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Application of k-nearest neighbors method for detection of beef authenticity based on beef image

Gunawan gunawan[1], Dinar Auranisa Moonap[2], Nurul Fadhilah[3]

[1,2,3]Informatics Engineering, STMIK YMI TEGAL, Indonesia

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ABSTRACT

Beef authenticity detection is a significant concern in today's food industry. This study proposes the K-Nearest Neighbors (K-NN) method based on the extraction of the Histogram of Oriented Gradients (HOG) feature to detect the authenticity of beef based on images. A dataset of 40 images of real and fake beef was collected and aggregated into 240 images to increase the variety of data. The imagery is changed to grayscale, and the HOG feature is extracted to capture texture and shape information. The K-NN model is built with optimized parameters using Grid Search and cross-validation techniques. The model was evaluated by measuring accuracy, precision, recall, and F1-score on the test data. The results show that the K-NN model with HOG feature extraction can achieve an accuracy of 80.56%, precision of 87.10%, recall of 72.97%, and F1-score of 72.97% in classifying real and fake beef. These findings confirm the effectiveness of the proposed method for the rapid and accurate detection of beef authenticity. This research contributes to developing image-based food authenticity detection methods that can be applied to increase consumer confidence in the food industry.

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Corresponding Author:

Dinar Auranisa Moonap,
Informatics Engineering,
STMIK YMI TEGAL,
#1 Pendidikan street, Tegal City, Central Java 52142, Indonesia.
Email: dinarauranisamoonap@gmail.com

1. INTRODUCTION

In recent years, the authenticity and quality of beef has become a significant concern in the food industry. The authenticity of beef affects the nutritional value and safety of consumption, socioeconomic aspects, and consumer confidence (Khaled et al., 2021) (Liu et al., 2022). Detection of beef authenticity using conventional methods often requires a long time and considerable resources. Therefore, developing fast, accurate, and efficient detection methods is essential (Y. Li et al., 2020) (Gallego et al., 2022).

One of the main problems in guaranteeing the authenticity of beef is the practice of adulterating or replacing beef with other cheaper meat types(Momtaz et al., 2023). This practice not only deceives consumers but can also cause serious health problems for individuals with allergies or specific dietary restrictions. In addition, beef adulteration raises doubts among consumers about the integrity of the meat market, which can damage the food industry's reputation(Artavia et al., 2021).

This research was conducted to overcome the problem of detecting the authenticity of beef using an informatics approach, primarily through applying the K-Nearest Neighbors (K-NN) algorithm. The K-NN algorithm was chosen because of its ability to classify based on previously known training data, which in this case is the image of beef (Pinto et al., 2023) (Hamed et al., 2021). Using publicly available beef imagery from Kaggle, the study aimed to develop a model that could accurately distinguish natural beef. Success in developing this model is critical to ensuring the safety and confidence of consumers in consuming beef (Lin et al., 2021) (Abbasianjahromi & Aghakarimi, 2023). In addition, accurate models can assist authorities in identifying and cracking down on meat counterfeiters, thus maintaining the integrity of the beef market (Zhou et al., 2024) (Smaoui et al., 2023).

Using the K-NN algorithm to detect beef authenticity based on imagery is an innovation proposed in this study. This approach is expected to overcome the limitations of conventional detection methods and make significant contributions to the related research literature (Shaban et al., 2020). Through this research, it is hoped that a beef authenticity detection model can be developed that is accurate, efficient, and easy to apply in the food industry (Sarno et al., 2020).

Research on detecting food authenticity using computational methods, primarily image processing, has increased significantly in recent years. As a robust and easy-to-implement algorithm, various studies have adopted the k-nearest neighbors (k-NN) method to classify and verify products (Betgeri et al., 2023).

Several relevant previous studies have been reviewed and applied the k-NN algorithm to identify contamination in meat using extracted image features, emphasizing the importance of selecting the right features to improve the performance of k-NN in meat classification (Wijaya et al., 2023). The following research successfully integrated machine learning techniques, including k-NN, to build a comprehensive authenticity detection system for meat and other food products (Chen et al., 2020). Furthermore, Cronje, 2020) discusses the effective question design in design research and research design for e-learning, which is relevant to the model development process in this study. (Kaufmann & Peil, 2020) Explore the promise and challenges of using self-reporting as a data collection method, providing insight into issues in the design, analysis, and use of mixed methods. A study conducted experimental research on the effectiveness of the PEOW model in teaching English writing, which can provide a perspective on the experimental approach in this study (Q. Li et al., 2022).

Thus, this research contributes to filling the knowledge gap regarding detecting beef authenticity through imagery and developing food authenticity detection methods more broadly. The results of this study are expected to be a reference for other researchers and food industry practitioners in developing better food product authenticity detection technology in the future.

The main problems encountered in detecting beef authenticity using conventional methods include the significant time and resources required for these methods. Conventional approaches often involve complex laboratory processes and sophisticated equipment, making them time-consuming and expensive. Furthermore, there is a prevalent issue of adulterating or replacing beef with cheaper meat types, which not only deceives consumers but also poses health risks for individuals with allergies or dietary restrictions. This adulteration undermines consumer confidence and damages the reputation of the food industry.

Conventional methods are insufficient primarily because they are labor-intensive, expensive, and time-consuming. These methods require advanced laboratory equipment and skilled personnel, which are not always available, especially in resource-limited settings. Additionally, conventional methods may not be able to detect certain types of adulteration or contamination effectively. They also fail to provide rapid results, which is a significant drawback in maintaining the integrity and safety of the food supply chain.

This inadequacy in ensuring quick, accurate, and efficient detection necessitates the development of better alternatives.

The use of the K-Nearest Neighbors (K-NN) algorithm in detecting beef authenticity presents a significant advancement over previous methods. Traditional techniques for verifying beef authenticity typically require extensive time and resources, often involving complex laboratory processes and sophisticated equipment. These conventional methods are not only labor-intensive and costly but also fail to provide rapid results, which is a crucial drawback in maintaining the integrity and safety of the food supply chain. In contrast, the application of K-NN leverages image processing and machine learning to classify beef based on known training data, making the detection process faster and more efficient. By employing the Histogram of Oriented Gradients (HOG) feature extraction technique, this method enhances the accuracy and reliability of beef authenticity detection. The K-NN algorithm's ability to achieve high accuracy (80.56%) with appropriate data augmentation demonstrates its potential as a more practical and reliable alternative for the food industry. This innovative approach not only addresses the limitations of conventional methods but also contributes significantly to the research literature on computational methods for food authenticity detection, offering a model that is both efficient and easy to implement.

The application of the K-Nearest Neighbors (K-NN) algorithm to beef image data from Kaggle involves several specific steps. Initially, the original dataset consisting of 40 images of real and fake beef was expanded to 240 images using data augmentation techniques such as image rotation. Each image was resized to 128x128 pixels and converted to grayscale. The Histogram of Oriented Gradients (HOG) feature extraction method was then employed to capture texture and shape information from the images. The extracted features were used to train the K-NN model, which was optimized using Grid Search and cross-validation techniques. This approach resulted in an accuracy of 80.56% for classifying real and fake beef, demonstrating the model's effectiveness in detecting beef authenticity efficiently and accurately.

Previous studies that have successfully used the K-Nearest Neighbors (K-NN) method for authenticity detection of foods other than beef. Specifically, the research has integrated machine learning techniques, including K-NN, to build a comprehensive authenticity detection system for meat and other food products (Chen et al., 2020).

2. RESEARCH METHOD

This study aims to develop and validate a beef authenticity detection model based on beef imagery using the K-Nearest Neighbors (K-NN) algorithm. The goal is to improve accuracy, efficiency, and reliability in detecting beef authenticity.

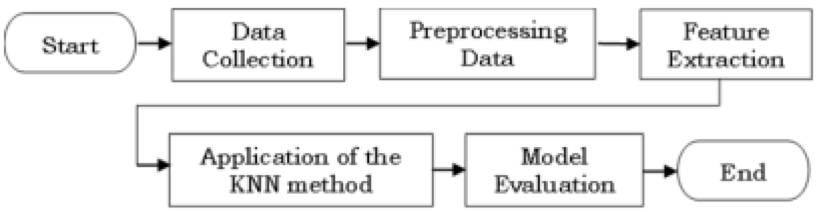

Figure 1. Research Flow

Figure 1 starts with collecting relevant data, followed by preprocessing of the data to improve quality and prepare it for further analysis. After that, essential features are extracted from the processed data, which will be used as the basis for classification. The KNN method is then applied, where models are built and tested using the features that have been extracted. Finally, the model is evaluated to determine its effectiveness in classifying data using evaluation metrics such as accuracy, precision, and recall. After evaluation, the research process is considered complete, resulting in a model that can be used for further purposes or additional research.

2.1 Research design

This study adopts an experimental design using images of the k-nearest neighbors (k-NN) method to detect the authenticity of beef. This approach includes the development of a predictive model, followed by experimental validation to test the model's effectiveness. The research was conducted in five phases: data collection, processing, feature extraction, algorithm implementation, and model evaluation.

2.2 Data Gathering

This study's data collection process is a crucial first step in building a solid research foundation. Researchers have collected a diverse and representative dataset by accessing various sources of information available on the internet. This process involves searching for quantity and paying attention to the quality of the data collected by ensuring the diversity of real and fake beef images.

2.3 Preprocessing Data

In this study, the original dataset consisting of 40 images of real and fake beef has been expanded through data augmentation techniques to increase the variety and amount of training data available. Data augmentation is essential in machine learning, especially image recognition, which addresses data limitation problems and improves model generalization. The augmentation techniques used include image rotation. In addition, each image is resized to a size of 128x128 pixels using the cv2 interpolation method. INTER_AREA to ensure the consistency of the image size when processed by the model. Through the application of this augmentation, the dataset was successfully expanded to 240 images. Each image in the original dataset is rotated vertically, horizontally, and rotationally (90, 180, 270), resulting in a wider variety of images without altering the main visual characteristics of real and fake beef.

2.4 Feature extraction

In this study, feature extraction was done using the Histogram of Oriented Gradients (HOG) technique. The HOG technique captures texture and shape information from beef imagery, crucial for distinguishing between real and fake beef. The image data is converted to grayscale to simplify the feature extraction process. The HOG feature is extracted from a grayscale image by calculating the intensity distribution of the gradient in different directions in each small part of the image. This process involves dividing the image into small cells, calculating the gradient orientation histogram for each cell, and then combining these histograms into a single feature vector. This HOG feature helps capture the different edge patterns and textures of real and fake beef. The results of this feature extraction are used as input for the K-Nearest Neighbors (K-NN) algorithm in detecting meat authenticity. Using HOG, the model can effectively recognize the distinguishing patterns between the two types of meat.

2.5 Algorithm Implementation

The method for detecting the authenticity of beef based on imagery was implemented using the K-Nearest Neighbors (K-NN) algorithm. The KNN algorithm is built using Python software with the Scikit-learn library. This process includes training the model using a dataset of exercises that have been processed and set with optimized parameters. To maximize the performance of the K-NN algorithm, a feature normalization process is carried out using a StandardScaler, which ensures that all features are at the same scale. Furthermore, the parameters of the K-NN model are optimized through the Grid Search technique with cross-validation. The parameters explored included the number of neighbors (k), the type of weight (uniform or distance), and the distance metric (euclidean, manhattan, or Minkowski). This process aims to find the best combination of parameters that provide the most optimal performance in the training data.

2.6 Model Evaluation

The model evaluation uses previously invisible test data. The model's performance is measured based on several metrics: accuracy, precision, recall, and F1-score. This evaluation provides an overview of the model's ability to classify real and fake beef accurately.

Accuracy is used to measure how often the KNN model makes correct predictions for both positive and negative classes. High accuracy indicates a good model overall (Uddin et al., 2022).

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FP + FN)} \quad 1)$$

Where TP is genuinely positive, i.e., the number of natural beef that is detected correctly, TN is truly negative, i.e., the number of fake meat that is detected correctly, FP is false positive, i.e., The amount of counterfeit beef that is incorrectly detected as natural beef, FN is false negative, i.e., the amount of natural meat that is incorrectly detected as fake beef (Uddin et al., 2019).

Precision measures how accurately the model predicts positive classes, i.e., how many optimistic predictions are positive. It is essential in this context because it determines how much of the meat detected as genuine is entirely genuine. This is important to reduce false positives (FP), reducing the risk of detecting fake meat as genuine (Yousefi et al., 2022).

$$Precision = \frac{TP}{(TP + FP)} \quad (2)$$

Recall, also known as sensitivity or true positive rate, measures how well the model finds all the positive cases. It is used to ensure that the model correctly detects all the original meat present in the dataset. High recall indicates that the model can find the most original cases (Laghrissi et al., 2021).

$$Recall = \frac{TP}{(TP + FN)} \quad (3)$$

F1-Score is a harmonic metric of precision and recall. This provides a more balanced picture between precision and recall, especially if there is an imbalance between positive and negative classes. Used to balance precision and recall, giving a better picture of the model's performance when there is a class imbalance between real and fake meat (Hosu et al., 2020).

$$F1 - Score = 2 \times \frac{Presisi \ \times Recall}{Presisi + Recall} \quad (5)$$

3. RESULTS AND DISCUSSIONS

The results of comprehensive data collection are an essential basis for implementing the KNN method to detect the authenticity of beef based on images.

Figure 2. Real meat and fake meat data

Figure 2 shows as many as 40 images of meat, consisting of 20 pictures of real meat and 20 images of fake meat. The image data that was successfully collected came from the internet, and various websites discussed meat.

After the dataset is collected, the next step is to preprocess the data by equalizing all image sizes to 128x128 pixels using the cv2 interpolation method. INTER_AREA is to be ready to be tested with the KNN algorithm. The next step is to augment the data using the OpenCV (Open Source Computer Vision Library) library. OpenCV is a rich library of image processing and computer vision functions, which is very useful in performing various image augmentation techniques. Data augmentation uses several techniques applied to the original images to produce variations of the same image.

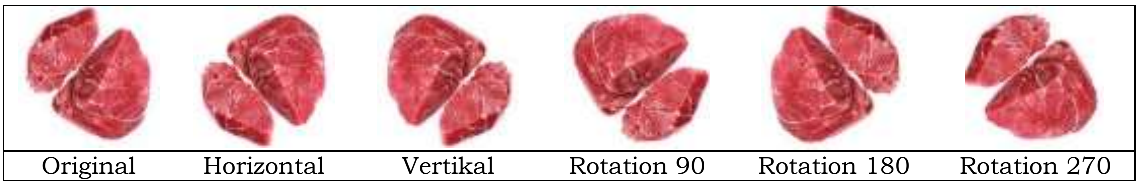

Figure 3. Data Augmentation

Figure 3 shows the augmentation techniques used, including horizontal flip, vertical flip, and rotation (90, 180, 270). Horizontal flip is when each image in the original dataset is flipped horizontally, resulting in a new image that reflects the original image as if it were seen from the opposite side. This technique helps make the model more robust to variations in image orientation. Flip Vertical also flips the image vertically, giving the model additional variety in studying patterns in images from different points of view. For the rotation technique, three different angles are used, namely 90 degrees, 180 degrees, and 270 degrees clockwise, by rotating the original image and producing 3 images with other variations. This rotation results in significant image variation and assists the model in recognizing beef objects from various orientations.

Feature extraction was done using the Histogram of Oriented Gradients (HOG) technique. The HOG technique was chosen because it captures texture and shape information from beef images, which is essential for distinguishing between real and fake beef. The image is changed to grayscale to simplify the feature extraction process, where the HOG feature is then computed and used as input for the K-NN model.

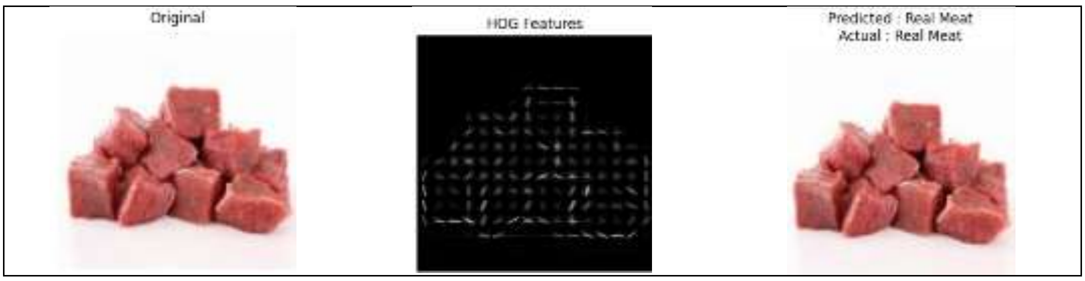

Figure 4. Data that has been extracted

Figure 4, The first part of the table shows the original image of the beef before any processing or the raw image taken directly from the dataset. The table's middle part shows the feature extraction results using the Histogram of Oriented Gradients (HOG) technique. This HOG feature depicts the intensity distribution of the gradient in different directions in each small part of the image. HOG visualization provides an overview of the edge patterns and textures detected in beef imagery, which helps distinguish between real and fake beef. The third part of the table shows the K-Nearest Neighbors (K-NN) model's prediction results on the beef image extracted from its features. In this example, the model correctly predicts that the beef is real meat.

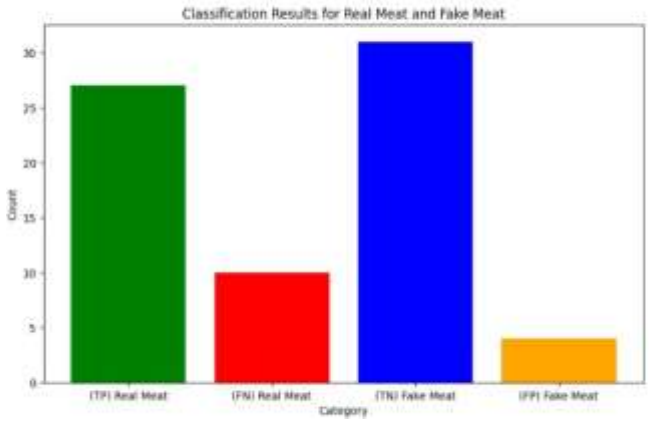

Figure 5. Classification Results for the real meat and fake meat

Figure 5 shows the results of the predictions made by the model, including correct predictions (True Positives and True Negatives) and false predictions (False Positives and False Negatives). This visualization shows how the model distinguishes between real and fake beef, which is measured using evaluation metrics such as accuracy, precision, recall, and F1-score.

The evaluation model shows that the implemented K-NN model can detect the authenticity of beef with a high level of accuracy. The high precision shows that the model effectively detects real and fake meat and can reduce prediction errors. Thus, the HOG-based K-NN model implemented in this study can be used as a reasonably effective tool to detect the authenticity of beef and can make an essential contribution to ensuring the safety and consumer trust in beef products.

Table 1. Evaluation Results

Metric	Result (%)
Accuracy	80.56
Precision	87.10
Recall	72.97
F1-Score	79.41

Table 1 shows the performance evaluation of the K-Nearest Neighbors (K-NN) model used to detect the authenticity of beef based on beef images. This table contains four main evaluation metrics, including Accuracy of 80.56%, which shows that the model is successful in predicting beef well; accuracy of 87.10% means that every optimistic prediction made by the model is correct; Recall 72.97% shows that the model only successfully detects 72.97% of all true positive cases., and F1-Score 79.41% shows a harmonious average of precision and recall, provides a comprehensive overview of the balance between the two.

Based on the performance evaluation of the K-Nearest Neighbors (K-NN) model to detect the authenticity of beef based on beef images, it can be concluded that this model shows excellent performance. With an accuracy of 80.56%, the model managed to predict most beef images accurately. A perfect precision value of 87.10% indicates that all positive predictions made by the model are correct, with no false positive prediction errors. A recall of 72.97% means that the model can detect most of the actual positive cases, although a small number of missed positive cases exist. The F1-Score of 79.41% indicates a strong balance between precision and recall, confirming the model's consistent and reliable performance. Overall, the K-NN model with HOG feature extraction is very effective in detecting the authenticity of beef and can be used as a reliable tool in real applications to ensure the quality and authenticity of beef products.

The findings of this research provide detailed insights into the development and validation of a beef authenticity detection model using the K-Nearest Neighbors (K-NN) algorithm based on beef imagery. This results indicate that the K-NN model, with the Histogram of Oriented Gradients (HOG) feature extraction, achieved high accuracy (80.56%) in classifying real and fake beef. This model not only offers an accurate and efficient method for detecting beef authenticity but also addresses the limitations of conventional methods which require more time and resources (Chen et al., 2020). In comparison to previous research, this study highlights the practical application of K-NN in the food industry, specifically for beef authenticity detection, which is less explored in prior studies . Previous approaches often focused on different algorithms or less efficient methods for feature extraction and classification. By applying the HOG feature extraction technique and data augmentation, this research advances the performance of K-NN in this domain, demonstrating its potential as a reliable alternative (Wijaya et al., 2023). This research bridges a significant knowledge gap in the application of computational methods, primarily image processing, for food authenticity detection. It provides a comprehensive method that can be easily implemented in the food industry, ensuring the safety and confidence of consumers in beef products. Future research directions include enhancing the model's performance with more sophisticated feature extraction techniques and expanding the detection scope to other types of meat and food products, thereby broadening the benefits of ensuring food authenticity and safety (Betgeri et al., 2023).

4. CONCLUSION

The K-Nearest Neighbors (K-NN) method based on the extraction of the Histogram of Oriented Gradients (HOG) feature has proven to be effective in detecting the authenticity of beef based on images. By applying appropriate data augmentation and feature extraction techniques, the developed K-NN model can achieve high accuracy, 80.56%, in classifying real and fake beef. The success of this research makes an essential contribution to answering the problems faced by the food industry related to detecting beef authenticity quickly, accurately, and efficiently. The proposed method can be a more reliable alternative than conventional methods, requiring more time and resources. From the results of this study, in the future, the focus can be on improving the model's performance by exploring more sophisticated feature extraction techniques or combining several feature extraction methods. In addition, further research can expand the scope of detection in beef and other types of meat or other food products. This will provide more comprehensive benefits in ensuring the authenticity and safety of food products for consumers.

This research significantly contributes to addressing beef authentication issues through informatics, particularly using the K-Nearest Neighbors (K-NN) algorithm based on Histogram of Oriented Gradients (HOG) features. The developed K-NN model, with 80.56% accuracy, is efficient and easily applicable in the food industry, providing a quicker, more reliable alternative to conventional methods. This study fills knowledge gaps in digital image-based food authenticity detection and opens opportunities for future advancements. Implications include increased consumer confidence and aiding authorities in combating meat adulteration, ensuring the integrity of the beef market and broader food safety.

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