Design of a Cow Body Recognition System Based on Deep Learning

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Abstract: With the advancement of modern animal husbandry in China, it is particularly important to establish smart farms through technologies such as the internet and 5G communication to achieve fine-grained management. Achieving smart farming through cattle identification is a crucial step. To improve the accuracy of cattle identification in the animal husbandry industry, this project establishes a dataset of cattle body features. Then, a cattle identification system is designed based on computer vision to extract cattle body features. Specifically, the YOLOv5 model is used to detect and extract the image features of cattle bodies. Finally, the detected cattle body image features are compared and updated with the database on the server to complete the cattle identification.

Keywords: Deep Learning; Cattle Body Identification; Artificial Intelligence; YOLOv5 Model; Feature Matching

1. Project Introduction

Animal husbandry is a major source of food economy in China, not only providing good grain products for Chinese people, but also greatly enhancing the national economy. With the development of the social economy, people pursue a high-quality lifestyle, resulting in a significant increase in the demand for animal husbandry resources. In the early days, animal husbandry was mostly conducted on an individual scale and was relatively small in size. However, this singular mode of rearing was unable to meet the growing demands of the people. Therefore, expanding the scale of animal husbandry and promoting the modernization process of the industry have become urgent priorities for China. The main characteristics of modern animal husbandry are large-scale, standardized, and intelligent [1]. However, while expanding the scale of breeding, safer and more efficient management methods are also required. With the rapid development of the internet, big data analysis, and artificial intelligence computing, the integration of animal husbandry with various modern technologies to achieve modern livestock farming can effectively promote the scientific and precise transformation of the animal husbandry industry. This project utilizes a balanced dataset, the YOLOv5 detection model for feature extraction, and server comparison techniques to collect information about cattle in the ranch. This includes locating the position of cattle, identifying their identity, assessing their health status, monitoring their estrus status, and other relevant information collected throughout the ranch. Based on this collected data, a smart management platform is established to conduct risk analysis and processing of the aggregated information. The development of this project is conducive to driving the digital industrial upgrading of the entire animal husbandry industry. By establishing a digital platform through this project, real-time cattle information can be grasped, enabling precise feeding in cattle farms, avoiding feed waste, and maximizing cost savings. This is beneficial for the sustainable and healthy development of the ranch industry.

2. Research Content

2.1 Research Content

By deploying multi-directional cameras in cow barns and milking passageways, we completed the creation of a cow body image dataset. Using Opencv, we captured key frames from the collected image and video data. To address the issue of high similarity between consecutive frames, we filtered the images using the SSIM (Structural Similarity Index) to eliminate blurred images of cow bodies and images with incomplete cow body information, while retaining images containing complete cow bodies. To ensure that the final detection and recognition model of this study possesses strong robustness and generalization characteristics, the establishment of the dataset included selecting a sufficient number of cow samples with a balanced distribution of image numbers for each cow, thereby guaranteeing the universality of the trained model. Images of cow bodies were captured from multiple angles, primarily focusing on the back view of the target cow, with side views serving as supplementary information. Finally, the region where the cow body is located and the key points of the cow body are labeled using a label software to create a cow body detection dataset. By applying the YOLOv5 model based on deep learning, a cow body image detection model is constructed. Methods such as feature fusion modules, attention mechanisms, and multi-scale convolutional kernels are then introduced to enhance the receptive field, allowing for better feature extraction from cow body image information and improving the detection accuracy and efficiency of cow body detection. Transfer learning methods are also introduced to train the model and achieve the detection and key point localization of cow bodies. Finally, the detected cow body image features are compared and updated with the dataset in the server's database to complete the identification of the cow's identity.

2.2 Research Status at Home and Abroad

Cattle identification is a crucial requirement for achieving intelligent management in pastures. It facilitates cattle registration, recording authorized cattle activities, and managing herds in pastures. Additionally, it serves as an important tool for tracking public and cattle health issues. Cattle identification mainly includes physical, electronic, and biological identification methods. Physical-based identification methods primarily involve the use of physical techniques such as ear tags, cold branding, and hot iron branding. In the early stages, these physical identification methods effectively reduced human resources and improved management efficiency. However, as the scale of animal husbandry expanded, the use of these identification methods significantly limited the development of pastures. Additionally, physical methods can easily cause harm to cattle and, more seriously, affect food safety. However, this technology poses potential risks. It tracks the tags on the cattle, rather than the animals themselves. In the event of tag loss, it poses a significant economic risk to the ranch owners. Biometric identification offers considerable advantages because the identification relies on unique and unchangeable biological characteristics. The biometric identification methods for cattle mainly include iris and retina recognition, nasal pattern recognition, and facial recognition.

Cattle identification based on iris and retina recognition utilizes the unique, stable, and highly accurate biological markers of cattle eyeballs. The retina contains a vast vascular system, and each retina possesses a unique vascular pattern. Wang Xiaoqiang [2] divided the iris images of cattle into blocks, extracted features from all blocks using two-dimensional Gabor filtering, and then performed feature comparison and recognition based on a certain rule of phase encoding. Additionally, he combined two-dimensional Gabor filtering with Kernel Principal Components Analysis (KPCA) [3]. to enhance the recognition performance of cattle iris. Finally, a hierarchical circular ring localization algorithm was integrated into the Hamming distance model to optimize the feature matching method.

Cattle identification based on nasal pattern recognition is preferred due to the high cost of acquisition equipment and methods for cattle iris and retina, which are not suitable for practical use in pastures. The nasal pattern of cattle is also an important biometric feature, similar to human fingerprints in that it can distinguish different individuals. The required equipment and methods for collecting nasal patterns are relatively easier to obtain. Gaber et al. [4]. extracted robust features from cattle nasal patterns using Weber's Local Descriptor (WLD) [5]. Additionally, they employed an AdaBoost [6]. classifier to identify cattle heads based on their WLD features. Kumar et al. [7]. utilized texture feature descriptors to extract features from cattle nasal pattern images at different smoothing levels of the Gaussian pyramid. They combined the feature descriptors obtained at each Gaussian smoothing level using a fusion-weighted and rule-based approach. In a database of 500 cattle nasal pattern images, they achieved a recognition rate of 93.8%.

For cattle identification based on facial recognition, the collection of nasal patterns can also be cumbersome, requiring manual collection for each individual, which consumes significant human resources. The appearance image of cattle is also a distinguishing biological characteristic. The use of structured facial features and skin texture information for cattle face recognition can be considered an affordable, non-invasive, easy-to-operate, and robust method for cattle identification. Chen Juanjuan et al. [8]. introduced spatial pyramid matching into the traditional Bag-of-Features (BOF) [9]. model to improve recognition performance. To reduce the feature dimension and computational complexity of the model, they also integrated an optimized Histogram of Oriented Gradients (HOG) [10]. as a feature extractor. This optimization was primarily achieved by reducing the projection process during dense feature mapping in traditional HOG, thereby reducing the feature dimension from 36 to 31. Finally, a Support Vector Machine (SVM) [11]. classifier with a histogram intersection kernel was used for classification and recognition, significantly improving recognition performance and operational efficiency. Sun Xi et al. [12]. utilized the LeNet-5 network model to achieve cattle face recognition.

3. Research Approach

The identification techniques based on cattle iris and retina recognition, nasal pattern recognition, and facial recognition require the collection of a large amount of data, which consumes significant manpower. For modern large-scale cattle farms, this generates excessive economic pressure. However, this project aims to develop cattle body recognition technology to complete individual cattle identification, reducing manual labor and meeting the needs of large-scale cattle farms.

3.1 Establish a Cattle Body Image Dataset

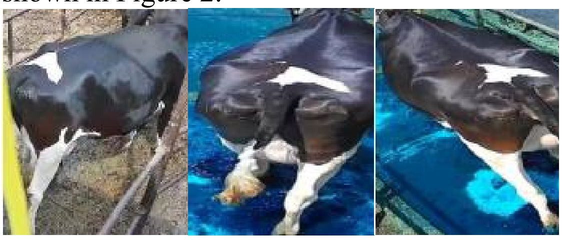
The quality of dataset samples largely determines the performance of the model. Currently, there is a lack of public image databases specifically for cattle body recognition. Therefore, we adopted the approach of collecting our own dataset from local cattle farms. The main collection methods included setting up multi-directional cameras in cattle barns and milking channels for data collection.

3.1.1 Collection of Cattle Body Image Dataset in the Milking Channel

The milking channel is a passageway established to ensure that cows can pass through quickly and orderly during the milking process, without crowding. This channel is relatively narrow and can typically accommodate one or two cows at a time. A schematic diagram of the milking channel is shown in Figure 1.

Figure 1. Schematic Diagram of the Milking Channel

In the milking passageway, three cameras are set up above to capture the cow from three different angles: the cow's right side (a), the cow's back (b), and the cow's left side (c), as shown in Figure 2.



The Cow's Right Side (a) **The Cow's Back (b)** **The Cow's Left Side (c)**

Figure 2. Shows Images of Cattle Bodies Captured from Three Different Angles

3.1.2 Collection of Cattle Body Image Dataset in the Barn

The cow barn is in a completely enclosed state, making it easier to manage the herd when cows are reared inside. Three cameras are arranged above the cow barn, aligned in a straight line with a relatively wide spacing, to capture images from different angles. The shooting angles are set to focus on the left side of the herd (1), the back of the herd (2), and the right side of the herd (3), as shown in Figure 3.

The Left Side of the Herd (1) **The Back of the Herd (2)** **The Right Side of the Herd (3)**

Figure 3. Shows Images of Cattle Bodies Captured from Three Different Angles in the Barn.

3.1.3 Preprocessing of Cattle Body Image Data Collection

Using OpenCV, key frames are extracted from the collected image and video data. To address the issue of high similarity between consecutive frames, the Structural Similarity Index (SSIM) is employed for filtering. This helps to eliminate images with blurred cattle bodies or incomplete cattle body information, while retaining images that contain complete cattle bodies. To ensure that the final detection and recognition model of this study exhibits strong robustness and generalization capabilities, the establishment of the dataset includes selecting a sufficient number of cattle samples, with a balanced distribution of image quantities for each cow. This ensures that the trained model is universally applicable.

3.1.4 Deployment of Cameras in Cattle Farms

In cattle barns where cows are free to roam, it is necessary to ensure that they can be identified in real-time from any position within the barn. To achieve this, cameras need to be deployed to cover all areas of the barn. However, the height of the cameras can have an impact on both image quality and equipment costs. If the cameras are placed too high, the clarity of the captured images may be compromised, affecting the performance of cow identification. Conversely, if the cameras are placed too low, more cameras would be required to cover the entire barn, leading to increased equipment costs. Therefore, when deploying cameras, they should be installed at a height of approximately 3 meters from the ground. Additionally, the camera angles should not be perfectly vertical, but should be tilted to a certain degree. Excessive tilting can result in nearby cows blocking the view of cows in the distance.

3.2 Training of the YOLOv5 Detection Model

Since the YOLOv5s object detection algorithm combines high accuracy with real-time detection capabilities, this project adopts the YOLOv5s model to identify the body features of cattle [13]. The YOLOv5s model consists of four processing stages: input, backbone (feature extraction), head (feature fusion), and prediction (multi-scale prediction). During the input processing stage, the images are resized to 640px×640px for consistent input. The feature extraction processing stage comprises four components: focus, bottle neck, CSPn (Component Scale Pooling), and SPP (Spatial Pyramid Pooling). The focus operation involves dividing the image data into four parts, performing 2x upsampling on each part, concatenating them along the channel dimension, and finally applying a convolutional operation. The bottle neck is a classical residual structure. The Spatial Pyramid Pooling module enhances the receptive field, enabling the extraction of the most important body features of cattle. The feature fusion processing stage comprises two parts: PANet (Path Aggregation Network) and detection. It involves two rounds of upsampling and downsampling, followed by concatenation of feature maps of the same scale. Finally, the fused features are sent to the detection module for processing, realizing the operation of the path aggregation network. After feature fusion, three scales of features are obtained with sizes of 80 px×80 px, 40 px×40 px, and 20 px×20 px, respectively. The YOLOv5 model uses multiple independent logistic classifiers to calculate the probability of an input belonging to a specific label, and employs binary cross-entropy loss for each label to reduce computational complexity. Therefore, the YOLOv5 model can classify cattle body features, and its multi-scale prediction component can predict the output results. Additionally, the binary cross-entropy loss function can calculate the loss for both class probabilities and object confidence scores. The YOLOv5 model uses the ciouloss function to train the bounding boxes for cattle body recognition, ultimately identifying the body features of cattle.

3.3 Distinguishing Cattle Body Features

After identifying cattle body features using the

YOLOv5 detection model, the detected images of cattle body features are transmitted to the server. These features are then compared with the template library stored on the server, and a ranking is performed to find the minimum matching value. Based on the minimum matching value, it is determined whether the detected cattle belongs to the template library. If it has not appeared in the template library before, the image of the cattle is added as a new entry to the template library. If the image of the cattle is already present in the template library, a decision is made on whether to update it. Old templates in the library are deleted, and the new image of the cattle is updated in the template library. After determining whether an update is necessary, the recognized results are then displayed in the video.

The technical roadmap of the project is shown in Figure 4.

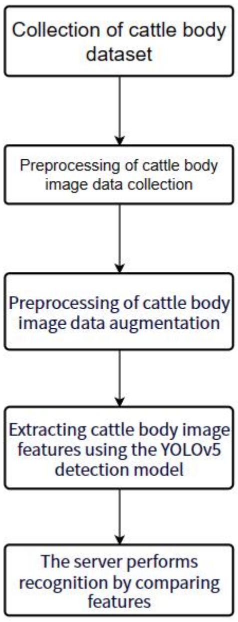


Figure 4. Technical Roadmap of This Project

4. Conclusion

With the development of artificial intelligence and the internet, combining relevant technologies with ranching has become a popular research direction. Achieving accurate cattle identification is an important prerequisite. However, methods based on physical markers such as ear tags can cause harm to cattle, and using other body parts to identify cattle information requires a high labor cost. This project aims to establish a dataset by deploying camera modules in cattle sheds and milking passages, utilizing video processing techniques. Subsequently, the YOLOv5 detection model is used to extract cattle body features, and finally, the server compares and identifies the cattle's identity information through these features. In summary, the design of the cattle body recognition system based on deep learning possesses the following functionalities:

(1) Compared to feature recognition using other body parts, using cattle body features for recognition can reduce labor costs.

(2) Cattle body feature recognition can complete cattle identification with relatively fast speed.

(3) Cattle body feature recognition is suitable for large-scale cattle farms.

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