Applications of Computer Image Recognition Technologies for Animal Behavior Analysis

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Abstract. Animal behavior analysis is crucial for understanding the mechanisms of survival, adaptation, and evolution in species. It provides insights into animal cognition, social structures, and ecological roles. In this thesis, the authors discuss the application of computer image recognition technology in animal behavior analysis. Firstly, this work summarizes the basic principles and development of image recognition technology, and then introduces the specific applications of this technology in animal behavior monitoring, including animal species recognition, behavior pattern analysis and abnormal behavior detection. This work also delves into the application of various algorithms and models such as Convolutional Neural Network (CNN) in object detection and image classification. Through real case studies and experimental data, this work demonstrates the great potential of image recognition technology in improving the efficiency, safety and accuracy of animal behavior research. Finally, this work discusses current technological challenges and future directions, emphasizing the importance of interdisciplinary collaboration and the far-reaching impact of technological advances on ecological conservation and animal detection.

Keywords: Animal Behavior Analysis, Image Recognition, Convolutional Neural Network.

1 Introduction

Animal behavior identification is an important part of the study of animal behavior and ecology. By monitoring and analyzing animal behavior, scientists are able to better understand animal survival strategies, social interactions, reproductive behavior, and relationships with the environment. Animal behavior recognition has been widely used in many fields, such as wildlife protection, domestic animal health monitoring, zoo management and so on.

Computer image recognition is a technology based on artificial intelligence and machine learning that automatically identifies and classifies animals and their behaviors from image data captured by cameras or sensors. Compared with traditional manual recording and observation methods, computer image recognition has the

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following significant advantages. Firstly, efficiency. Traditional animal behavior observation usually requires a lot of manpower and time, and the computer image recognition system can monitor 24 hours a day, greatly improving the efficiency of data acquisition. Secondly, accuracy. Human observation can be subject to errors due to subjective factors or environmental influences, while computerized image recognition systems rely on pre-trained models to maintain a high level of consistency and accuracy. Thirdly, data volume. Computerized image recognition systems can process and analyze massive amounts of data, helping researchers discover potential behavioral patterns and trends that are difficult to achieve with human observation. Fourthly, real-time monitoring. With the help of image recognition, researchers can monitor the behavior and state of health of the animals in real time, detect abnormal situations and take appropriate actions.

Animal behavior identification is quite meaningful and importance, which could be concluded to four aspects. Firstly, it benefits scientific research. Through precise monitoring of animal behavior, researchers can gain insight into the living habits and ecological needs of animals, providing a scientific basis for species protection and ecological environment management. Secondly, it benefits conservation and management. In urban conservation areas and zoos, image recognition technology helps managers keep track of animals in real time, detect and respond to potential threats, and ensure their safety and health. Thirdly, it benefits agriculture and animal husbandry. In the management of domestic animals, image recognition technology can monitor the health of livestock, diagnose diseases in time, and improve breeding efficiency and animal welfare. Fourthly, it benefits environmental monitoring. Through long-term monitoring of wildlife behavior changes, can reflect the changes in the ecological environment, environmental protection and recovery to provide data support.

In summary, computer image recognition technology is of great significance in animal behavior recognition, which not only improves the efficiency and accuracy of research and management, but also provides new means and methods for animal protection and ecological research.

2 Applications of Image Recognition for Domestic Animal Management

Enhancing the convenience and efficiency of animal breeding has become an important item for scientific and technological development. Furthermore, with the advancement of the overall economic status, domestic animals become a source of emotional sustenance for many. Additionally, the technological advancements in computer image recognition applied to animal behavior analysis can be extensively utilized for deep learning in the field of animal behavior, and can also provide enhanced data analysis for computer image recognition models.

2.1 Video-based Animal Epidemic Monitoring

The Animal Health Center of Dongguan City, Guangdong province used a remote video surveillance system to provide comprehensive coverage of 32 towns in Dongguan City during the epidemic. The specific process is as follows: First, save the video of each testing and quarantine link in 15-minute segments, and cover the video recording every 30 days as a cycle. Finally, the saved video recordings or images are sampled and observed manually. Therefore, when foreign livestock or domestic animals enter the Dongguan City Slaughterhouse, staff at the testing center will monitor them in real time. Once suspected epidemic symptoms appear on the skin of livestock through images or videos, the situation should be reported immediately to the relevant animal epidemic detection departments, and livestock or poultry with suspected epidemic symptoms should be isolated and observed. Likewise, this monitoring has certain drawbacks and inefficiencies. In the final analysis, remote real-time monitoring is still a preliminary manual judgment of videos and images. Observing videos and images for a long time will not only make the staff very tired, but also reduce the efficiency of monitoring. For example, staff who monitor for a long time will misjudge the symptoms of the monitored objects due to fatigue, resulting in unnecessary reporting and isolation. A series of processes may even lead to a major outbreak of the epidemic. After all, humans are still human with naked eyes and cannot automatically identify and screen suspicious lesions. Therefore, in view of the problems existing in animal epidemic monitoring, it is expected to use computer image recognition to automatically process and identify the images and videos obtained by the video surveillance system, monitor the animal epidemic in real time 24 hours a day, and automatically screen and identify animals with suspected epidemic symptoms. alarm, thus greatly easing personnel workload and improving monitoring efficiency. First of all, to achieve this goal, the sample features in the feature library should be trained to form a more accurate classifier, which can more accurately distinguish and analyze the samples. In an ideal state, an image recognition computer can extract main features from the monitored objects, and then compare and analyze them with the information in the inventory to determine whether to issue an early warning [1].

2.2 Image-based Fish Species Identification

Computer image recognition also plays a certain role in fish classification. Use computer technology to automatically identify and classify fish caught by fishing boats to prevent illegal fishing. First of all, the originally proposed manual feature selection method is based on the identification of 5 types of fish, and the identification accuracy of various types of fish is as high as 83.33%. The other method uses the back propagation neural network to classify crucian carp and carp by calculating the ratio of the average width and length of each segment in the long axis direction of the fish as a characteristic parameter, and the recognition accuracy is as high as 92.5%. All of the above are based on manual selection of features. After all, this method selects features based on human experience. There will be some oversights in feature

judgment, which reduces accuracy. Therefore, the deep learning convolutional neural network was used to classify fish, and the data set amplification method, dropout, and batch normalization methods were used to reduce the overfitting of the simulation. The data was collected through a camera fixed at a certain position on the fishing boat. A total of 3,777 fish photos were collected as classification samples, divided into 8 categories: albacore tuna, big eye tuna, yellowfin tuna, mahi, moon fish, Sharks, other, no fish. Then, stratified sampling was done according to a certain proportion, with 2984 images used as training set, 394 images used as verification set, and 399 images used as test set [2].

3 Applications of Image Recognition for Wild Animal Analysis

3.1 Wild Animal Disease Early Warning

Rare wildlife disease monitoring and early warning technology refers to the use of a series of scientific means and tools to monitor the health status of wild animals, and when suspicious diseases are detected, early warning is issued to reduce the impact of diseases on animal populations. The key technology of computer vision monitoring is feature extraction technology, that is, extracting key features from images that help to identify and classify, such as color, texture and shape. Among them, scale invariant feature transform, accelerated robust feature, directional gradient histogram and other algorithms are mainly used for target detection and tracking. In the computer vision model, roll neural network is the mainstream model in computer vision, which is used in image analysis and object detection. In recent years, the popular algorithms of object detection are divided into two categories. One is Recurrent Convolutional Neural Network (R-CNN) system algorithm, which is two-stage. The second category is You Only Look Once (YOLO), and the Single-Shot Detector (SSD) category is one-stage. The first kind of algorithm has higher precision but slower speed. The second type of algorithm is fast, but less accurate [3].

The performance of the main model still has room for improvement. Due to the hidden activities of animals, rapid location changes, complex background environment and other natural reasons, the characteristic data can be obtained less; The problem of underfitting due to the huge computation and network structure required by machine autonomous learning needs to be improved and solved. In the future, it is mainly necessary to improve and optimize the detection performance, improve the identification speed and accuracy; Improve network performance through data enhancement. Improve model performance; Speed up the training time of convolutional neural networks.

3.2 Wild Animal Identification

Wild animals inhabit expansive and intricate natural habitats, replete with unfamiliar and perilous elements. It is challenging for humans to directly intervene and observe the behavior and distribution of wild animals. Computer vision system, a technology within the field of computer science, facilitates the observation of wild animal

behavior and distribution. The process encompasses the automated extraction, analysis, and comprehension of valuable information from a single image or series of images.

This work has conducted comprehensive research and analysis on the current state of wildlife identification technology, and the predominant technologies in the market can be broadly classified into three stages.

Image Acquisition and Pre-processing. The current mainstream method for image acquisition in the market is to utilize a class of imaging equipment, such as cameras, to capture motion video or still frames of the target animal. Additionally, in order to meet the shooting requirements in various environments, auxiliary technologies like thermal imaging, laser matrix, and remote sensing technology can be integrated with basic imaging equipment.

The image data collected is processed by analyzing each video frame individually, and then deconstructing the video into a series of photos for further analysis.

To address the influence of environmental factors on image quality, it is crucial to implement de-noising techniques to mitigate the impact of lighting variations and shadows. Furthermore, employing methods such as contrast enhancement, image sharpening, and other advanced technologies can effectively enhance image quality and accentuate animal features.

Feature extraction. The Deep Snake model is a feature extraction model that utilizes contour extraction and gated transformer network to identify animal features, using contour features to characterize the spatial differences in various behaviors [4,5]. In contrast, Mask R-CNN is a pixel-based method for extracting animal contours.

Using deep learning feature extraction, convolutional neural networks CNN are used to automatically learn deep features of animal behavior, such as CNNs are also used to train a large number of markers on the animal body to filter out unlabeled data [6]. Max Hahn et al. multistep Convolutional neural networks identified three typical behaviors of zoo mammals. Liu et al. A method based on temporal and spatial characteristics of pig biting tail is proposed [7].

Behavior recognition. The extracted behavioral features are compared with the predefined behavioral patterns, and the data is aggregated and analyzed using deep learning algorithms by the cloud platform system to identify specific behaviors.

Advanced machine learning algorithms, such as support vector machines (SVM) and random forests, are employed for behavioral classification.

Recurrent neural networks (RNN) and Long short-term memory networks (LSTM) are employed for the processing of sequential data, with the aim of automatic identification and prediction of patterns in animal behavior.

For the current array of practical tools and specific programs, the scientific community possesses a viable solution: AlphaTracker [8], a multi-animal tracking and behavioral analysis tool derived from AlphaPose [9]. AlphaPose is a human pose estimation and tracking library renowned for its exceptional accuracy and efficiency.

The algorithm comprises three main steps: animal detection, key point estimation, and identity tracking across frames. YOLOv3, a state-of-the-art convolutional neural network designed for high-speed object detection, is employed to detect the precise location of animals in each frame [10]. The extracted frame is then utilized for isolating a single animal, and the individual images are subsequently input into the Compression and Excitation Network (SENet). Utilizing the tracker, this component facilitates precise imaging of the target object within the framework of camera surveillance technology, followed by algorithmic analysis [11]. Furthermore, it serves as a fundamental element for an entirely automated system for identification and tracking, encompassing three essential modules: information acquisition, image analysis and processing, and execution. Within the information acquisition module, this work employs advanced imaging equipment, such as cameras, to capture high-resolution video or image frames of the target animal and transfer them to the cloud platform for storage and analysis. In the image analysis and processing module, AlphaTracker is utilized for comprehensive data analysis and processing [8]. The refined data and analytical outcomes are subsequently integrated and reported via the cloud platform.

When addressing the analysis module, Recognition Based on Wild Mammal Behavior Gated Transformer Network could be employed [12]. It is a methodology for identifying wild mammal behavior predicated on animal contour characteristics and variations in the angle of animal leg joints. The model incorporates contour features and fluctuations in joint coordinates as its input. The coordinated motion velocity for various behaviors is indicated by fluctuations in joint coordinates within a continuous coordinate system. Given that the temporal variation of the contour also reflects different behaviors to some extent, it is imperative to extract contour features and integrate them with temporal information. A network of gated transformers is utilized to discern distinct behaviors exhibited by wild mammals [12]. Contour features are employed to characterize spatial disparities between different behaviors.

When utilizing this technology, its convenience and safety could be observed. It enables the non-invasive observation of wild animals, and through deep learning technology, researchers are able to track animal behavior even during periods of rest. This significantly aligns with the requirements of scientists for wildlife observation. The system, however, has some drawbacks. Firstly, due to the complexity and uncertainty of the field environment, it is necessary to ensure the clarity and stability of the image acquisition device by timely adjustments according to the actual situation. Secondly, this technology requires a significant amount of graphics processing unit for information processing and relies on a cloud server as its foundation for use. In conclusion, this is an innovative technology with unlimited future potential, and the integration of multiple disciplines can enhance its comprehensiveness and efficiency.

4 Discussion and Outlook

Although the application of image recognition technology in wild animal identification and domestic animal health monitoring has achieved remarkable results, there are still some challenges and limitations. The current technical advantages lie in high efficiency, accuracy and big data processing capabilities, but in practical applications, the following problems have to be overcome.

Firstly, the complexity of data acquisition. The field environment is complex and changeable, and it is challenging to obtain high-quality image data. Weather, lighting, and camera installation location can all affect data quality, which can lead to a decline in recognition accuracy. There are some requirements for the setting of the scene.
Secondly, the diverse behavior patterns. Animal behavior is diverse and complex, and animal behavior varies greatly among different species, ages and genders, requiring image recognition systems to be highly flexible and adaptable.

Thirdly, the model training and updating. Existing image recognition models require a large amount of labeled data for training, which is time-consuming and laborious. As animal behavior and the environment change over time, the model needs to be updated and adjusted to maintain accuracy.

Fourthly, technical cost and operability. The high cost of high-performance image recognition systems and equipment has limited their use in some resource-limited research and conservation projects.

There are several future directions for further improvements. Firstly, the data quality and diversity could be improved: Improve data quality and diversity: Improve image quality and diversity by improving data acquisition equipment and methods to build a more comprehensive and diverse training dataset. Secondly, the model adaptability could be enhanced: Develop more flexible and adaptive recognition algorithms that can automatically adjust and optimize to respond to different environments and changes in animal behavior. Thirdly, the multi-disciplinary could be cooperated: Strengthen cooperation with ecology, animal behavior and other fields, and combine multidisciplinary knowledge to improve the application effect of image recognition systems. Fourthly, the costs could be further reduced: Make efficient image recognition technology more affordable through technological innovation and cost control, driving its widespread use in more fields.

5 Conclusion

This paper discusses the application of computer image recognition technology in field animal identification and domestic animal health monitoring. By analyzing the advantages and disadvantages of existing technologies and practical cases, this work shows the great potential of image recognition technology in improving the efficiency and accuracy of animal behavior research. Despite the challenges of data acquisition, behavioral diversity, model training, and cost, image recognition technology has broad application prospects in animal behavior analysis through measures such as

improving data quality, enhancing model adaptability, multidisciplinary cooperation, and reducing costs.

In the future, with the continuous progress and innovation of technology, computer image recognition technology will play an increasingly important role in the field of animal protection, ecological environment monitoring and agricultural production, and make greater contributions to animal welfare and ecological sustainable development.

Authors Contribution

All the authors contributed equally and their names were listed in alphabetical order.

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