Fake Beef Detection Using Lightweight Convolutional Neural Networks

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Abstract. This paper provides a method for automatically detecting fake beef by image analysis. High-quality classification models could have a major impact on ensuring food quality, supporting supply chain management in the meat industry, and preventing fraudulent commercial practices. Because low-quality meat is cheaper and more widely available than beef, it is common to use them as a substitute for fake beef. The problem is due to the differences in meat appearance, texture, mutilation, and color of cuts, as well as similarities between real beef and fake beef. These characteristics require a robust method to distinguish subtle characteristics to obtain reliable results. This paper combines the strength of Convolutional Neural Networks to detect a true classification of beef and fake beef. This model targets mobile applications and is suitable for the practical deployment of various environments.

Keywords: Convolutional Neural Network, Fake Beef Detection, Mobilenetv2

1. Introduction

Currently, the issue of using cheaper or lower-quality meats, such as pork, buffalo, or even meat that has been stored for long periods, to create fake beef is becoming increasingly prevalent. Fraudsters often use techniques like chemical marinating, dyeing, or adding additives to transform these meats into products that resemble beef, selling them at a higher price for profit. However, the chemicals and additives used in this process not only degrade the quality of the product but also pose significant health risks to consumers, including food poisoning, chronic diseases, or long-term effects on the digestive and nervous systems [1,2]. The current test method relies on sensory assessment and experience, which leads to inaccuracy and subjectivity in distinguishing real beef from false beef. Therefore, a strong motivation exists to develop accurate and automated models to ensure food safety and quality. These models can combine images, spectroscopy, sensors, and biological data to quickly and accurately detect the differences between real and false beef. This protects consumers' health and helps manufacturers, regulators, and retailers maintain stronger control over the food supply chain.

In response to this situation, we have researched and analyzed scientific studies related to distinguishing between real and fake beef. From this, we observed that many current methods still have significant limitations. Among the various molecular techniques available for detecting meat adulteration, DNA barcoding has proven to be highly accurate in species identification, even in processed or cooked meat products. However, its implementation is often limited by high costs, the need for specialized equipment, and the requirement for expert personnel, making it less practical for routine or large-scale testing [1,2]. Spectroscopic methods, such as near-infrared (NIR) spectroscopy, provide a non-destructive and real-time approach to analyzing the composition of meat. Despite their advantages, these methods face significant challenges due to their sensitivity to environmental factors and the need for precise calibration, which restricts their wider adoption in large-scale operations [3].

The advent of artificial intelligence (AI) and machine learning (ML) in food quality assurance has introduced promising improvements in detection efficiency and automation. These technologies have the potential to analyze complex datasets de-rived from imaging or spectroscopic measurements, offering faster and potentially more accurate detection capabilities. However, the effectiveness of AI and ML mod-els is highly dependent on the availability of large, high-quality datasets and incurs substantial computational costs, posing barriers to their widespread implementation [4,5]. Furthermore, while these technologies show promise, they continue to struggle with detecting meats that have been chemically altered to resemble beef, a method commonly used by fraudsters [6,7].

Based on these limitations, this study proposes a convolutional neural network (CNN) model to solve the problem of distinguishing real beef from fake beef through image analysis. The CNN model can automatically extract and analyze distinctive features such as texture, color, and surface characteristics, improving accuracy while reducing costs and processing time. Notably, this solution can be deployed on mobile cameras or automated inspection systems, offering high efficiency and practical applicability. We believe that the application of CNN addresses the drawbacks of existing methods, helps protect consumer health, and enhances transparency in the food supply chain.

2. Data collection and processing

2.1 Data collection

The data used in this study are divided into two main categories: beef and fake beef, and images were collected from several reliable sources to ensure quality and diversity. The authentic beef image was obtained from Istock, a premium image platform, and from the publicly available LOCBEEF datasets [8], which provide a comprehensive collection of beef images curated for deep learning applications. These sources ensured a high quality and diverse representation of beef. (see Figures 1 and 2)

Fig. 1. Beef from Istock

Fig. 2. Beef from LocBeef

In the case of the fake beef class, images were obtained from Istock and online platforms such as Soha [9], which showed visual evidence of falsified beef used in consumer fraud. However, due to the limited availability of labeled images of counterfeit beef, most of the manufactured beef was destroyed after discovery, which poses a challenge in building a complete set. To address this, we have added images of pork and buffalo meat, which are commonly used as alternatives to counterfeit beef. Additional data sets, such as the Meat Freshness Image Dataset [10], have also contributed to extending the data set and improving its representativeness. This strategy ensures a balanced and robust set of data and increases the model's ability to effectively distinguish between beef and fake beef. (see Figures 3 and 4)

Fig. 3. Fake Beef

Fig. 4. Pork from Meat Freshness Image Dataset

2.2 Input Image Preprocessing

The data processing phase aims to create a varied and balanced database of beef and fake beef classes. For each class, segmentation techniques are used to extract important regions based on the redness thresholds of the beef in the HSV space. These regions are refined with morphological procedures to maintain the integrity of the beef surface. Contour filtering preserves the largest segment of beef and ensures class-specific processing [11, 12]. To ensure uniformity, the photos separated are sized to 224x224 pixels. Improvements such as random rotation, horizontal rotation, brightness scaling, Gaussian blurring [13], etc. are used to increase diversity.

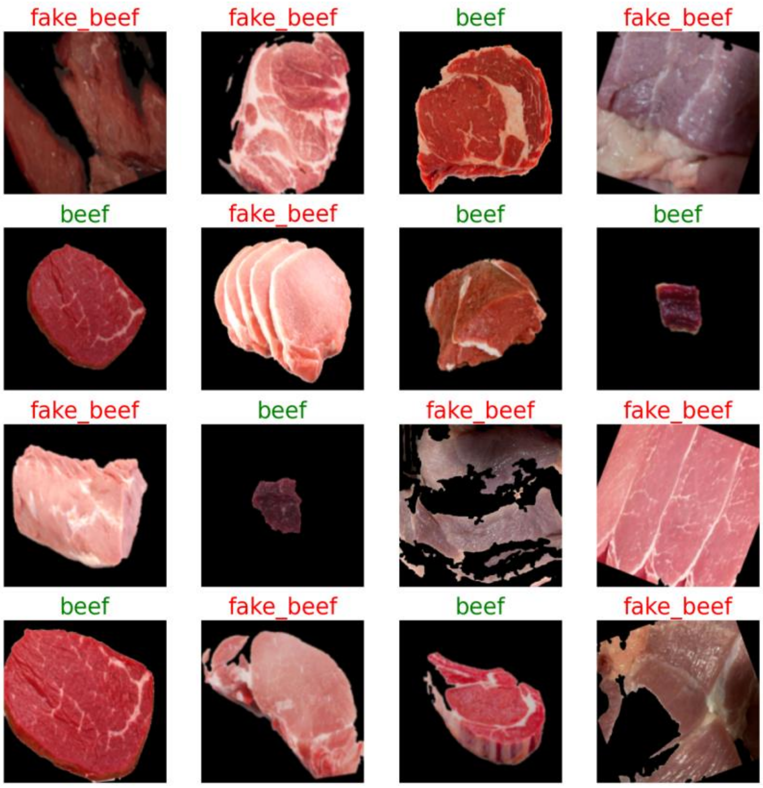

Fig. 4. Images of beef and fake beef after processing.

Fig.4 shows the outcomes of segmentation and enhancement. The processed beef photos highlight the desired parts with little influence from the backdrop. Augmentation modifies orientation, brightness, and texture, resulting in a diversified and well-prepared dataset for training a powerful model.

3. Research Methodology

This study explores the application of CNNs for the automatic classification of beef authenticity based on image data. CNNs, a state-of-the-art deep learning architecture, are particularly well-suited for image analysis tasks due to their ability to extract and learn complex hierarchical features [14]. These capabilities make CNNs highly effective for distinguishing between authentic beef and counterfeit products. The proposed system aims to address the limitations of traditional meat quality assessment methods by providing a reliable, consistent, and scalable solution for classifying meat. Specifically, the CNN model is designed to classify samples into two categories: beef and fake beef. By automating this classification process, the study seeks to enhance the efficiency and accuracy of meat quality control, thereby mitigating the risks associated with distributing counterfeit or substandard beef in the supply chain.

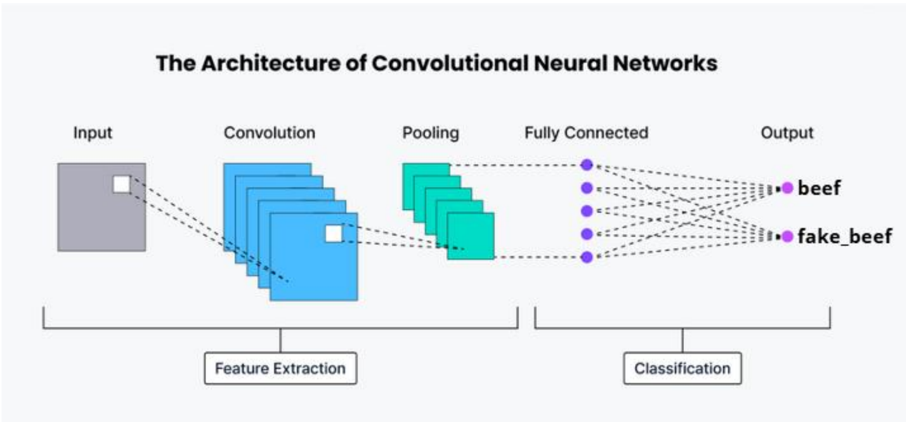

Fig. 5. CNN architecture [11]

The first step involves feeding images of beef and fake beef cuts into the CNN (Fig. 5). These images contain visual features important for classification, such as color, texture, and marbling. Beef versus fake beef can differ in texture and marbling. Once the images are fed into the network, the convolutional layers apply filters to detect specific features in the image. The CNN learns to distinguish beef and fake beef based on color, texture, and marbling differences [15]. To detect authenticity, after recognizing beef and fake beef, the convolutional layers will focus on detecting other meat features from fake beef. After each convolutional layer, a pooling layer is used to reduce the size of the feature maps. This process helps the network focus on the most salient features while reducing computational complexity.

The most used loss function for classification tasks is Categorical Crossentropy. This function measures the difference between the predicted probability distribution and the actual distribution, guiding the network to make more accurate predictions. CNNs often use the Adam optimization algorithm to minimize the loss function [16]. These algorithms adjust the network's weights to improve performance.

The CNN model was built using the Sequential API of TensorFlow/Keras. Each layer was sequentially added, increasing the network's complexity while maintaining efficiency. The first convolutional layer applies 35 filters with a 3x3 kernel, activated by ReLU. It detects local patterns such as edges and textures within the image. A 2x2 MaxPooling layer is introduced to downsample the feature maps, reducing spatial dimensions while preserving critical features. After extracting features through convolution and pooling, the Flatten() layer transforms the 2D feature maps into 1D vectors.

This process allows the model to transition from feature extraction to classification. A Dense layer with 64 neurons and ReLU activation follows, enabling the model to understand the relationships between the features extracted earlier. The output layer consists of two units corresponding to the two classes, making it suitable for binary image classification. The model is compiled using the Adam optimizer, and Sparse Categorical Crossentropy loss function, and trained for 10 epochs, leveraging validation data to assess performance on unseen data.

4. Experiment and Evaluation

During the training and testing phases, the performance of the CNN was assessed using various metrics, including accuracy and loss.

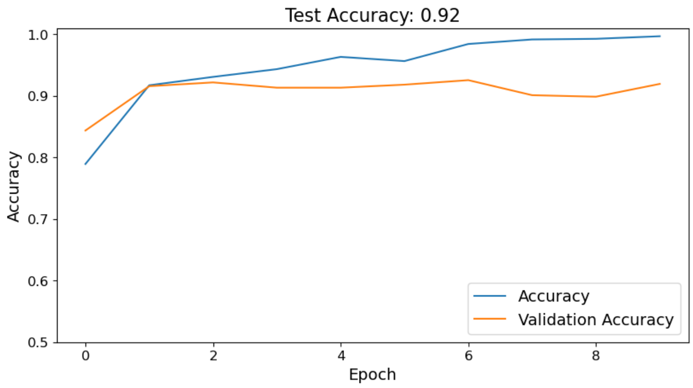

Fig. 6. Accuracy

The plot illustrated in **Fig. 6** shows the accuracy progression throughout the training process. The training accuracy consistently increased, reaching a maximum value of approximately 91.94%, while the validation accuracy exhibited a similar trend, peaking at around 91.09%. This suggests that the model not only learned well from the training data but also generalized effectively to unseen data.

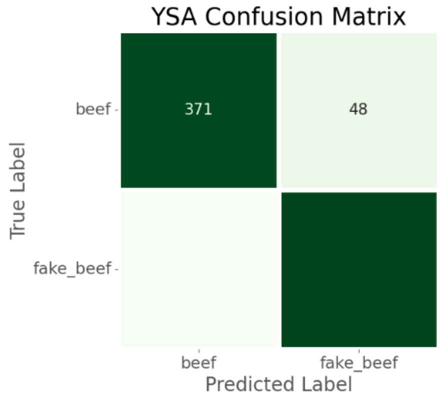

Fig. 7. Confusion matrix

The confusion matrix in Fig. 7 was used to visualize the model's performance across the two distinct categories: beef and fake beef. The matrix showed that the model achieved high accuracy with minimal misclassifications. Specifically, the confusion between real and fake beef was very low, indicating that the model was able to distinguish between the two categories effectively.

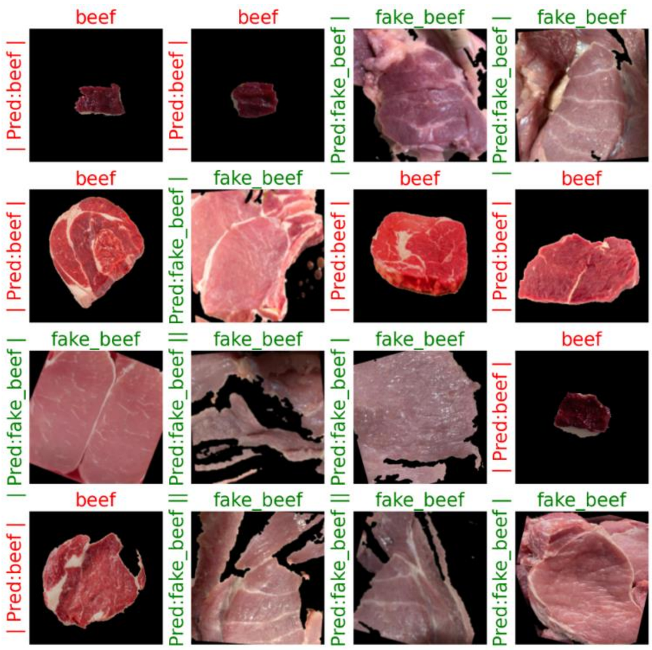

Fig. 8. Image after pred.

The images are detected with a very high accuracy rate, showing that the applied CNN model is working very well for detecting fake beef through images. (See **Fig. 8**)

Next, we use transfer learning with MobileNetV2 to improve the model performance. MobileNetV2, known for its lightweight architecture and efficient computation, was selected to improve the model's accuracy and efficiency [17].

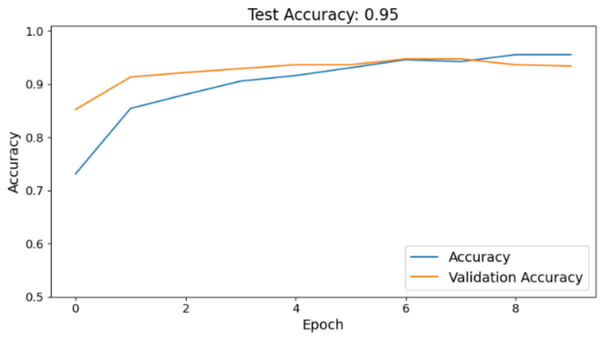

Fig. 9. MobileNetV2 Accuracy.

After evaluating the model on training and test data sets, we observed significant improvements in accuracy. In particular, the accuracy of the training set increased from 91.94% to 95.73%, and the accuracy of the test set improved from 91.09% to 95.13%. These improvements indicate that the model is better generalized with MobileNetV2 compared to previous CNN architectures. However, due to the more complex calculation of MobileNetV2, the calculation time has increased. The time for a single estimate increased from 0.55 seconds to 1.88 seconds. The size of the model has been reduced, from 254.63MB to 10.86MB, leading to faster deployment and reduced memory requirements during inference. These changes contribute to more accurate and efficient models that can manage larger datasets and make faster predictions, making them suitable for real-time applications.

5. Conclusion

This study examines the methods of fake beef detection, focusing on detecting real beef and imitation of beef. CNN models are ideal for real-time applications because they are the main architectures with 91.94% classification accuracy and rapid detection time. Replace CNN with MobileNetV2 architecture increased accuracy to 95,73% and proved its sensitivity to more complex classification tasks while maintaining the small model size. The experimental results show that the two models are very stable and practical and compatible with different platforms, including the web and mobile devices. The speed of the CNN model and the higher precision of the mobileNetV2 model complement each other, offering adapted methods for ensuring beef quality in different conditions.

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