Postprint: A Classification Method for Different Cuts of Yak Meat Based on an Improved Residual Network Model

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Date: 2023-08-14T00:00:00+00:00

Abstract

[Purpose/Significance] To achieve rapid and accurate identification of different yak meat cuts, this study proposes an improved residual network model and develops a smartphone-based yak meat cut identification software. [Methods] First, data augmentation was applied to expand the original image dataset collected for yak tenderloin, ribeye, shank, and brisket, resulting in a total of 17,640 yak meat cut images; second, a lightweight Convolutional Block Attention Module (CBAM) was integrated after the residual blocks in the original network model to enhance extraction of key detailed features from images of different yak meat cuts; the final fully connected layer of the original model was modified to reduce connections in subsequent network layers, prevent overfitting, and decrease image recognition time; then, different learning rates, weight decay coefficients, and optimizers were employed to verify their impact on network convergence speed and accuracy; finally, a mobile App was developed to deploy the improved model onto mobile devices. [Results and Discussion] Through ablation experiments, it was determined that among the four attention mechanism modules CBAM, SENet, NAM, and SKNet, CBAM achieved the best improvement. The improved ResNet18_{CBAM} model was tested on a dataset containing four different yak meat cuts: tenderloin, ribeye, shank, and brisket. The results showed that the improved residual network model achieved an identification accuracy of 96.31% on the test set, representing a 2.88% improvement over the original network model. In real-world scenario testing on mobile devices, the identification accuracies for yak tenderloin, ribeye, shank, and brisket reached 96.30%, 94.92%, 98.04%, and 96.49%, respectively. These results demonstrate that the improved ResNet18_{CBAM} model can effectively identify different yak meat cuts in practical applications with favorable outcomes. [Conclusion] The research findings contribute to ensuring food quality and safety in the yak

meat industry and provide technical support for the intelligent development of the yak meat industry in the Qinghai-Tibet Plateau region.

Full Text

Classification and Recognition Method for Yak Meat Parts Based on Improved Residual Network Model

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Abstract

[**Objective/Significance**] Yak meat, known as the "crown of beef," is a premium meat product with significant variations in nutritional content across different cuts. In 2022, China slaughtered approximately 3.8 million yaks, producing about 486,000 tons of carcass meat valued at 46.7 billion yuan [2]. Despite this substantial market, manual classification of yak meat parts remains costly and inefficient. To address this challenge, this study proposes an improved residual network model for rapid and accurate identification of different yak meat parts and develops a smartphone-based recognition application.

[**Methods**] First, we collected original images of four yak meat parts (tenderloin, high rib, shank, and brisket) and expanded the dataset through data augmentation, yielding 17,640 images. The augmentation methods included horizontal flipping, vertical flipping, contrast adjustment, saturation adjustment, hue adjustment, and random rotations of 30°, 120°, and 300°. Second, we integrated a lightweight Convolutional Block Attention Module (CBAM) after each residual block in the original network to enhance extraction of key detail features from different yak meat parts. We also modified the final fully connected layer by adding global average pooling and global maximum pooling before the fully connected layer to reduce connections in subsequent layers, prevent overfitting, and decrease image recognition time on mobile devices. Third, we evaluated different learning rates, weight decay coefficients, and optimizers to assess their impact on network convergence speed and accuracy. Finally, we deployed the improved model to mobile devices using PyTorch Mobile.

[**Results and Discussion**] Through ablation experiments comparing CBAM, SENet, NAM, and SKNet attention mechanisms, CBAM demonstrated the best improvement effect. The improved ResNet18_{CBAM} model achieved 96.31% accuracy on the test set containing four different yak meat parts, representing a 2.88% improvement over the original network. In real-world mobile testing, the recognition accuracies for tenderloin, high rib, shank, and brisket reached 96.30%, 94.92%, 98.04%, and 96.49%, respectively. These results demonstrate that the improved model can effectively identify different yak meat parts in practical applications.

[**Conclusion**] This research contributes to ensuring food quality and safety in the yak meat industry while providing technical support for the intelligent development of yak meat production in the Qinghai-Tibet Plateau region.

Keywords: image classification; attention mechanism; residual network; mobile applications; yak meat part classification; transfer learning

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1 Introduction

Yak meat, renowned as the "crown of beef," is a premium meat product with significant differences in protein, fatty acid, and other nutritional components across different cuts [1]. In 2022, China slaughtered approximately 3.8 million yaks, producing about 486,000 tons of carcass meat with an output value of approximately 46.7 billion yuan [2]. Despite the large-scale yak meat trade market, manual classification of meat parts remains costly and inefficient. Currently, yak slaughtering in China is becoming increasingly mechanized and standardized, with regions such as Dangxiong County in Tibet and Gannan Prefecture in Gansu promoting mechanized slaughtering. In 2023, the primary direction for industry development and technical research will focus on partitioning, typing, and classifying beef and its products [3]. Therefore, developing an accurate and rapid method for identifying yak meat parts can enhance industry quality and safety standards, improve trade efficiency, reduce costs, and provide technical support for intelligent industry development.

Current meat detection technologies for beef, pork, and mutton primarily include Laser-Induced Breakdown Spectroscopy (LIBS), multispectral imaging, and infrared/near-infrared techniques. While these methods achieve high accuracy, their expensive experimental costs and stringent conditions limit widespread adoption, confining them mostly to laboratory research. Image recognition offers advantages of low cost, high portability, and operational convenience, attracting considerable research attention. However, applications of image recognition for differentiating yak meat parts remain relatively scarce.

Deep learning [4-6], a prominent field within machine learning [7,8], features strong learning capabilities, high transferability, and parallel processing. Recent rapid development has produced increasingly deep networks with larger parameters and more complex structures [9,10]. Deep learning methods have been widely applied in agriculture for crop disease and pest detection [11-14], biomass identification [15-18], and phenotypic monitoring of plants and animals [19-22]. With the rapid advancement of smartphone technology, research on mobile-based detection of beef and mutton products has gradually increased [23,24]. Using mobile phones for image acquisition and detection offers low cost, operational convenience, and broader applicability, though it requires models with low complexity and few parameters.

To prevent confusion and adulteration of different yak meat parts during production and sales, this study investigates yak meat part recognition to enhance industry transparency, traceability, and food safety. We integrate the Convolutional Block Attention Module (CBAM) into the residual network model to improve accuracy and performance, then deploy the improved model to mobile devices. By developing a classification recognition mobile App, we achieve real-time identification of yak tenderloin, high rib, shank, and brisket using smartphone-acquired images, offering high convenience and 普及性.

2 Materials and Methods

2.1 Data Collection

All experimental yak meat materials were sourced from the Xining beef and mutton wholesale market in Qinghai Province. From January 2023, we photographed tenderloin, high rib, shank, and brisket samples daily for 14 days, covering sunny, cloudy, and rainy weather conditions. The imaging device was a smartphone with a shooting distance of 30-80 cm, image resolution of 3024 × 4032 pixels, and *.jpg format. We collected 2,000 original images and manually screened them to obtain 1,960 original images of yak meat parts. Considering the practical usage environment, images were captured under various lighting conditions (front lighting, backlighting), backgrounds, and times of day, as shown in [Figure 1: see original paper].

2.2 Data Preprocessing

Given the limited size of our self-built dataset, we employed data augmentation to improve network generalization and classification performance. Augmentation methods included horizontal flip, vertical flip, contrast adjustment, saturation adjustment, hue adjustment, random rotation of 30°, random rotation of 120°, and random rotation of 300°, as illustrated in [Figure 2: see original paper]. After augmentation, the dataset expanded to nine times its original size, comprising 17,640 images. We divided the dataset at a 4:1 ratio, yielding 14,112 training images and 3,528 test images.

2.3 Algorithm Design

2.3.1 Residual Network In deep learning, network degradation occurs when training loss fails to decrease and instead increases with network depth. He et al. [25] proposed residual network structures composed of residual blocks containing conventional convolutional layers and residual mappings. The direct mapping in residual structures ensures that layer t+1 has more parameters than layer t, preventing information loss during feature extraction. This study selected ResNet18 and ResNet34 as network prototypes, with structures detailed in .

2.3.2 Attention Mechanism In classifying yak tenderloin, high rib, shank, and brisket, the primary distinguishing features are fat, tendon, and membrane, as the lean portions show minimal differences. This requires the network to extract useful information from these features to improve accuracy. To address this, we integrated attention mechanisms into ResNet18.

CBAM comprises Channel Attention Module (CAM) and Spatial Attention Module (SAM), as shown in [Figure 3: see original paper]. For an input yak meat feature map of size W×H×C (width, height, channels), the channel attention mechanism generates a channel attention feature map, which is multiplied with the original input to produce a new feature map. This new feature map then undergoes spatial attention processing to generate a spatial attention feature map. Multiplying the new feature map with the spatial attention map yields the final output. The channel attention mechanism is illustrated in [Figure 4: see original paper] and the spatial attention mechanism in [Figure 5: see original paper].

2.3.3 Improved ResNet18 Model for Yak Meat Part Recognition We first trained the original ResNet18 and ResNet34 models on our dataset, with results shown in [Figure 6: see original paper]. The test set accuracy on ResNet18 was higher and more stable than on ResNet34, leading us to select ResNet18 as the backbone network.

The improved ResNet18_{CBAM} network structure is shown in [Figure 8: see original paper]. Our improvements include: (1) adding CBAM modules after each residual block in the original ResNet18 network, which enhances attention mechanisms with minimal computational overhead and parameter count; and (2) modifying the final layer by replacing the direct fully connected layer with global average pooling, global maximum pooling, and then a fully connected layer, which improves accuracy, prevents overfitting, reduces subsequent network connections, accelerates execution speed, and reduces mobile image recognition time.

2.3.4 Evaluation Metrics We used accuracy (%) as the evaluation metric for yak meat part recognition models, analyzing classification of four parts through confusion matrices. Accuracy is calculated as the ratio of correctly classified samples to total samples, as shown in equation (1):

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100\%$$

where TP, FP, FN, and TN represent true positives, false positives, false negatives, and true negatives, respectively.

2.4 Software Implementation

To achieve fast and accurate yak meat part recognition on mobile devices, we converted the trained ResNet18_{CBAM} network model to TorchScript format (*.ptl) using PyTorch Mobile. We then developed the yak meat part recognition App using Android Studio, comprising front-end interface and back-end processing components. The front-end uses* .xml for button and text box layout, while the back-end is developed in Java. The *.ptl TorchScript model is called to implement yak meat part recognition, with the interface shown in [Figure 9: see original paper].

3 Experiments and Results Analysis

3.1 Experimental Environment

The network model was trained on Windows 11 using the PyTorch deep learning framework with Python 3.9. Hardware specifications included an AMD R9 5900HX CPU (16 GB) and Nvidia GeForce RTX 3080 GPU, with CUDA acceleration in an Anaconda3+PyCharm environment.

3.2 Training Strategy

To achieve optimal training results for the improved ResNet18_{CBAM} network, we employed the strategy outlined in .

3.2.1 Optimizer Selection Optimizer selection significantly impacts model training. Common optimizers include SGD, Momentum, RMSProp, and Adam. We compared SGD and Adam, with accuracy performance on the training set shown in [Figure 10: see original paper]. Adam exhibited greater fluctuation throughout training, while SGD provided more stable convergence, leading us to select SGD as the optimizer.

3.2.2 Loss Function We selected Cross Entropy Loss as the loss function for the improved ResNet18_{CBAM} network. Cross entropy, an important concept in information theory, measures the difference between true and predicted probability distributions in machine learning. In deep learning, larger gradients during training enable faster optimization. The loss function is expressed as:

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{c=1}^{M} y_{ic}\log(p_{ic})$$

where Loss is the loss function, N is the number of samples, M is the number of categories, p_{ic} is the predicted probability that observation i belongs to category c, and y_{ic} is the true label (1 if sample i belongs to category c, 0 otherwise).

3.2.3 Learning Rate Adjustment We employed Cosine Annealing LR as the learning rate decay algorithm for the ResNet18_{CBAM} network model.

3.3 Hyperparameter Optimization

3.3.1 Learning Rate Selection In the SGD optimizer, excessively small learning rates slow convergence and increase training costs, while excessively large rates can cause the loss function to overshoot optimal solutions, preventing convergence. To select an appropriate learning rate, we compared coarse and fine adjustments.

For coarse adjustment, we tested learning rates of 0.1, 0.01, 0.001, 0.0001, and 0.00001. As shown in [FIGURE:11(a)], learning rates of 0.1 and 0.01 produced stable but extremely slow loss reduction. A learning rate of 0.001 achieved the fastest convergence and best performance, while 0.0001 showed inferior results and 0.00001 performed worst.

Based on these results, we fine-tuned around 0.001, testing values of 0.001, 0.002, 0.003, 0.004, and 0.005. [FIGURE:11(b)] shows that a learning rate of 0.003 provided the best convergence with minimal fluctuation after stabilization. Therefore, we selected 0.003 as the optimal learning rate.

3.3.2 Batch Size Selection Batch size also affects neural network training performance. With the learning rate fixed at 0.003, we evaluated batch sizes of 8, 16, 32, and 64. As shown in [FIGURE:12(a)], batch sizes of 8, 16, and 64 exhibited large loss fluctuations and slow convergence, while batch size 32 showed minimal fluctuation and fast convergence. [FIGURE:12(b)] demonstrates that batch size 32, though not the fastest to converge, produced the highest accuracy with minimal late-stage fluctuation. Therefore, we selected a batch size of 32.

3.4 Results Analysis

3.4.1 Ablation Experiments on Improved ResNet18_{CBAM} Model Our improved ResNet18_{CBAM} model incorporates two modifications: (1) integrating CBAM modules after each residual block in the backbone network, and (2) adding two pooling layers at the network's end. Ablation experiments validated these improvements: ResNet18+Pooling achieved 93.88% accuracy, while ResNet18+CBAM reached 96.31%. The pooling layers reduce feature map size, decreasing computational load while preserving important features, thereby improving accuracy and reducing detection and training time. CBAM modules adaptively weight channel and spatial information, emphasizing important features and further enhancing accuracy.

3.4.2 Comparison of Different Attention Mechanism Modules We compared CBAM against SENet, NAM, and SKNet attention modules integrated into ResNet18. As shown in , CBAM achieved 96.31% accuracy, surpassing SENet (94.12%), NAM (92.51%), and SKNet (93.85%). These results confirm that CBAM is the most effective attention mechanism for this application.

3.4.3 Comparison of Different Network Models Using transfer learning, we pretrained all models on ImageNet before fine-tuning on our yak meat dataset. We compared ResNet18_{CBAM} against AlexNet, VGG11, ResNet34, and ResNet18. As shown in and [Figure 13: see original paper], ResNet18_{CBAM} achieved the highest accuracy (96.31%) while maintaining competitive training and detection times. Compared to VGG11 and ResNet34, ResNet18_{CBAM} reduced training time by 173.96 s and 24.16 s, respectively, and decreased average detection time by 0.7537 s and 0.0248 s. Accuracy improved by 3.19% and 2.93% compared to VGG11 and ResNet34. While VGG11 and ResNet34 have larger floating-point operation counts and more complex structures, ResNet18_{CBAM} offers superior performance. Compared to the classic ResNet18, our improved model increased accuracy by 2.88% with only modest increases in average detection time (0.0128 s) and training time (10.62 s).

3.4.4 Real-World Testing of ResNet18_{CBAM} Network Model To verify algorithm reliability, we tested the developed App at the Xining beef and mutton wholesale market. We collected 54 tenderloin, 59 high rib, 51 shank, and 57 brisket samples. Recognition accuracies were 96.30% for tenderloin, 94.92% for high rib, 98.04% for shank, and 96.49% for brisket, as shown in [Figure 14: see original paper] and summarized in . These results demonstrate reliable performance in real-world scenarios.

4 Conclusion

This study addresses yak meat part identification by integrating CBAM modules into the ResNet18 network, proposing an improved ResNet18_{CBAM} model. CBAM enhances attention mechanisms from both channel and spatial dimensions, achieving significant performance improvements with minimal overhead. We modified the final fully connected layer by adding global average pooling and global maximum pooling to reduce computational load. Key conclusions include:

1. Integrating CBAM modules after each residual block in ResNet18 effectively extracts distinguishing features (fat, tendon, membrane) to improve model accuracy.
2. The improved ResNet18_{CBAM} model achieved 96.31% accuracy across four yak meat parts, outperforming AlexNet, VGG11, ResNet34, and ResNet18.

3. Combining the improved ResNet18_{CBAM} model with a mobile App provides technical support for intelligent yak meat industry development. Real-world testing yielded accuracies of 96.30% for tenderloin, 94.92% for high rib, 98.04% for shank, and 96.49% for brisket, demonstrating robust practical performance.

Conflict of Interest Statement: The authors declare no conflicts of interest.

References

[1] YAN Z X. Study on the quality characteristics and mechanism of yak meat from different parts[D]. Yangling: Northwest A & F University, 2022.

[2] CAO B H, LI J Y, WANG Z S, et al. Report on industrial technology development of beef cattle and yak in 2022[J]. Chinese journal of animal science, 2023, 59(3): 330-335.

[3] CAO B H, LI J Y, WANG Z S, et al. Development trend and policy suggestions of beef cattle and yak industry in 2023[J]. Chinese journal of animal science, 2023, 59(3): [in press].

[4] BEN M. Spectrum sensing and modulation recognition using a novel CNN Deep Learning model and Learning transfer technique[J]. Przegląd elektrotechniczny, 2023, 1(5): 95-99.

[5] ZHONG Y, ZHAO M. Research on deep learning in apple leaf disease recognition[J]. Computers and electronics in agriculture, 2020, 168: ID 105146.

[6] SAHA S, PARK C, KNAPIK S, et al. Deep Learning Discrete Calculus (DLDC): A family of discrete numerical methods by universal approximation for STEM education to frontier research[J]. Computational mechanics, 2023, 72(2): 311-331.

[7] WANG J J, CHENG Y H, NIE X, et al. Fast calculation method of high-altitude electromagnetic pulse environment based on machine learning[J]. Computer science, 2023, 50(S1): 853-857.

[8] MENG X F, HAO X L, MA C H, et al. Research on machine learning for scientific discovery[J]. Chinese journal of computers, 2023, 46(5): 877-895.

[9] BROSSARD M, BONNABEL S. Learning wheel odometry and IMU errors for localization[C]// 2019 International Conference on Robotics and Automation (ICRA). Piscataway, NJ, USA: IEEE, 2019: 291-297.

[10] KRIZHEVSKY A, SUTSKEVER I, HINTON G E. ImageNet classification with deep convolutional neural networks[C]// Proceedings of the 25th International Conference on Neural Information Processing Systems-Volume 1. New York, USA: ACM, 2012: 1097-1105.

[11] CHANG R Y, YANG H B. Research on crop pest identification based on convolution neural network[J]. Wireless Internet technology, 2023, 19(2): 159-161.

[12] CHEN T J, ZENG J, XIE C J, et al. Intelligent identification system of disease and insect pests based on deep learning[J]. China plant protection, 2019, 39(4): 26-34.

[13] TAO Z, KONG J L, JIN X B, et al. Design of image recognition App system for crop diseases and insect pests based on deep learning[J]. Computer applications and software, 2022, 39(3): 341-345.

[14] ZHOU Q L, MA L, CAO L Y, et al. Identification of tomato leaf diseases based on improved lightweight convolutional neural networks MobileNetV3[J]. Smart agriculture, 2022, 4(1): 47-56.

[15] GONG R X, LU X H, ZHANG H N, et al. Study on soybean aboveground biomass estimation model based on hyperspectral vegetation index[J]. Soybean science, 2023, 42(3): 352-359.

[16] SCHNEIDER S, TAYLOR G W, KREMER S C, et al. Bulk arthropod abundance, biomass and diversity estimation using deep learning for computer vision[J]. Methods in ecology and evolution, 2022, 13(2): 346-357.

[17] ZHENG C W, ABD-ELRAHMAN A, WHITAKER V M, et al. Deep learning for strawberry canopy delineation and biomass prediction from high-resolution images[J]. Plant phenomics, 2022, 2022: ID 9850486.

[18] BU L X, LAI Q, LIU X Y. Study on the adaptability of different machine learning algorithms for estimating the biomass of grassland[J]. Journal of grassland science, 2022, 30(11): 3156-3164.

[19] CHEN Z Q, ZHANG Y A, WANG W Z, et al. Multiscale feature fusion yak face recognition algorithm based on transfer learning[J]. Smart agriculture, 2022, 4(2): 77-85.

[20] HAIFA T, BAHRAM S, MASOUD M, et al. Comparison of machine and deep learning methods to estimate shrub willow biomass from UAS imagery[J]. Canadian journal of remote sensing, 2021, 47(2): 209-227.

[21] ZHU J Y. Research on phenotypic data determination of Macrobrachium prawn based on deep learning compression model[D]. Hangzhou: Zhejiang University, 2022.

[22] YUAN D M. Research on soybean phenotype measurement method based on deep learning[D]. Ji'nan: Shandong University, 2021.

[23] ZHAO X L, PENG Y K, LI Y Y, et al. Mobile phone evaluation system for grading beef marbling based on deep learning[J]. Transactions of the Chinese society of agricultural engineering, 2020, 36(13): 250-256.

[24] MENG L F, ZHU R G, BAI Z X, et al. Discrimination of chilled lamb from different carcass parts at different storage times based on mobile phone images[J]. Food science, 2020, 41(23): 21-26.

[25] HE K M, ZHANG X Y, REN S Q, et al. Deep residual learning for image recognition[C]// 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Piscataway, NJ, USA: IEEE, 2016: 770-778.

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