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# Automatic detection of scratches on chicken carcass in slaughter factory using image processing and machine learning

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## Abstract

**Importance of the work:** Ensuring the quality of chicken products is paramount, as low-quality chicken not only impacts consumer health but also results in time and financial losses. Automation can improve production by reducing labor costs and increasing efficiency.

**Objectives:** To develop a software program to process video images acquired on a chicken carcass production line and categorize each carcass based on identified scratches.

**Materials & Methods:** The treatment consisted of counting the scratches on chickens to categorize them in terms of meat quality. The developed software used machine learning and model building to create models to detect scratches on the chicken carcass. The software identified and marked groups of pixels defined by the patterns on the image. Results were compared to those from manual assessment by an experienced operator.

**Results:** The software achieved 95% accuracy and directly processed videos without the need for pre-processing, such as background removal. The carcass categories were determined based on the number of scratches based on calibration with the software. Each of the three mislabeled chickens had a significant scratch, but no large scratches are observed. The grade of the chicken was directly affected by these scratches, with important factors being poor detection and the absence of a large scratch pattern.

**Main finding:** The program could be improved by incorporating calibration from both sides of the carcass. This would improve the adaptability of the developed system. It should be possible to develop a system using visual image data to automatically sort chickens on the production line into different categories.

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## Introduction

The chicken is a domestic animal in the family Phasianidae and the species *Gallus gallus domesticus* that is raised for its meat and eggs. In a system raising chickens without litter, appropriate provision of specific materials has a positive effect on animal welfare (Somparn, 2016). Chicken is a type of poultry that is widely used for human consumption around the world, being a popular staple food due to its low fat and high protein content that can be cooked in many ways, such as grilling, roasting, frying and boiling (Nova Scotia Health, 2022). Chicken production is an important sector of agriculture in many countries, and there is a high demand for chicken products for export, including Thailand, which is a major producer in Asia, with an annual production of around 1.5 million t (Office of the Permanent Secretary Ministry of Commerce, 2022).

Chicken can be processed in many different ways and marketed as cooked or fresh, cut or whole; nonetheless, the demand for chicken is constantly increasing, whatever the final product, which has driven increased production (Preechajarn and Nicely, 2019; Prasertsri and Stange, 2022). The growth prospects for Thai chicken production were around 2% for 2022; however, at December 2022, the average annual growth rate of chicken production prior to the covid-19 pandemic was 5–8%. This trend is expected to continue in 2023, with the predicted production of chicken meat increasing slightly to 3% (Prasertsri and Stange, 2022). Furthermore, since the start of the conflict between Russia and Ukraine, the average price of the cereals required to feed animals has increased 26% during the first seven months of 2022. Cereals represent 60–65% of the total cost of broiler production. With the return of foreign tourists, Consumption in Thailand was expected to rise 3% in 2023 (Prasertsri and Stange, 2022).

Chicken production is a complex process that involves multiple steps, including raising, slaughtering and processing. Automation can be used to improve various aspects of this process, including reducing labor costs and increasing efficiency, for example, inspection of poultry carcasses to detect scratches or other injuries on the chicken skin that occur during rearing, handling, transportation and production at the plant (Fletcher, 2002; Casey et al., 2010). In addition, image processing technology and deep learning could be used to better detect sick broiler chickens (Zhuang and Zhang, 2020). While advances and developments in computer vision systems relative to the monitoring of poultry have been substantial and have led to interesting datasets for analysis, some problems have been encountered, such as poor lighting conditions (Okinda et al., 2020). In addition, evisceration is an important step in carcass processing and automation of this task has been commonly considered, with image processing being used to recognize the visceral contours of poultry carcasses (Barsoum, 2022). A camera installed on a robot has been used to acquire images of the carcass to allow the robot to eviscerate the poultry (Barsoum, 2022). In another study, image processing of the carcass was applied to conduct anal incisions, with the algorithms using a range of detected shapes to analyze the colorimetry of the image obtained from a camera integrated into a robot (Chen et al., 2020). Detection methods have used convolutional neural networking, consisting of extracting the features of each image of the dataset and then training a classifier based on these features (Calvin et al., 2020). Nonetheless, although the use of vision-based automatic inspection is common, there are still many limitations for its use in difficult situations; validating the effectiveness of this technology requires a comparison between the results obtained by human operators and the latest technologies (Aust and Pons, 2022). All these image processing systems need good operating conditions to have acceptable results, with sufficient light being an important parameter in this kind of application (Adelkhani et al., 2012).

The main goal of the current study was to develop software to acquire video images and undertake subsequent processing, with the image processing being able to count the number of scratches on chickens in a slaughter line. The goal was to use the collected data to categorize the carcasses into different levels of meat quality. This system would allow automation of this task. The software was required to be efficient enough to produce the same results as a human operator based on an on-site comparison of the results between the algorithm and an operator.

## Materials and Methods

### *Data acquisition device and software*

The data collection was carried out in a poultry slaughterhouse belonging to KVS Fresh Products Company Limited in Nakhon Sawan, Thailand (15.93 °N, 100.11 °E).

*Determination of parameters for data acquisition*

The chickens were filmed hanging upside down on a moving rail at a speed of 120 chickens per minute; thus, a chicken passed in front of the camera every 500 ms. Therefore, the program had to have this acquisition frequency to be able to identify all the chickens. Furthermore, the position of the chickens had to be suitable to have a good view of the scratches. In addition, the brightness was important to take pictures with good quality (Adelkhani, 2012).

Although taking a photo of the front of the chicken was easier than from the side and the frontal plane presents every chicken part, this did not offer appropriate photos for the image processing technique. Most scratches on a poultry carcass were on the leg quarter with the backbone on the midsagittal plane (Barsoum, 2022). Consequently, the chickens were filmed from the side, with left side first. Patterns were made using the images on the left side. Subsequently, a test of the developed algorithm was conducted based on the images of the right side of the chickens.

A facility for the acquisition of chickens was created next to the production line, having the best possible view of the chickens and good light. The installation consisted of a webcam, notebook computer and the LabVIEW (Laboratory Virtual Instrument Engineering Workbench) program (National Instruments; Austin, Texas, USA). A high definition Logitech C270 webcam (Logitech; Lausanne, Switzerland) with a 63°wide-angle lens was used capture more image detail (Fig. 1).

The webcam was connected via a USB 2.0 cable to a Lenovo IdeaPad GAMING 3 computer (Lenove; Bratislava, Slovakia) powered by an Intel Core i7 processor, a dual storage system and a NVIDIA GeForce graphics card. The system ran on the Windows 10 operating system and had 16.00 GB of random-access memory. LabVIEW is a system-design platform and development environment for visual programming that was designed to improve engineering productivity and help tackle engineering challenges. The acquisition and vision assistant modules were used in this study.


**Fig. 1** Webcam used in slaughterhouse for image capture

*Image processing to detect scratches*

LabVIEW is an integrated development environment for creating image processing programs. It allows users to design visual applications for image acquisition, processing and analysis using visual programming graphics. The core functionality of LabVIEW for image processing is its ability to create image processing programs using built-in image processing functions. These functions include basic operations such as noise reduction, filtering, image segmentation, edge detection and pattern recognition. It also allows the use of third-party image processing libraries for more advanced tasks, such as face or shape recognition. In addition, LabVIEW offers tools for real-time image acquisition from various sources, such as digital cameras, video cameras and sensors. The Vision Builder AI 2019 program was used to configure acquisition parameters, control cameras and process images in real time (National Instruments, 2023).

For data acquisition, the camera was placed so that the lighting was optimal to detect all forms on the chickens. Each image was captured in RGB format with a resolution of 1,280 × 720 pixels. After capture, the only preprocessing was conversion from RGB format to grayscale format (Fig. 2).

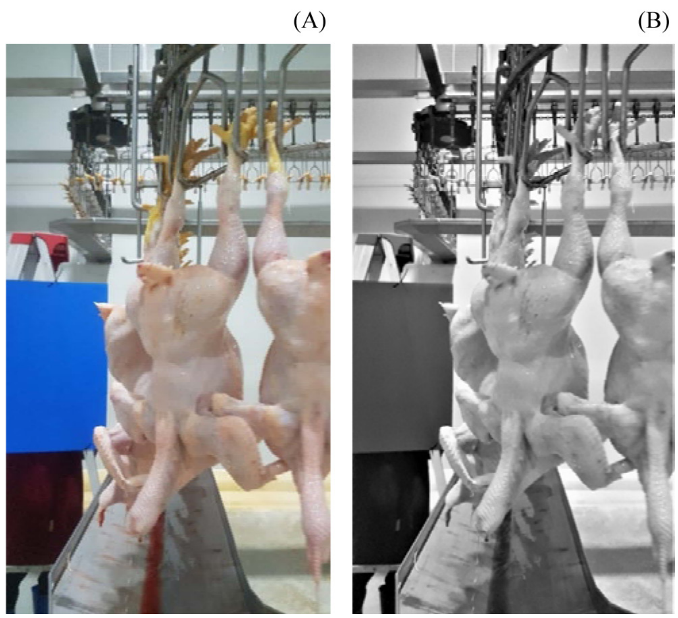


**Fig. 2** Image: (A) captured in slaughterhouse; (B) grayscale version

The grayscale allowed for better image processing. The pixel intensity was categorized, with black representing the lowest intensity, while white corresponded to the highest intensity. Pixel values ranged from 0 to 255. IMAQ (Image Acquisition) is an image processing library built into LabVIEW that allows users to acquire, process and analyze digital images. It provides a complete set of functions for acquiring images from different sources, such as digital cameras, video cameras and sensors. This capability facilitates the customization of acquisition parameters, camera control and real-time image processing, allowing the image to be captured in RGB and transformed into grayscale. The intensity of the pixels of the image then makes it possible to characterize the scratches in order to be able to identify them. Intensity similarity detection of a pixel cluster will indicate a scratch on a new image. Notably, this process can only be undertaken using intensity data with the RGB and HSL formats. The vision assistant facilitates the creation of patterns to detect the chicken carcasses and the different scratches on them (Fig. 3).

The chicken was detected on the image using previously learned patterns. The scratches were also determined based on predefined patterns using the The LabVIEW vision assistant component, where a pattern is a set of determined pixels that define an object (in this case, the chickens and the scratches on the chickens). The presence of each pattern was checked on the incoming image. The calibration of these patterns was performed using a set of chicken images that had been taken beforehand. Each scratch on the chickens was identified and a pattern was associated with each one. The created patterns served as the tools within the software for identifying chicken scratches in the analyzed videos. The more patterns that are recorded, the more accurate the software becomes. The objects detected on the image are defined by their position. If this positioning corresponds to the surface of the chicken on the image, the object is counted by the software. A pattern defines a cluster of scratches. The more patterns defined, the better the software can identify the scratches on the chickens, with greater reliability of detection (Fig. 4).

Each pattern detected in the detection zone (the chicken in this case) was transformed into a Boolean pattern to be counted. The scratches on a chicken were used to define the level of quality, which was indicated by green lights depending on the level of quality determined. An individual chicken component classified in a quality level was counted to determine the overall chicken quality level. The criterion design for quality level sorting was developed with the assistance of a specialist in visual inspection on the same set of chicken images. The criterion range for each level is provided in Table 1 based on the number of perceived scratches.

**Table 1** Levels of quality standards due to scratches

| Quality level | Number of scratches |
|---|---|
| A | 0–4 |
| B | 5–6 |
| C | More than 6 |

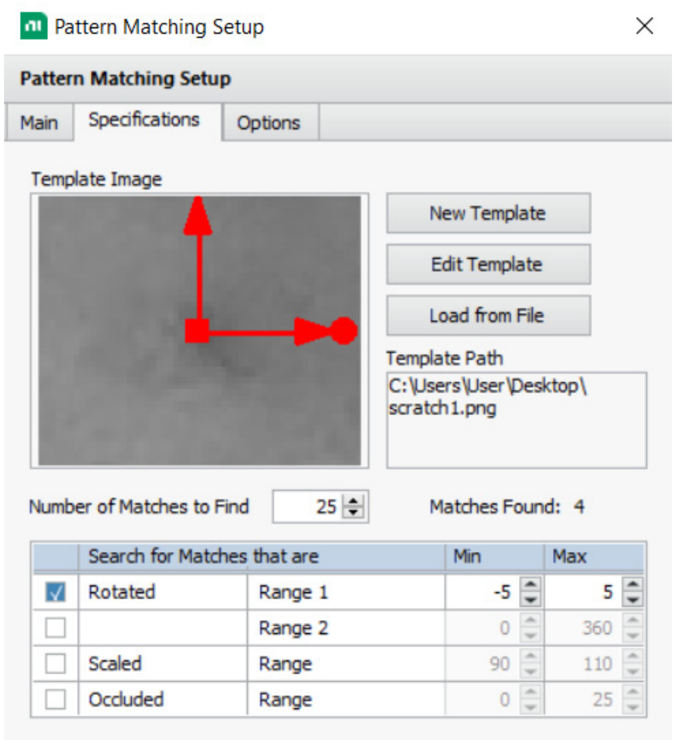


**Fig. 3** Pattern creation screen in IMAQ (Image Acquisition) image processing library built into LabVIEW


**Fig. 4** Schematic diagram of image capture process

All data were inspected and sorted into a Boolean format with two possible values as displayed in the block diagram in Fig. 2. A value of +1 was allocated if true and +0 if false according to the condition met for each quality level. Fig. 5 shows the programming steps from entering data to grading chicken quality using the number of objects as a condition. The program counts the total data that has been analyzed.

*Experimental procedure*

The objective of the study was to evaluate the developed algorithm to check the quality of each chicken on a slaughter production line using the webcam, computer and analytical package described above. In total, 70 chickens were tested using the system on one side of the chicken and 70 others were tested on the other side using the same system.

Fig. 5 and Fig. 6 show how the information obtained on the image was processed. The pixel clusters defined by the patterns were identified and marked by the software on the image. Each scratch on the chicken was counted to determine the category for the total carcass, with a light emitting diode illuminating according to the classification of the chicken in the current image. The main modules used were vision acquisition, vision assistant and binary manipulation, where vision acquisition recovered the video data and vision assistant analyzed determined patterns in the acquired data, which was then processed using the binary module.

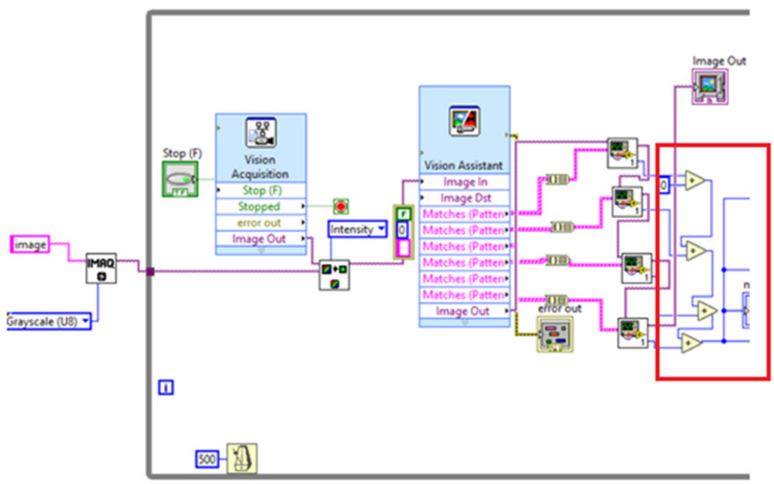


**Fig. 5** Block diagram for patterns in LabVIEW program

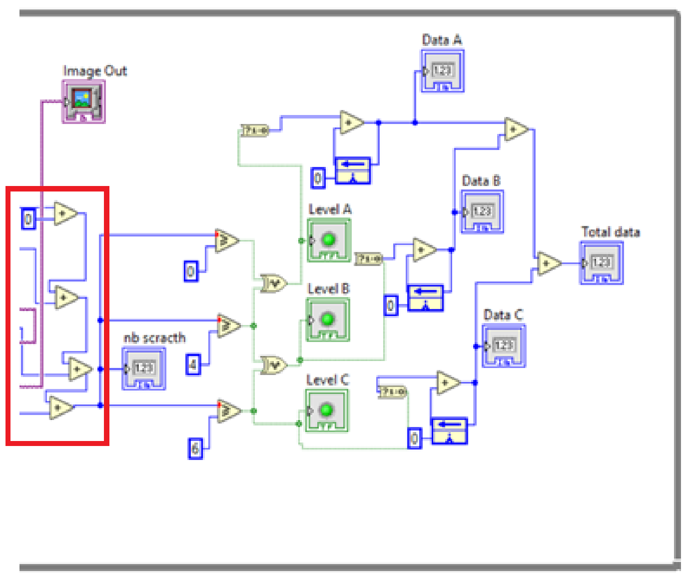


**Fig. 6** Block diagram for grading chickens in LabVIEW program

### *Scratch detection and results display*

The LabVIEW program has an integrated graphic user interface which allows the visualization of all the parameters in associated software. The interface used in the current project is shown in Fig. 7. The current image is displayed, having already undergone the conversion to grayscale. In Fig. 7, the scratches detected are framed with red rectangles to allow them to be identified. The number of scratches on the chicken are indicated in position (2). After counting the number of scratches, the software indicates with a light the overall chicken category (A, B or C) in position (3). The number of chickens treated (4) and the chickens in each category are counted and these numbers are displayed, with Fig. 7 showing the output from processing two chickens, with one categorized as B and the other as C (5). The chicken under consideration in Fig. 7 was categorized as quality B, having four scratches detected.

### *Test scores*

In a company, working time can be an important indicator of the efficiency of processing. The working capacity of this research was defined as the number of chickens per time spent (birds per minute). In addition, the scratch level detection accuracy percentage was measured using Equation 1:

$$\text{Detection accuracy} = \frac{\text{Accuracy count}}{\text{Number of chickens}} \times 100 \quad (1)$$

Finally, the scratch detection accuracy was compared between the developed software algorithm and the regular manual method used by employees. The results were analyzed and presented in table form. The errors in each case were analyzed to determine the factors causing inaccuracies in the detection program.

### *Statistical analysis*

A two-tailed z-test was chosen due to the substantial sample size exceeding 30. The primary objective was to determine whether there was a significant difference between the results produced by the operators and the developed techniques. The statistical analysis was conducted using the Microsoft Excel software (Microsoft Corp.; Redmond, WA, USA).

Two hypotheses were formulated:

Null Hypothesis ($H_0$): There is no significant difference between the sample means for operator performance and the developed technique.

Alternative Hypothesis ($H_1$): There is a significant difference between the sample means for operator performance and the developed technique.


**Fig. 7** Program results displaying: (1) output image for detecting scratches, (2) total number of objects detected on one carcass, (3) perceived quality level, (4) number of verified chickens and (5) number of chickens qualified for each level

## Results

### Results of analysis and comparison

The developed algorithm was run on each side of a series of 70 chickens. It was tested on the production line and resulted in 70 chickens being graded using left side analysis. Then, the results obtained by the simulation were compared with the grading done by a specialist. The simulation was created based on chicken video from the left side. The patterns learned in the software were limited to the left sides of chicken for this development. The first test was therefore on this side. The program results are shown in Table 2, indicating a discrepancy for three chickens between the software and the operator, with the program classifying 58 chickens in category A compared to the 61 by the specialist and 12 classified in category B, in contrast to the 9 by the specialist. None of the chickens was classified in category C. The three misclassified chickens each had a major scratch which was not detected by the algorithm because large scratches were not detected due to the lack of a scratch pattern (Zhuang and Zhang, 2020). The software was configured to detect small scratches; consequently, new patterns should be added for large scratches to be identified. Therefore, it was necessary to pass any chickens presenting such scratches through the calibration program to learn to detect them.

**Table 2** Results of algorithm analysis and comparison with specialist operator grading

| Level | Number of chickens (birds) | | Annotation |
|---|---|---|---|
| | Operator | Developed technique | |
| A | 61 | 58 | 3 misclassified (should have been A) |
| B | 9 | 12 | |
| C | 0 | 0 | |
| Total | 70 | 70 | |

The right side of the chickens was also tested with the same software by moving the camera to a location allowing a good view of the right side of the chickens. Again, 70 chickens were filmed and then analyzed. The algorithm had trouble detecting chickens passing in front of the camera because the chickens were positioned differently compared to the previous test and the learning calibration had not been done on this side. If the factory chose to move the system to different places in the production line, with a different side view of the chickens, then new patterns would have to be developed for scratch detection on the chickens (Chen et al., 2020). However, the scratches were detected, the change in rating did not affects this detection. Rather, it was the difference in the position and configuration of the chickens that generated the inaccurate results.

The scratch level detection accuracy percentage based on Equation 1 was 95%.

### Results of statistical analysis

The z-test results (Table 3) indicated non-significant difference between the mean number of scratches attributed to operators and those associated with the developed technique. The *p*-value of 0.787532 indicated that the observed difference was not significant at the 0.05 test level.

**Table 3** Results of z-test

| Statistical analysis | Number of scratches | |
|---|---|---|
| | Operator | Developed technique |
| Mean | 1.7 | 1.742857 |
| Known Variance | 0.85 | 0.92 |
| Observations | 70 | 70 |
| z | -0.26952 | |
| $P(Z \leq z)$ two-tail | 0.787532 | |
| z Critical two-tail | 1.959964 | |

## Conclusion

The study developed a system based on an algorithm for application in the LabVIEW software to recover video images of chicken carcasses on a slaughterhouse production line and to use subsequent analysis to detect scratches on the carcasses. Using machine learning and the creation of patterns, the developed system achieved an accuracy of 95%. The video was directly acquired and processed by the software without any pre-processing, such as removing the background. Category levels based on the number of scratches per carcass were developed to calibrate with the software. The camera should be positioned so that lighting of the image is as good as possible. Positioning of the camera was important, as the software had been calibrated based on patterns on the left side of the carcass. Applying the developed algorithm to the right side led to reduced performance due to the different positioning of the chickens. Applying the learning calibration from the right side could improve the system to make it more adaptable to the plant configuration. If the various image processing optimization parameters, such as light, are well considered, this system could carry out automated inspection of the carcass production line based on counting the number of scratches on each chicken and categorizing them according to their quality. With further development, it should be possible carry out automated sorting of the chicken carcasses on the production line according to their quality category.

## Conflict of Interest

The authors declare that there are no conflicts of interest.

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