Domestic Animal Breed Identification

CSA301 Deep Learning
Bachelor of Computer Science (AI Development and Data Science)
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1 Literature Review

1. Animal breed identification has emerged as a critical area of research, particularly with the advent of deep learning techniques, which offer promising solutions for accurately classifying and distinguishing various breeds. For the domestic breed identification, deep learning model can be trained on the datasets containing images of different breeds, enabling the models to learn the distinct features of each breed.

   In this research [1], Chao Ma et al. explored the development of a sheep recognition algorithm based on the deep learning, specifically utilizing the Faster R-CNN (Region-Convolutional Neural Network) model enhanced with the Soft-NMS (Non-Maximum Suppression) to improve the accuracy and efficiency of sheep breed identification . Faster R-CNN is a powerful tool for object detection that integrates a region proposal network (RPN) with a convolutional neural network (CNN) for feature extraction, classification, and bounding box regression. The research demonstrated that the Faster R-CNN model with Soft-NMS achieved a detection accuracy of 95.32 percent. This approach allows for real-time detection and localization of sheep, providing a solid foundation for further research.

   In this article [2], it highlights the use of Deep Neural Networks (DNNs) for animal image identification and classification, particularly focusing on predators. It is employed to deal with noisy labels within data sets. Some of the works include the following: iterative label refinement, feature extraction from pretrained networks and network optimization. If the problem of noisy labels is solved, then the models will be able to produce more accurate classifications, which will benefit from the monitoring of various populations of animals.

   In the context of image classification, features such as deeper networks like ResNet use a variety of Convolution Neural Network (CNN). This particular type of models is built special to identify various animal species and are the basis of datasets such as the Snapshot Serengeti and the Panama-Netherlands. These datasets are in form images which are captured through camera traps; they offer large datasets, through which the CNNs can in the process learn features that can enable them to distinguish between different species. CNNs proves pivotal in enhancing high levels of accuracies on the species identification hence being a strong pillar in wildlife research.

   Camera trapping is important in this study as a non-intrusive approach to assessing populations of these animals in their ecosystem. Unlike other intrusive methods, for example, GPS that require fixing devices on animals' bodies or the use of sensor networks that would interfere with animal's environments, camera traps provide non-intrusive ways of observing animal behaviour. The images obtained after that are analysed by the deep learning models for the detection and classification of animals from the visual data obtained from the traps. This has the effect of improving the quality of the data gathered as well as extending the overall subject area of monitoring to more species and habitats.

   Sometimes it is also difficult to differentiate between two closely related animal species or breeds and hence Fine-Grained Classification (FGC) techniques are also used in the study. FGC, on the other hand, entails the process of extracting more detailed features from the images which are used to classify the animals deeper. The incorporation of FGC techniques in the deep learning models makes the study more comprehensive and practical since the techniques improve the model performance in identifying and classifying the animals.

The study shows how integrating deep learning and image processing in animal detection and classification systems is efficient. By looking into critical areas and considering the techniques to minimize the effect of noisy labels, the study presents how the efficacy of these systems enhances in the long run. Employing such technologies as camera traps also supports the applicability of these methods in conservation and studying the wild fauna and flora.

Deep learning has the ability to automate animal monitoring and thereby improving efficiency and accuracy. The paper [3], presents a detailed approach to wild animal detection and identification by using YOLOv3 algorithm. The studies have investigated the applications of deep learning in the classification of wildlife images and object detection in natural settings. Nonetheless, challenges such as variations in the appearance of animals, poor quality camera trap images as well as the need for large data sets still exist. The reviewed paper addresses these challenges with support from YOLOv3, and state-of-the-art object detection model.

The method used in this paper involves collection of animal videos data set, preprocessing the data, and then training YOLOv3 model. The findings demonstrate a great accuracy when it comes to recognizing various species of animals, demonstrating the potential of deep learning for this task. Even though the article provides insightful information; however additional research is required to deal with limitations and challenges experienced while monitoring wildlife in real life scenarios. Deep learning offers a promising avenue for automating wild animal detection and identification. The paper by Pukale et al., shows how effective YOLOv3 can be on such projects.

In the study "Dog Breed Prediction Using Deep Learning" [4], the researchers developed a CNN model trained using a large collection of dog images, covering a wide range of breeds. Before feeding the images into the model, they were pre-processed to improve their quality and ensure they were all the same size and format. The CNN model itself included several layers of convolution and pooling, followed by fully connected layers that ultimately made the breed predictions. To evaluate the model's performance, the researchers used metrics like accuracy, precision, and recall, which demonstrated that the model was quite effective at identifying breeds.

The results were impressive, with the model correctly predicting dog breeds 90 percent of the time. The researchers also emphasized the importance of having a diverse dataset and how data augmentation techniques helped make the model more robust. These findings suggest that deep learning can significantly reduce the time and effort required for breed identification compared to traditional methods.

In this paper [5], it shows that snake biologists conducted studies using computer vision algorithms to identify various snake species. For instance, a CNN was trained on its own to identify up to an amazing 45 types of snakes better than humans could really do it. Another study focused on categorizing into poisonous or non-poisonous snakes and achieved accuracy levels of 91.3 percent with knowledge acquired from the evaluation of 1766 images dataset drawn from various parts of Africa.

Transfer learning has also become a prevalent approach in animal species identification with transfer learning using such pre-trained models, researchers can adapt existing networks to new datasets, significantly improving classification accuracy with limited data.

Vision transformers (ViT) have come up strongly as a great replacement for CNNs. The self-attention which the ViTs employ allows them to process images without convolutional layers. This alternative has done well in different image recognition tasks with some benchmarks recording state of the art score . The Data-Efficient Image Transform (DeiT) increases this capability further making it possible to effectively train using small data sets, achieving top-1 accuracy on ImageNet without external data.

Incorporation of deep learning especially CNNs as well as Vision Transformers has greatly enhanced the identification and even classifications of animals in tasks such as species and breed identification with high accuracy. Transfer learning and Ensemble methods, which combine multiple models to improve prediction accuracy, have also been explored in animal identification. By stacking predictions from diverse classifiers, the researchers have been able to improve their overall performance.

References

[1] C. Ma, X. Sun, C. Yao, M. Tian, and L. Li, "Research on sheep recognition algorithm based on deep learning in animal husbandry," in *Journal of Physics: Conference Series*, vol. 1651, p. 012129, IOP Publishing, 2020.

[2] T. Battu and D. S. R. Lakshmi, "Animal image identification and classification using deep neural networks techniques," *Measurement: Sensors*, vol. 25, p. 100611, 2023.

[3] D. D. Pukale, K. Dudhane, S. Dawghat, A. Deshmukh, and S. Deshmukh, "Wild animal detection and identification using deep learning," *International Journal of Creative Research Thoughts (IJCRT)*, vol. 11, no. 7, pp. a477–a482, 2023.

[4] K. Jagadesh, P. Kavya, A. Lavanya, A. L. Priya, B. Harshini, and D. G. Jerith, "Dog's breed prediction using deep learning," *International Journal for Research in Applied Science & Engineering Technology (IJRASET)*, vol. 12, no. VI, pp. 1161–1166, 2024.

[5] D. Dandeniya, B. Wickramasinghe, and C. Dasanayaka, "A web-based application for snake species identification using vision transformer and cnn-based ensemble meta classifier," in *2022 IEEE Pune Section International Conference (PuneCon)*, pp. 1–5, IEEE, 2022.