belakang polos ketika sampel masih segar pada pagi hari, lalu posisikan ponsel tepat di atas sampel menggunakan penyangga ponsel pada alat untuk memastikan sudut pengambilan gambar yang konsisten.
    - Prosedur#2

      Ambil satu foto yang jelas untuk setiap sampel dan simpan file tersebut pada album khusus.
    - Prosedur#3

      Buka Gemini AI melalui handphone atau laptop jika tersedia, kemudian unggah gambar yang sudah diambil.
    - Prosedur#4

      Masukkan prompt standar: “Analisis gambar tempe ini dan evaluasi kualitas visual berdasarkan tekstur, sebaran granula (terlalu menyebar dianggap cacat), warna (kuning atau coklat dianggap cacat), dan cakupan miselium (cakupan di bawah 60% dianggap cacat). Klasifikasikan sampel sebagai ‘Cacat’ atau ‘Diterima’ dan berikan penjelasan singkat.”
    - Prosedur#5

      Salin hasil dari Gemini ke dalam log inspeksi, catat klasifikasi dan penjelasannya, lalu simpan gambar bersama hasil AI untuk keperluan inspeksi.

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