Journal of Intelligent Decision Support System (IDSS) 7 (2) (2024), pp. 163-172

Published by: Institute of Computer Science (IOCS)

Journal of Intelligent Decision Support System (IDSS)

Journal homepage: www.idss.iocspublisher.org

Detection of normal chicken meat and tiren chicken using naïve bayes classifier and glcm feature extraction

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Article Info

Article history:

Received Jun 03, 2024
Revised Jun 04, 2024
Accepted Jun 14, 2024

Keywords:

Bernoulli Kernel;
Chicken detection;
Gaussian Kernel;
GLCM feature extraction;
Naive Bayes Classifier.

ABSTRACK

The chicken farming industry is an important sector in the Indonesian economy, but there are food security issues with the presence of tiren chicken. This research aims to develop a more accurate and efficient method of detection of tiren chickens using Naive Bayes Classifier with Gaussian and Bernoulli kernels and GLCM feature extraction. Data is collected from various internet sources, then pre-processing and feature extraction is carried out. The Naive Bayes Classifier algorithm is implemented with two kernels and evaluated using accuracy, precision, recall, and f1-score metrics. The Gaussian kernel showed an accuracy of 0.75, higher than Bernoulli's kernel which was only 0.50. Models with Gaussian kernels have high performance in detecting tiren chickens and normal chicken precision. The combination of Gaussian and Bernoulli kernels and GLCM feature extraction is effective in improving the detection accuracy of tiren chickens, contributing significantly to food safety and consumer confidence.

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Introduction

The chicken farming industry is one of the important sectors in the Indonesian economy. Chicken meat is an important source of nutrients for humans because it contains protein, fat, vitamins, and minerals needed for growth (Govoni et al., 2021). The increasing demand for chicken meat led to competition among traders for greater profits (Ragasa et al., 2020) (Pourmohammad-Zia et al., 2021) (Mizik, 2021). Unfortunately, this triggered fraud from some irresponsible traders by selling chicken meat that was not fit for consumption, known as Tiren Chicken (Januardi et al., 2024) .

The safety and quality of chicken meat products is an important issue in the food industry, especially in detecting the presence of tiren chicken (dead chicken before slaughter) which has the potential to endanger consumer health (Ahmed et al., 2023) (Jahir et al., 2023) (Cousins et al., 2022). Tiren chicken can contain harmful bacteria and toxins, so it is important to have an accurate and efficient method to distinguish between tiren chicken meat and normal chicken (Das et al., 2024) (Ramlucken et al., 2020). Although various methods have been developed to detect fraud and contamination in meat products, there are still some limitations, such as data complexity, the need for large sample data, and the lack of detection specificity (Chen et al., 2024) (Khaled et al., 2021) (Haque et al., 2020).

Conventional methods commonly used to detect chicken quality include visual inspection, microbiological testing, and chemical testing. Visual inspection involves a direct inspection by an officer to detect signs of tiren chickens (chickens that die before slaughter), such as discoloration and texture. Microbiological tests include testing meat samples to detect the presence of pathogenic bacteria, while chemical tests can detect harmful compounds or meat degradation. However, these methods have drawbacks, such as the subjective nature of visual inspection that relies on individual expertise, the high time and cost of microbiological tests as well as chemical tests, and the need for well-equipped laboratories. To overcome these weaknesses, this study chose the Naive Bayes method because of its simplicity and speed in the process pelatihan dan prediksi, efisiensi dengan data sampel yang terbatas, as well as the ability to provide accurate results using simple features such as those extracted from images through the Gray Level Co-occurrence Matrix (GLCM). The combination of Bernoulli and Gaussian kernels and GLCM feature extraction improves detection performance by combining the power of both types of kernels in classifying complex data. Bernoulli kernels are good for binary or categorical features, while Gaussian kernels are good for continuous features, and GLCM feature extraction produces important texture features that are very helpful in differentiating between normal and tiren chickens. This combination allows Naive Bayes' algorithm to harness the power of both kernel types, thereby improving the accuracy and efficiency of tire chicken detection.

Previous studies have shown the success of the Naive Bayes method in a variety of applications (Gu & Lu, 2021) (Ke et al., 2021) (Siva Subramanian & Prabha, 2021). used deep learning with Gaussian kernels to detect disease-related dead trees, showing that a combination of statistical methods and machine learning can improve detection accuracy (Han et al., 2022). Developed an improved feature selection method with Naive Bayes and kernel density estimators for opinion mining, which proves the reliability of Naive Bayes in complex data analysis (Sethuraman & Athisayam, 2021). In addition, research on the detection of skin diseases using dynamic graph cut algorithms and Naive Bayes demonstrated the effectiveness of this combination of methods in disease detection and classification (Balaji et al., 2020). Another study on the identification of jamming interference in wireless communication using Naive Bayes with small sample data demonstrated the efficiency of this method under conditions of limited data(Shi et al., 2021). Finally, detection of undeclared chicken meat using lateral flow immunoassay emphasizes the importance of rapid and sensitive detection in food quality monitoring(Hendrickson et al., 2021).

However, few researchers have focused on the detection of tiren chickens using the Naive Bayes method with a combination of Bernoulli and Gaussian kernels and GLCM feature extraction(Lin et al., 2023). Research relating to the detection of contamination in meat products often does not consider the efficiency and accuracy of detection under conditions of complex and limited data. Therefore, this study intends to overcome the gap by applying the Naive Bayes Classifier method using Bernoulli and Gaussian kernels and GLCM feature extraction for the detection of tiren chickens and normal chickens. The aim of this study is to develop a more accurate and efficient method for detecting tyrant chickens as well as provide a workable solution with limited sample data while still providing reliable results.

The methods to be used in this study include the collection and pre-processing of tiren and normal chicken meat sample data, feature extraction using GLCM, and the application of Naive Bayes Classifier with Bernoulli and Gaussian kernels for data classification. The main innovation of this research is the combination of the use of Bernoulli and Gaussian kernels on the Naive Bayes Classifier with the extraction of GLCM features to improve the accuracy and efficiency of detection of tyrant chickens.

This research could provide a better solution in the detection of tiren chicken, which is important for consumer safety and trust in chicken meat products. The contribution of this research will help fill gaps in existing detection methods and provide a basis for further development in food quality control. By overcoming the limitations of previous research and proposing innovative methods, this research is expected to have a significant impact in the field of detection and monitoring of chicken meat quality.

Method

This study conducted several stages by applying naïve bayes classifier to process chicken image data. Here are the research steps.

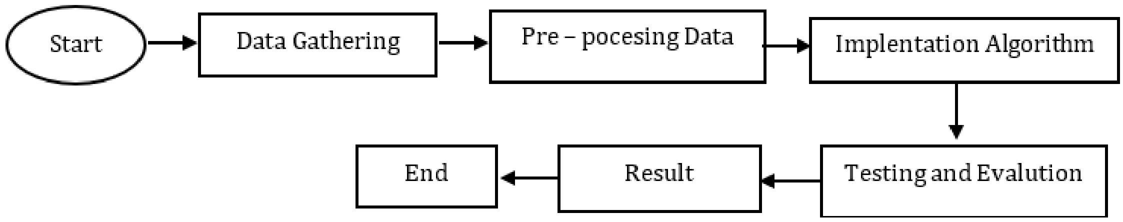

Figure 1. Research Flow

Figure 1, is a research flow that begins with data collection in the form of pictures of tiren chickens and normal chickens. After the data is collected, the pre-pocesing stage of the data is cleaned and extracted features using the Gray-Level Co-Occurrence Matrix (GLCM). Furthermore, the extracted data is then calculated with the naïve bayes classifier algorithm. After the algorithm is implemented, testing and evaluation are carried out to see the performance of the algorithm in processing data until finally the results are analyzed.

Research Design

This research uses a quantitative approach with a combination design of experimental methods, quantitative analysis, and model validation. Experimental methods were used to collect data on chicken imagery from various conditions and variations, such as differences in age, sex, and environment. Quantitative analysis is performed by extracting features from image data using GLCM and applying the Naive Bayes Classifier algorithm with a combination of Bernoulli and Gaussian kernels for classification. Model validation is done by evaluating model performance using metrics such as accuracy, precision, recall, F1-Score.

Data Collection

Data collection was carried out by taking samples of chicken meat from various internet sources. Chicken meat data includes pictures of normal chickens and pictures of tiren chickens. The amount of data collected was 20 images consisting of 10 chicken meat data and 10 tiren chicken meat data.

Data Pre-processing

The collected data undergoes data pre-processing by adjusting all images to the same size of 100 x 100 pixels. The resized image then involves selecting texture features using the Gray Level Co-occurrence Matrix. The extracted features include contrast, energy, homogeneity, and correlation. The extracted data is separated into two, namely training data and testing data. The optimized model in this study is the Naive Bayes Classifier with a combination of Bernoulli and Gaussian kernels.

Implementation Algorithm

The Naive Bayes Classifier algorithm with a combination of Bernoulli and Gaussian kernels is implemented using the Python programming language and libraries such as scikit-learn. The implementation of the algorithm in this study involves the application of the Naive Bayes Classifier method using two types of kernels, namely Bernoulli and Gaussian.

Algorithm Configuration and Model Evaluation

Algorithm configuration involves adjusting key parameters such as the probability of prior for each class and the selection of appropriate distribution functions for numerical or categorical features. Tuning these parameters is important to optimize algorithm performance and ensure high prediction accuracy. Model evaluation is done using metrics such as accuracy, precision, recall, and F1-score.

This study measures the accuracy and efficiency of the detection method developed using various evaluation metrics such as accuracy, precision, recall, and F1-score. After the image data of tiren chickens and normal chickens were collected and processed through feature extraction using the Gray Level Co-occurrence Matrix (GLCM), the data was then classified using the Naive Bayes algorithm with a combination of Bernoulli and Gaussian kernels. The resulting model is then evaluated by comparing the prediction results with the actual values in the confusion matrix for each kernel. The accuracy of the model is measured by calculating the proportion of correct predictions out of all predictions. Precision measures how many positive predictions are correct, recall measures how many of the positive cases are detected correctly, and F1-score is a harmonious average of precision and recall that provides a balance between the two metrics.

Precision formula as in equation (1)

$$Presisi = \frac{TP}{TP + Fp} \tag{1}$$

Where FP adds the overall number of type I (false positives) in the denominator, precision becomes a crucial metric when the cost of false positives is high (Long, 2021) (Hancock et al., 2023) (Movahedi et al., 2023).

The recall formula as in the equation (2)

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

Where FN adds the number of type II errors (false negatives) in the denominator, recall is an important metric for capturing all positive cases (Farhadpour et al., 2024) (Wineman et al., 2020).
The F1-Score is a harmonized average of precision and recall, providing a balance between the two metrics. The F1-Score formula is like the equation (3)

$$F1 - Score = 2 \times \frac{Presisi \ \times Recall}{Presisi + Recall} \tag{3}$$

Here the F1-Score reaches the highest value at 1 (precision and perfect recall) and the lowest at 0 (precision or zero recall).

Results and Discussions

The application of the naïve bayes classifier method for the detection of tiren chickens and normal chickens using two kernels, namely Gaussian and Bernouli has carried out a series of steps in the dataset.

Table 1. Chicken Meat Data

Types of chickens	Image	Information
Normal Chicken		10 Image
Tiren Chicken		10 Image

Table 1, is data on chicken meat image data used in this study, which consists of two main categories, namely normal chicken and tiren chicken. Each category comes with sample images and the number of images used for analysis. The column "Breed of Chickens" indicates the two meat breeds of chickens analyzed. Normal chickens are shown with pictures showing healthy and properly cut chickens, while tiren chickens are shown with images showing chickens that died before slaughter, with different meat color features and less fresh conditions than normal chickens. The "Images" column displays representative images of each breed of chicken, while the "Description" column provides information on the number of images collected for each category, i.e. 10 images each for normal chickens and tiren chickens.

The data that has been obtained is then processed so that it can be processed at the next stage.

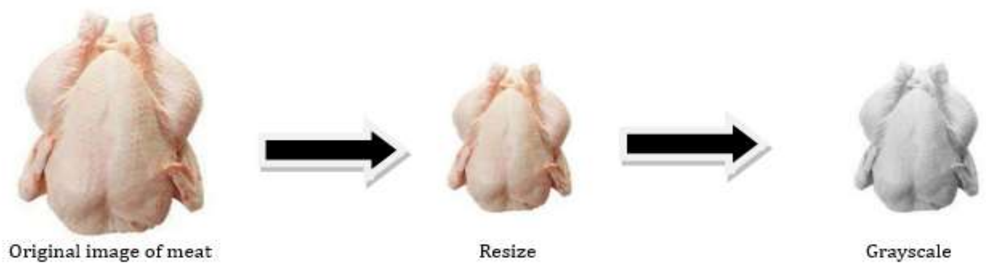

Figure 2. Image data processing

Figure 2, is the stage of image data processing that will be used in this study includes changes in changing the size of images that have been taken from several internet sources with different sizes to be the same all with a size of 100 x 100 pixels. After the data has been converted to the same size then the image is converted into a gray image to improve the accuracy of the algorithm in analyzing the image data. The grayed out image is then extracted features using GLCM.

Table 2. Feature Extraction Results

Constart	Dissimilarity	Homogeneity	Energy	Label
80.5049609810564	4.69127090301054	0.315253913968319	0.0209019501775174	Ayamtiren
526.031337792683	8.82357859531832	0.202787434839812	0.0171458665851628	Ayamtiren
119.39558528429	6.47085841694587	0.217066364019452	0.0151334086771548	Ayamtiren
⋮	⋮	⋮	⋮	⋮
12.5087402452629	1.2592642140469	0.764843986593905	0.4558159539367	Ayamnormal
28.2201337792675	1.69440356744722	0.75952582903856	0.651616391822229	Ayamnormal
19.9324637681178	1.80082497212944	0.643212869950318	0.358760460397733	Ayamnormal

Table 2, is the result of the extraction of features of 20 chicken meat images using GLCM which include features Constrat, Dissimilarity, Homogeneity, Energy based on 2 labels taken from two pictures of chicken meat used.

Data that has been extracted using GLCM will be separated into two parts with an 80:20 ratio between the training data and the test data. The test data is then calculated using the naïve bayes classifier with the implementation of 2 kernels namely Gaussian and Bernoulli.

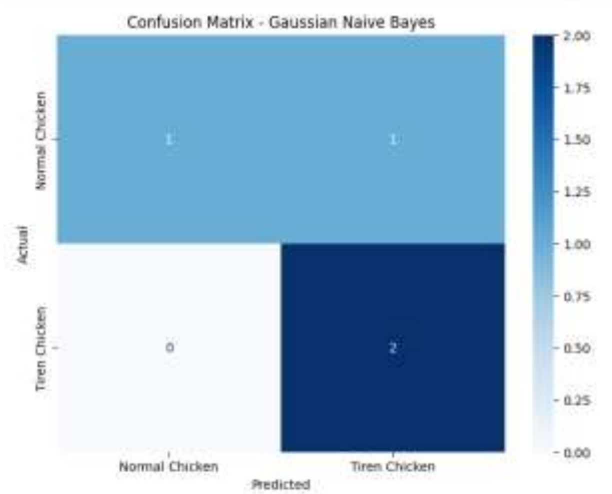

Figure 3. Confusion Matrix Gaussian

Figure 3, is a confusion matrix from the Naive Bayes model for the classification of tiren chickens and normal chickens. This confusion matrix helps understand the performance of the classification model by displaying the number of correct and incorrect predictions compared to the actual values. The matrix shows that the model successfully identified two cases of Tiren Chicken correctly as Ayam tiren (True Positive, TP = 2) and one case of Ayam normal correctly as Normal Chicken (True Negative, TN = 1). However, the model also incorrectly classified one case of a normal chicken as a tyrant chicken (False Positive, FP = 1), and no case of a tyrant chicken was incorrectly classified as a normal chicken (False Negative, FN = 0). The Naive Bayes model shows that despite having a fairly good ability to detect tyrant chickens, it also makes some mistakes in identifying normal chickens.

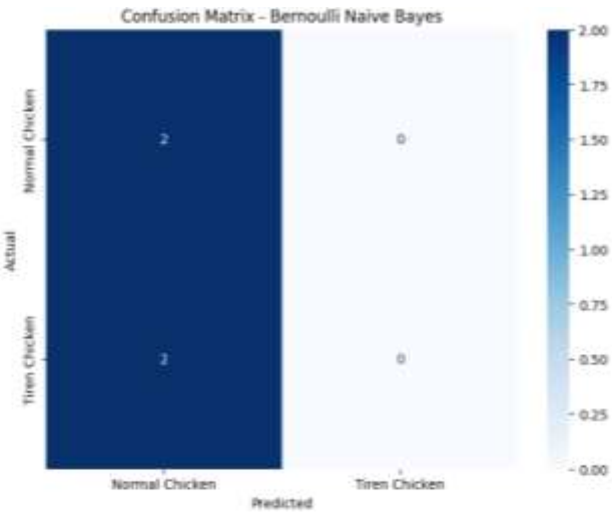

Figure 4. Confusion Matrix Bernoulli

Figure 4, is a confusion matrix from the Bernoulli Naive Bayes model for the classification of tiren chickens and normal chickens. This confusion matrix shows the model's performance in classifying the two types of chickens by displaying the number of correct and incorrect predictions compared to actual values. In this matrix, there are no cases of tiren Chicken that have been correctly identified as tiren Chicken (True Positive, TP = 0). In contrast, the model managed to correctly identify

2 cases of normal Chickens as normal Chickens (True Negative, TN = 2). In addition, there were no cases of normal chickens being misclassified as tiren chickens (False Positive, FP = 0), but there were 2 cases of tyrant chickens being misclassified as normal chickens (False Negative, FN = 2). This analysis showed that the Bernoulli Naive Bayes model performed poorly in detecting tyrant chickens, but was quite good at identifying normal chickens.

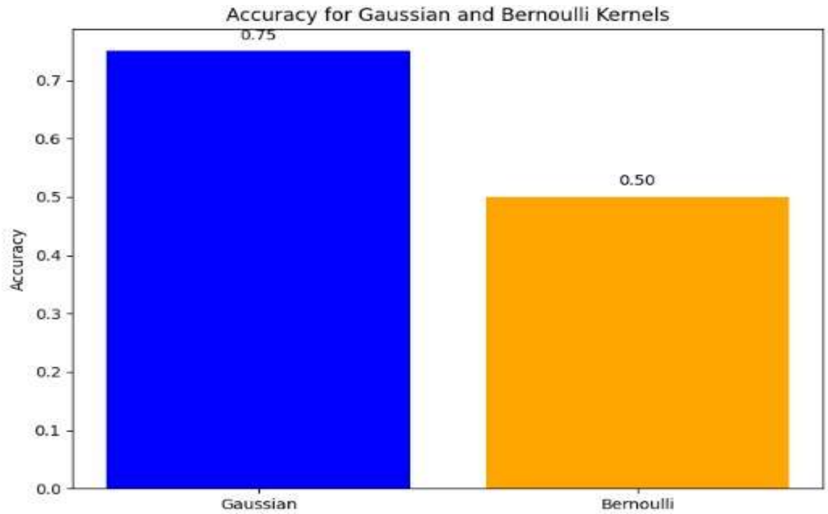

Figure 5.Accuracy for Gaussian and Bernoulli Kernels

Figure 5, is the result of the accuracy of the Naive Bayes model using the Gaussian and Bernoulli kernels. The Gaussian kernel achieved an accuracy of 0.75, showing better performance in classifying normal and tiren chickens compared to the Bernoulli kernel which only achieved an accuracy of 0.50. This indicates that models with Gaussian kernels are more reliable in detecting both types of chickens. The results of the Naïve Bayes Classifier calculation using the Gaussian kernel and Bernoulli kernel are then evaluated using Precision, Recall, and F1-Score.

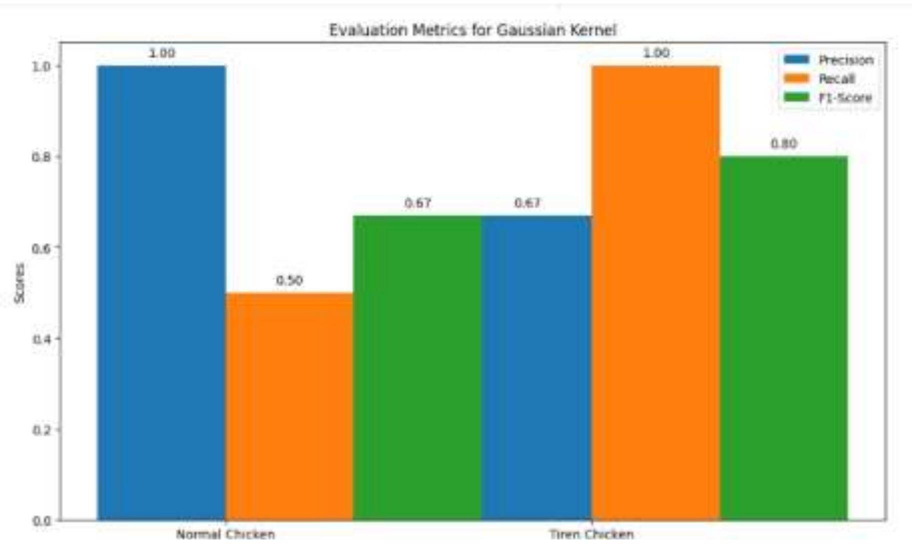

Figure 6. Evaluation Gaussian Kernel

Figure 6, is the result of evaluation of the Naive Bayes model with Gaussian kernels to detect normal chickens and tiren chickens. For "Normal Chicken," the precision reached 1.00, but the recall was only 0.50, resulting in an f1-score of 0.67. This shows the model is very precise but does not detect all normal chickens. In contrast, for "Tiren Chicken," the precision is 0.67 and the recall is perfect 1.00, resulting in an f1-score of 0.80. This model is very good at detecting all tiren chickens despite some prediction errors. This graph illustrates that the Gaussian kernel has high performance in tiren chicken recall and normal chicken precision.

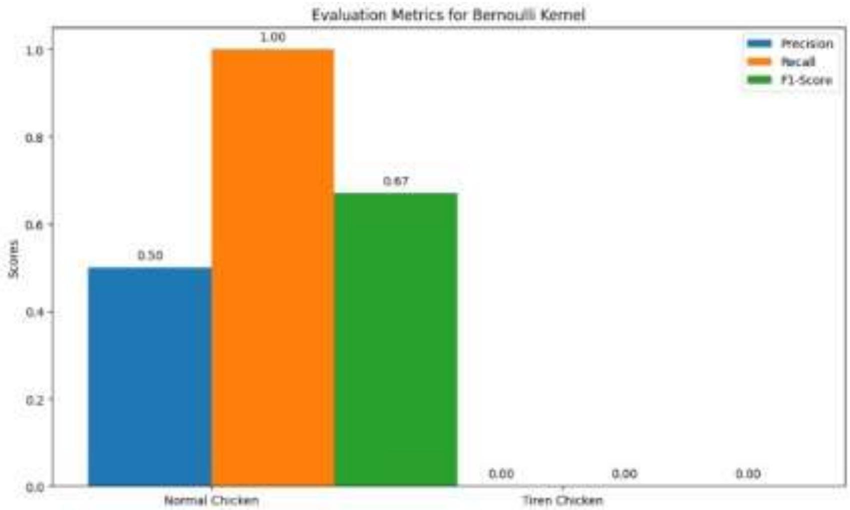

Figure 7. Evaluation Bernoulli

Figure 7, is the result of evaluation of the Naive Bayes model with Bernoulli kernels to detect normal chickens and tiren chickens. For "Normal Chicken," the precision is 0.50 and the recall reaches 1.00, resulting in an f1-score of 0.67. This shows that the model detected all normal chickens, but half of the predictions were wrong. For "Tiren Chicken," both the precision, recall, and f1-score were all 0.00, indicating the model failed to detect the tiren chicken. This graph illustrates that the Bernoulli kernel performs well in normal chicken recall but is not able to detect tiren chickens at all.

This study successfully showed that the Naive Bayes method with Gaussian kernels had a better performance compared to Bernoulli kernels in detecting tiren chickens and normal chickens. The evaluation results show that the Gaussian kernel achieves an accuracy of 0.75, while the Bernoulli kernel only achieves an accuracy of 0.50. This shows that the model with the Gaussian kernel is more reliable in detecting both types of chickens. In addition, the evaluation of metrics such as precision, recall, and F1-score showed that the Gaussian kernel had high precision in detecting tiren chickens, although the recall for normal chickens was slightly lower. These findings suggest that the combination of Gaussian and Bernoulli kernels along with the extraction of GLCM features can improve the accuracy and efficiency of tiren chicken detection.

Comparison with previous studies shows that this approach is more effective in overcoming detection limitations under complex and limited data conditions. Previously, detection methods often had problems with data complexity and the need for large data samples. This research, with the combination of kernels used, successfully overcomes some of these limitations and provides a more reliable and efficient solution. Previous research such as those conducted by Han et al. (2022) using deep learning with Gaussian kernels to detect disease-related dead trees, shows that a combination of statistical methods and machine learning can improve detection accuracy. In the context of the detection of tiren chickens, this study introduces innovations in the use of Naive Bayes with Gaussian and Bernoulli kernels as well as the extraction of GLCM features, which has not been done much by previous studies

Conclusions

This study concluded that the Naive Bayes Classifier method with Gaussian kernels was superior in detecting tiren chickens and normal chickens compared to Bernoulli kernels, with an accuracy of 0.75 and 0.50, respectively. The combination of Bernoulli and Gaussian kernels and GLCM feature extraction improves detection accuracy and efficiency, making a significant contribution to the safety and quality of chicken meat products. The results of this research can be applied in the food industry to better identify tiren chickens, reducing the risk of contamination. Research limitations include a limited number of samples and data complexity; Further research can expand the sample and explore other combinations of methods for further improvement. Future research may expand the sample and explore combinations of other methods for further improvement.

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