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Animal Footprint Detection

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Abstract:

Animal footprint detection is a powerful tool in wildlife monitoring, ecological research, and conservation efforts. By identifying and analyzing footprints left by animals, researchers can gain valuable insights into species presence, movement patterns, population size, and behavior without the need for direct observation. Traditional methods of footprint analysis are often time-consuming and prone to human error. With advancements in computer vision and machine learning, automated systems can now detect, classify, and track animal footprints from images captured in natural environments, enabling faster and more accurate data collection.

This project aims to develop an automated animal footprint detection system using image processing techniques and deep learning models. The system will preprocess input images to enhance footprint visibility, then apply trained neural networks to recognize patterns specific to various animal species. Such a system has broad applications, including poaching prevention, biodiversity assessment, and habitat protection. By leveraging technology, we can support more efficient wildlife tracking and contribute to the sustainable management of ecosystems.

INTRODUCTION

Animal footprint detection is a cutting-edge technique increasingly used in ecological and conservation research. It allows researchers to gather critical information about wildlife without disturbing their natural habitat. Footprints, also known as spoor, provide evidence of an animal's presence, direction of movement, and sometimes even behavior. Traditionally, trained experts manually analyzed animal tracks, a process that is both time-consuming and subjective. Human interpretation of footprints can vary, leading to inconsistencies in data collection and analysis. With the evolution of technology, particularly in computer vision and artificial intelligence, a shift toward automation has emerged.Automated systems can now process images of footprints captured by field cameras or researchers to identify species. Such systems significantly reduce the time and effort needed to analyze large datasets collected from the wild. These tools also improve accuracy and consistency by eliminating human bias in footprint identification.In this project, we explore the development of an automated animal footprint detection system using deep learning.

The system involves preprocessing raw images to enhance the visibility of animal tracks.Image preprocessing may include techniques such as contrast adjustment, noise reduction, and edge detection.After preprocessing, images are passed through trained deep learning models that classify the footprints by species.Convolutional Neural Networks (CNNs) are especially useful due to their effectiveness in pattern recognition tasks.The model learns from a labeled dataset of animal footprints to distinguish between different types of tracks.This system is trained and tested on publicly available footprint datasets, such as those found on platforms like Kaggle.Support Vector Machines (SVMs) are also employed in tandem with CNNs to enhance classification accuracy.By combining multiple models, the system benefits from both the learning capability of deep networks and the robustness of classical algorithms.The goal is to create a user-friendly tool that field researchers can use with minimal technical expertise.This system has practical applications in poaching prevention by helping identify the movement of endangered species.It can also be employed in biodiversity studies to assess species richness in various habitats.

Monitoring animal footprints contributes to better understanding of migration patterns and seasonal behaviors.Conservationists can use this data to design more effective protection strategies for vulnerable ecosystems.Automated detection also facilitates long-term ecological monitoring by providing consistent and scalable data.Real-time detection capabilities can be integrated with GPS and GIS systems for spatial analysis.This offers opportunities for dynamic mapping of animal routes and habitat use over time.With accurate data, policy makers and environmental managers can make informed decisions.The project emphasizes sustainability by reducing the need for intrusive methods like physical tagging.Furthermore, it showcases the power of interdisciplinary approaches, merging ecology, computer science, and data analytics.Ultimately, this work aims to advance wildlife research and conservation through the smart application of technology.

LITERATURE SURVEY

1. Alibhai, S. K., Jewell, Z. C., & Towindo, S. S. (2008). Using footprint identification technique (FIT) for non-invasive monitoring of black rhino (Diceros bicornis). ***Journal of Zoology*****, 274(2), 117–124.**

An objective, non-invasive technique was developed for identifying individual black rhino from their footprints (spoor). Digital images were taken of left hind spoor from tracks (spoor pathways) of 15 known black rhino in Hwange National Park, Zimbabwe. Thirteen landmark points were manually placed on the spoor image and from them, using customized software, a total of 77 measurements (lengths and angles) were generated. These were subjected to discriminant and canonical analyses. Discriminant analysis of spoor measurements from all 15 known animals, employing the 30 measurements with the highest F-ratio values, gave very close agreement between assigned and predicted classi®cation of spoor. For individual spoor, the accuracy of being assigned to the correct group varied from 87% to 95%. For individual tracks, the accuracy level was 88%.

2. Gonzalez, R. C., & Woods, R. E. (2018). ***Digital Image Processing*** **(4th ed.). Pearson Education.**

Brain tumors, whether cancerous or noncancerous, can be life-threatening due to abnormal cell growth, potentially causing organ dysfunction and mortality in adults. Brain tumor segmentation (BTS) and brain tumor classification (BTC) technologies are crucial in diagnosing and treating brain tumors. They assist doctors in locating and measuring tumors and developing treatment and rehabilitation strategies. Despite their importance in the medical field, BTC and BTS remain challenging. This comprehensive review specifically analyses machine and deep learning methodologies, including convolutional neural networks (CNN), transfer learning (TL), and hybrid models for BTS and BTC. We discuss CNN architectures like U-Net++, which is known for its high segmentation accuracy in 2D and 3D medical images. Additionally, transfer learning utilises pre-trained models such as ResNet, Inception, etc., from ImageNet, fine-tuned on brain tumor-specific datasets to enhance classification performance and sensitivity despite limited medical data. Hybrid models combine deep learning techniques with machine learning, using CNN for initial segmentation and traditional classification methods, improving accuracy. We discuss commonly used benchmark datasets in brain tumors research, including the BraTS dataset and the TCIA database, and evaluate performance metrics, such as the F1-score, accuracy, sensitivity, specificity, and the dice coefficient, emphasising their significance and standard thresholds in brain tumors analysis. 3.**Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks.** ***Advances in Neural Information Processing Systems*****, 25, 1097–1105.**

We trained a large, deep convolutional neural network to classify the 1.2 million high-resolution images in the ImageNet LSVRC-2010 contest into the 1000 dif ferent classes. On the test data, we achieved top-1 and top-5 error rates of 37.5% and 17.0% which is considerably better than the previous state-of-the-art. The neural network, which has 60 million parameters and 650,000 neurons, consists of five convolutional layers, some of which are followed by max-pooling layers, and three fully-connected layers with a final 1000-way softmax. To make train ing faster, we used non-saturating neurons and a very efficient GPU implemen tation of the convolution operation. To reduce overfitting in the fully-connected layers we employed a recently-developed regularization method called "dropout" that proved to be very effective. We also entered a variant of this model in the ILSVRC-2012 competition and achieved a winning top-5 test error rate of 15.3%, compared to 26.2% achieved by the second-best entry.

4.He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

Deeper neural networks are more difficult to train. We present a residual learning framework to ease the training of networks that are substantially deeper than those used previously. We explicitly reformulate the layers as learning residual functions with reference to the layer inputs, instead of learning unreferenced functions. We provide comprehensive empirical evidence showing that these residual networks are easier to optimize, and can gain accuracy from considerably increased depth. On the ImageNet dataset we evaluate residual nets with a depth of up to 152 layers - 8× deeper than VGG nets [40] but still having lower complexity. An ensemble of these residual nets achieves 3.57% error on the ImageNet test set. This result won the 1st place on the ILSVRC 2015 classification task. We also present analysis on CIFAR-10 with 100 and 1000 layers. The depth of representations is of central importance for many visual recognition tasks. Solely due to our extremely deep representations, we obtain a 28% relative improvement on the COCO object detection dataset. Deep residual nets are foundations of our submissions to ILSVRC & COCO 2015 competitions1, where we also won the 1st places on the tasks of ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation.

EXISTING METHOD

Existing methods for animal footprint detection have evolved significantly over time, ranging from manual observation to advanced computer vision techniques.Traditional tracking involves trained experts visually identifying footprints in the field, often using field guides or reference books.These methods are labor-intensive and rely heavily on the expertise and experience of the observer.Manual methods also include taking plaster casts of footprints for detailed analysis in laboratory settings.

While these techniques provide valuable insights, they are limited by human error, environmental conditions, and scalability issues.One widely used traditional method is grid sampling, where researchers record footprints found within marked sections of an area.Grid sampling helps in estimating animal population density but requires extensive time and manpower.Camera trapping, though not a direct footprint detection method, often captures footprints incidentally in photographs or videos.In some cases, footprint tunnels or track plates coated with soot or ink are used to capture clear imprints for later analysis.Semi-automated approaches involve using software tools like ImageJ or Adobe Photoshop to enhance and manually analyze digital images of footprints.Researchers may apply thresholding and segmentation manually to highlight footprint edges in these software platforms.

With the advent of digital imaging, databases of animal footprints have been created to assist in manual comparison and classification.Some studies have employed template matching techniques, where digital footprint images are compared to known patterns.Edge detection algorithms, such as Canny or Sobel, have been applied to footprint images to extract outlines for further analysis.More advanced existing methods utilize machine learning classifiers such as k-Nearest Neighbors (k-NN), Random Forests, and Decision Trees.These classifiers require feature extraction, which includes calculating metrics like footprint area, perimeter, and number of toes.Support Vector Machines (SVMs) have been used in several studies for their ability to handle high-dimensional data and provide robust classification.Some researchers have combined handcrafted feature extraction with statistical models to improve detection accuracy.Despite these advancements, most existing methods still require a significant amount of preprocessing and manual intervention.As such, there is a clear need for fully automated, end-to-end systems that can operate efficiently in diverse and natural environmental conditions.

PROPOSE METHOD

The proposed method aims to address the limitations of traditional and semi-automated animal footprint detection techniques by introducing a fully automated system based on deep learning and image processing.The core idea is to design a pipeline that processes raw images captured in natural habitats and accurately identifies the animal species based on their footprints.

The system begins with image acquisition, where high-resolution photographs of footprints are collected using mobile devices, trail cameras, or drones.To handle varying lighting conditions, terrain textures, and background noise, the captured images undergo preprocessing steps such as grayscale conversion, histogram equalization, and Gaussian filtering.One of the critical preprocessing techniques includes edge enhancement, which helps in clearly outlining the footprint contours for accurate feature extraction.

A segmentation algorithm, such as Otsu's thresholding or adaptive thresholding, is used to isolate the footprint from the background.Morphological operations like dilation and erosion are applied to remove small noise artifacts and fill gaps in the footprint region.Once the footprint region is segmented, the system extracts both handcrafted features (e.g., area, perimeter, aspect ratio) and learned features using Convolutional Neural Networks (CNNs).

CNNs are particularly effective in learning hierarchical patterns from raw pixel data, allowing the model to recognize even subtle differences between similar species.The proposed model architecture is based on a pre-trained ResNet-50 network, fine-tuned on a dedicated animal footprint dataset to balance performance and computational efficiency.Transfer learning is employed to utilize knowledge from large-scale image datasets, reducing the training time and improving model accuracy on limited footprint data.To complement the CNN, a Support Vector Machine (SVM) classifier is used on the extracted features to further improve classification accuracy, particularly for classes with fewer examples.

The dual-model approach ensures robust detection even in challenging environmental scenarios and improves generalizability across different species and terrains.During training, the dataset is augmented using rotation, scaling, flipping, and contrast adjustments to simulate various real-world conditions.The performance of the model is evaluated using cross-validation and tested on unseen data to ensure it can generalize well.Accuracy, precision, recall, F1-score, and confusion matrices are used to assess the model's effectiveness and identify any misclassification trends.

RESULT

Fig: User Interface for animal footprint detection

This is graphical user interface created by using tkinter library for animal footprint detection. Here we are using SVM(machine learning) and CNN(deep learning) algorithm.

Fig: Loading Dataset

First step is loading the animal footprint dataset which is taken from Kaggle site. Once dataset is loaded, it will type of animal footprints and number of animal footprint in dataset.

Fig: Feature extraction

Feature extraction needs to be done from images and data is split into training and testing. There are total 342 images in dataset. 273 images will go for training and 69 will be for testing.

Fig: SVM algorithm performance

After training with SVM algorithm , accuracy is getting approx. 44% only which is very for prediction animal footprint detection. So further we used CNN algorithm for better performance.

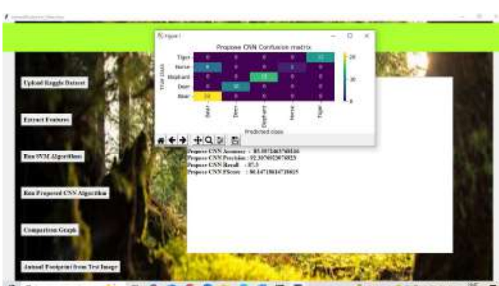

Fig: CNN Performance

CNN algorithm is giving better accuracy than SVM. That's why we will use CNN for prediction of animal footprint prediction.

Fig: Footprint prediction

When test image is uploaded from testimages folder, it will predict footprint by using CNN algorithm.

CONCLUSION

The development of an automated animal footprint detection system marks a significant advancement in the field of wildlife monitoring and conservation. By leveraging image processing techniques and deep learning models, the system offers a non-intrusive, efficient, and scalable solution for identifying animal species from their footprints. This approach not only reduces the reliance on manual observation but also enhances accuracy and consistency in data collection, even under challenging environmental conditions.

Furthermore, the integration of technologies such as CNNs, SVMs, and image augmentation contributes to robust model performance across diverse habitats and species. The proposed method supports critical applications including biodiversity assessment, anti-poaching surveillance, and ecological research. As a result, it empowers conservationists, researchers, and park authorities with real-time insights, enabling informed decision-making for sustainable ecosystem management and wildlife protection.

REFERENCES

1. Alibhai, S. K., Jewell, Z. C., & Towindo, S. S. (2008). Using footprint identification technique (FIT) for non-invasive monitoring of black rhino (Diceros bicornis). *Journal of Zoology*, 274(2), 117–124.

2. Gonzalez, R. C., & Woods, R. E. (2018). *Digital Image Processing* (4th ed.). Pearson Education.

3. Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). ImageNet classification with deep convolutional neural networks. *Advances in Neural Information Processing Systems*, 25, 1097–1105.

4. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 770–778.

5. Dalal, N., & Triggs, B. (2005). Histograms of Oriented Gradients for Human Detection. *IEEE CVPR*, 886–893.

6. Cortes, C., & Vapnik, V. (1995). Support-vector networks. *Machine Learning*, 20(3), 273–297.

7. Otsu, N. (1979). A threshold selection method from gray-level histograms. *IEEE Transactions on Systems, Man, and Cybernetics*, 9(1), 62–66.

8. Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. *arXiv preprint arXiv:1804.02767*.

9. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.

10. Simonyan, K., & Zisserman, A. (2014). Very Deep Convolutional Networks for Large-Scale Image Recognition. *arXiv preprint arXiv:1409.1556*.

11. Lowe, D. G. (2004). Distinctive image features from scale-invariant keypoints. *International Journal of Computer Vision*, 60(2), 91–110.

12. Bishop, C. M. (2006). *Pattern Recognition and Machine Learning*. Springer.

13. Chollet, F. (2015). Keras. https://keras.io

14. Pedregosa, F., et al. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825–2830.

15. OpenCV Team. (2024). OpenCV: Open Source Computer Vision Library. https://opencv.org/

16. Srivastava, N., et al. (2014). Dropout: A simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research*, 15, 1929–1958.

17. Schmidhuber, J. (2015). Deep learning in neural networks: An overview. *Neural Networks*, 61, 85–117.

18. Breiman, L. (2001). Random forests. *Machine Learning*, 45(1), 5–32.

19. Lin, T.-Y., et al. (2017). Focal loss for dense object detection. *Proceedings of the IEEE International Conference on Computer Vision (ICCV)*, 2980–2988.

20. Kaggle Dataset. (2023). Animal Footprints Dataset. https://www.kaggle.com/datasets/ (adjust link depending on the specific dataset used).