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A Review of Lightweight Techniques for Animal Recognition Algorithms in Smart Cameras and Analysis of Application Prospects

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ABSTRACT

In today's rapidly evolving smart camera technology, animal recognition has emerged as one of its significant applications, showcasing immense potential across various fields. This technological innovation not only enhances the functionality and practicality of smart cameras but also establishes a solid foundation for their widespread application in ecological protection, security monitoring, and other areas. However, existing high-precision animal recognition models are computationally complex and demand substantial hardware resources, making real-time operation on embedded devices challenging and leading to several application difficulties. Therefore, incorporating lightweight techniques into animal recognition algorithms can significantly broaden the application scope of smart camera animal recognition technology while also reducing resource consumption and improving algorithm accuracy. This paper summarizes relevant articles and proposes the introduction of lightweight techniques to optimize algorithms, aiming to provide comprehensive and in-depth theoretical guidance and practical reference for the application of smart camera animal recognition technology.

KEYWORDS

Animal Recognition; Smart Camera; Convolutional Neural Network; Optimization Path; Lightweight Techniques

1 Introduction

In many fields, smart cameras reduce labor costs compared to traditional cameras while offering various intelligent solutions and extended functions. For instance, in wildlife conservation, smart cameras can accurately identify animal species, numbers, behaviors, and other related data. These data not only facilitate the statistical protection of animal populations, reflecting conservation effectiveness, but also significantly aid in studying the behaviors of some rare protected animals[1]. In environmental monitoring, smart cameras can quickly identify environmental issues through algorithms, greatly reducing labor costs compared to manual identification. Additionally, smart cameras can monitor illegal activities that harm the environment. Current animal recognition algorithms often employ deep learning techniques, which, although significantly improving recognition accuracy, also increase algorithm complexity, thereby raising computational demands [2]. Real-time performance is a crucial consideration in many scenarios. To achieve real-time recognition, algorithms must complete numerous computational tasks in a short time, posing high computational power requirements. Consequently, animal recognition algorithms often need to be deployed on high-performance computers or servers, which are costly and unaffordable for resource-limited regions or institutions.

2 Overview of Lightweight Techniques (Introduction to Theoretical Foundations)

Given the aforementioned reasons and benefits, it is necessary to optimize smart camera animal recognition algorithms using lightweight techniques. Quantization techniques significantly enhance model inference speed and reduce memory usage by converting high-precision numerical values into low-precision representations.

2.1 Quantization Techniques

TensorRT INT8 quantization is one of the most commonly used methods. The TensorRT INT8 quantization process involves converting a model to low precision. During this process, the model's weights and activation values are mapped to an 8-bit integer range. This mapping is typically achieved through quantization parameters (such as scale factors and zero-point offsets) to retain as much information from the original model as possible in the low-precision representation. The quantization process may lead to a loss of model accuracy, hence the introduction of Quantization Aware Training (QAT) to adjust model parameters during quantization to maintain accuracy.

2.2 Pruning Techniques

Pruning techniques reduce model complexity and computation by removing unimportant or unnecessary parameters from neural networks. L1/L2 regularization pruning algorithms are representative methods. L1 regularization tends to push some weights towards zero, generating a sparse weight matrix that facilitates feature selection. In contrast, L2 regularization reduces weight values but does not directly lead to sparse weights, lacking feature selection capability, though it effectively controls model complexity. Pruning can lower model power consumption and enhance inference speed, but it also requires balancing the extent of pruning with model accuracy. Pruning is divided into structured pruning and unstructured pruning: structured pruning removes entire neurons or convolution kernels, while unstructured pruning removes individual weights or connections, such as Deep Compression and Sparse-Winograd. Each pruning method has its advantages; the former is more amenable to hardware accelerator support, while the latter is more effective in pruning, broadly applicable without requiring specific algorithm libraries and hardware support, allowing more flexible removal of unimportant parameters.

2.3 Attention Mechanism

In addition to quantization and pruning techniques, attention mechanisms (such as SENet, CBAM) can be introduced into lightweight models. These mechanisms dynamically adjust feature map weights, enhancing the model's focus on important features and improving performance. Furthermore, feature fusion and data augmentation techniques also assist in enhancing model performance. In summary, lightweight techniques effectively reduce the complexity and computational load of deep learning models through quantization, pruning, and attention mechanisms, providing robust support for efficient deployment in resource-constrained environments.

3 Application of Lightweight Techniques in Smart Camera Animal Recognition

Currently, many researchers have proposed studies on lightweight techniques for smart camera animal recognition algorithms in various directions.

3.1 Lightweight Model for Fish Recognition Based on YOLOV5-MobilenetV3

For example, the lightweight model for fish recognition based on YOLOV5-MobilenetV3 and sonar images addresses the lightweight issue of fish recognition algorithms, significantly reducing model parameters and computation [3]. It also reduces the average inference time per image to 0.08868 seconds, improving the modified model's mAP by 0.97%.

3.2 Sheep Face Recognition Method Based on Lightweight Neural Networks

The study on sheep face recognition methods using lightweight neural networks introduces the ECAS module into the deep feature extraction layer of the Mobile Face Net network, increasing the recognition rate by 7.21% and reducing the model size by 0.3MB [4]. Existing studies have introduced lightweight techniques for specific animal types with significant results. However, a lightweight algorithm suitable for multiple animal recognition, applicable in wildlife protection and marine biology exploration, is still lacking. The success of existing research also demonstrates the rationality of introducing such techniques and improves success rates [2].

3.3 Application Scenarios and Advantages

Lightweight techniques are increasingly applied in the smart camera field, particularly in wildlife protection, marine biological exploration, and reducing human-wildlife conflicts [1]. In wildlife protection, traditional wildlife monitoring often relies on numerous cameras and manpower, incurring high costs and inefficiencies. Lightweight techniques reduce model complexity and computation, enabling smart cameras to maintain recognition accuracy while enhancing endurance and data processing capabilities. This allows cameras to operate for extended periods, capturing more valuable wildlife activity footage, providing more comprehensive and accurate data support for conservationists. In marine biological exploration, lightweight techniques also show great potential. Due to the complexity and uniqueness of the marine environment, traditional detection methods often fall short. Smart cameras equipped with lightweight animal recognition algorithms can operate stably underwater, monitoring and identifying marine life in real-time. This aids scientists in understanding marine life distribution and migration patterns and promptly identifying potential ecological issues, providing scientific evidence for marine ecological protection. In reducing human-animal conflicts, smart cameras efficiently identify wildlife invading human habitats and quickly respond by playing specific sounds [5]. These applications highlight the practical effects of lightweight techniques in enhancing camera endurance and reducing data transmission pressure, further promoting smart cameras' widespread application in more fields, providing efficient and reliable technical support for ecological protection, scientific research, and public safety.

4 Challenges and Future Prospects

Introducing lightweight techniques into animal recognition algorithms presents several new challenges and advantages. These challenges mainly involve accuracy loss in lightweight techniques, balancing model complexity with performance, and adapting to specific platforms, such as differences in computational power and real-time requirements.

Lightweight techniques aim to minimize model data size while ensuring usability. However, during the lightweight process, overemphasizing data reduction may lead to decreased accuracy or loss of detail [6]. For example, in industrial design, small features of product models may affect assembly and functionality; in digital preservation of cultural heritage, detailed textures and structural details of models are crucial for research and display. Therefore, before performing lightweight operations, it is essential to identify core features and application requirements, using precise parameter settings and algorithm adjustments to remove redundant information while preserving key structures, dimensions, and details. Different devices vary significantly in computational power, graphics processing capability, and memory capacity. For instance, high-end PCs have powerful GPUs and ample memory to handle complex models, while mobile devices are constrained by processor performance, battery life, and screen resolution. Additionally, users may access models over high-speed broadband or low-bandwidth mobile networks. Therefore, designing lightweight solutions must consider these differences. For mobile devices, further simplification of model structures, reduction of texture resolution, and data volume are necessary to ensure smooth operation and quick loading.

In the smart camera field, lightweight techniques also face challenges in hardware platform adaptability. Different camera models may feature varying processors and memory configurations, requiring lightweight algorithms to flexibly adapt to various hardware platforms, ensuring efficient operation on different devices. Moreover, real-time performance is a significant challenge in the smart camera field. In some application scenarios, such as intelligent traffic management and urban security monitoring, cameras must respond swiftly. Hence, lightweight techniques must maximize inference speed while maintaining model accuracy to meet real-time requirements.

Combining lightweight techniques with smart camera animal recognition algorithms significantly expands their future application scope. With the continuous development of artificial intelligence, animal recognition systems are becoming an emerging industry. In the smart camera field, lightweight techniques will drive animal recognition systems toward higher efficiency and precision. In the future, more efficient pruning algorithms and mixed-precision quantization techniques will become prevalent. Pruning algorithms reduce model size by removing unimportant weights and connections while maintaining high accuracy. Mixed-precision quantization techniques further reduce computational and storage demands by combining different precision representations.

5 Conclusion

Smart camera animal recognition technology has garnered significant attention as a vital tool in ecological protection, agricultural management, and other fields. However, the high computational complexity and resource consumption of traditional algorithms limit their widespread application on edge devices. In response, lightweight techniques have emerged as a key solution to this challenge. By optimizing model structures and reducing parameter quantities, these techniques effectively lower algorithm operational burdens, enhancing real-time performance and energy efficiency. This paper reviews lightweight techniques for animal recognition algorithms in smart cameras, covering mainstream methods, specific application scenarios, and optimization effect evaluations, and discusses future development trends. This review provides researchers with a comprehensive research perspective and practical reference, emphasizing the importance of lightweight techniques in promoting the popularization and optimization of smart camera animal recognition technology.

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