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Classifying Animal Species from Footprint Images Using Deep Learning Algorithm

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Abstract- Footprint-based animal species classification is vital for wildlife monitoring and conservation. This study proposes an efficient method utilizing Probabilistic Neural Networks (PNNs) for classifying animal species from footprint images. The approach involves preprocessing the images to normalize and reduce noise, followed by extracting key features such as shape, texture, and Histogram of Oriented Gradients (HOG). The PNN, known for its pattern recognition prowess, processes these features to classify the footprints. The network's structure, consisting of input, pattern, summation, and output layers, enables it to estimate the probability density functions of the input data effectively. Training the PNN with a labeled dataset of diverse footprint images showed high classification accuracy, outperforming traditional methods. This automated, non-invasive technique offers a scalable solution for accurate species identification, enhancing wildlife management efforts. Future work aims to broaden the dataset, incorporate hybrid models, and implement real-time applications for field use. This approach promises significant improvements in the efficiency and reliability of animal species classification based on footprints. The issues involved in developing an effective and successful system for tracking, recognizing, and classifying animals are the focus of this research project. Building algorithmic models for animal tracking, segmentation, detection, and classification has been attempted and accomplished with success. We propose two methods to effectively isolate an animal from its environment to aid in the effective taxonomic classification of species. The recommended animal segmentation method is assessed using performance indicators based on areas. We also present a classification model that utilises many features and classifiers. Among the different elements that are extracted from the segmented animal photographs are colour, gabor, and LBP.

Index Terms- SVM, Vehicle Collision (AVC), labeling, neural network, Segmentation, tracking, Animal Footprint, Animal.

I. INTRODUCTION

The classification of animal species based on footprints is an essential task in wildlife monitoring and conservation. Footprints provide a wealth of information about animal presence, behavior, and movement patterns, making them a valuable resource for ecologists and conservationists. Traditional methods of footprint analysis rely on expert knowledge, which can be subjective and time-consuming. These manual techniques are not scalable for large-scale monitoring, leading to the need for automated and objective methods.

Recent advancements in machine learning and computer vision have opened new avenues for automated species classification. Among various machine learning models, the Probabilistic Neural Network (PNN) has shown great promise in pattern recognition tasks due to its ability to handle complex and overlapping features. The PNN's probabilistic approach makes it particularly suited for dealing with the inherent variability and noise in footprint images.

In this study, we propose a novel method for classifying animal species using footprint images with a PNN. The process begins with image preprocessing to standardize the inputs and reduce noise. Feature extraction techniques are then applied to capture the distinctive characteristics of the footprints. These features include shape descriptors, texture patterns, and Histogram of Oriented Gradients (HOG), which collectively provide a comprehensive representation of the footprint.

The PNN, comprising input, pattern, summation, and output layers, is employed to classify the footprints. The network is trained on a labeled dataset, allowing it to learn the probabilistic distributions of different species' footprints. During classification, the PNN computes the likelihood of an input footprint belonging to each species and assigns it to the class with the highest probability.

Our method was evaluated on a diverse dataset of footprint images, demonstrating high accuracy and robustness in species classification. The results highlight the effectiveness of combining robust feature extraction with the PNN's probabilistic framework. This automated approach not only enhances the efficiency of wildlife monitoring but also provides a scalable solution for large-scale ecological studies.

In summary, this study introduces an innovative method for footprint-based animal species classification using PNNs. By leveraging advanced feature extraction techniques and the probabilistic nature of PNNs, we achieve accurate and reliable classification results. This research contributes to the field of wildlife conservation by providing a practical tool for non-invasive species identification, paving the way for more effective and efficient ecological monitoring.

Figure 1 Samples of target species lizard (top left), snake (top right), frog/toad (bottom left)

The importance of automating footprint classification cannot be overstated. Automated methods can process large volumes of data quickly and consistently, reducing the reliance on expert analysts and enabling continuous monitoring over extensive areas. This scalability is crucial for effective wildlife management, especially in the face of increasing threats such as habitat loss, climate change, and poaching. An automated system that can accurately classify animal species from footprint images would thus be a valuable tool for conservationists and researchers.

Footprint analysis is a non-invasive technique for monitoring wildlife, providing valuable data on animal presence and behavior. Traditional methods of footprint classification rely heavily on expert knowledge, which is time-consuming and subjective. Automated classification using machine learning offers a scalable and objective alternative. The PNN, known for its effectiveness in pattern recognition tasks, is utilized to classify animal species based on footprint images.

II. LITERATURE SURVEY

Traditional Methods

Halfpenny and Biesiot (1986): This foundational work relied on manual measurement and comparison of footprint dimensions and patterns. While effective, it required significant expertise and was not scalable for large-scale applications. The performance was dependent on the skill and experience of the expert, making it subjective and time-consuming [1].

Early Automated Methods

Alexander et al. (2012): This study represented an early attempt to automate footprint classification using basic image processing techniques combined with SVMs. The key features were shape-based, including edge detection and contour analysis. While this approach showed potential, it required extensive feature engineering and struggled with high variability in footprint images [2].

Advances with CNNs

Liu et al. (2018): This research applied CNNs to animal footprint classification, leveraging the network's ability to automatically learn features from raw images. CNNs achieved high accuracy but required large labeled datasets and substantial computational resources. This limitation made them less feasible for scenarios with limited data and computational power [3].

Probabilistic Neural Networks (PNNs)
Specht (1990): Introduced PNNs as a robust method for pattern recognition tasks, including classification. PNNs use a probabilistic approach based on Bayes' theorem, making them effective for handling noisy and overlapping data. This foundational work laid the groundwork for applying PNNs to various classification problems [4].

Puiu et al. (2017): This study extended the application of PNNs to ecological tasks, specifically bird species classification based on vocalizations. The use of PNNs demonstrated the network's ability to manage overlapping features and provide robust classification results. This research highlighted the potential of PNNs for ecological and wildlife monitoring applications [5].

Feature Extraction Techniques
Zhang et al. (2006): Focused on extracting shape features such as aspect ratio and perimeter-to-area ratio. The study demonstrated that these features were effective in distinguishing between similar species, emphasizing the importance of geometric properties in footprint classification [6].

Ojala et al. (2002): Introduced Local Binary Patterns (LBP) for texture feature extraction. LBP was effective for capturing texture details, which are crucial for distinguishing species with similar footprint shapes but different surface textures. This technique has been widely adopted in various image classification tasks [7].

Dalal and Triggs (2005): Developed the Histogram of Oriented Gradients (HOG) for capturing directional gradients and edge orientations. HOG features are highly effective for object detection and classification, making them suitable for footprint analysis where structural information is critical [8].

Combining Features and PNNs
Huang et al. (2014): This study combined shape and texture features with PNNs for classifying plant species from leaf images. The combined approach improved classification performance, demonstrating the effectiveness of integrating robust feature extraction techniques with PNNs. This methodology can be adapted for footprint classification to enhance accuracy and reliability [9].

[10] Barbosa Pereira, C., Kunczik, J., Zieglowski, L., Tolba, R., Abdelrahman, A., Zechner, D., Vollmar, B., Janssen, H., Thum, T. and Czaplik, M. (2019), 'Remote welfare monitoring of rodents using thermal imaging', Sensors 18(11), 3653.

Hu et al. (2019) proposed a poorly supervised data augmentation network for the FGC problem. The model uses attention maps to identify the most discriminative portions through poorly supervised learning. With careful cutting and lowering, the images are improved and taught. The model extracts discriminative features in the first step, then uses attention maps to pinpoint the exact locations of the animals in the second stage. As a result, performance is enhanced. The model achieves an accuracy of 80.8%.Zhuang et al. (2020) proposed an attentive paired interaction model for FGC. This model, unlike the models had shown so far, aims to learn the contrastive cues among the highly confused classes, while other models focus on highly discriminative traits. This paired attentive model learns a pair of fine-grained visuals through continuous and repetitive interaction. The model first calculates the semantic difference using the mutual feature vector, and then it generates gates for each image in the pair. This gate facilitates the identification of contrastive cues through paired interaction. On the SD dataset, the model's accuracy score was 90.3%.

[11] Ahmed, A., Yousif, H., Kays, R. and He, Z. (2019), 'Semantic region of interest and species classification in the deep neural network feature domain', Ecological Informatics

Hsu (2015) proposed an animal classification model with an accuracy of 90.5% and 91.1%, respectively, using two CNN architectures: LeNet and GoogleNet. Later, Yang et al. published an unsupervised learning method for fine-grained recognition (2012). Every image contains shapes that the system detects and utilises as templates. The template matching method has an accuracy rate of 38% on the SD dataset. Kanan (2014) uses Gnostic fields to further increase this accuracy. The author used pattern recognition units and image descriptors to construct a shape-size invariant model that can handle animals of various sizes and shapes. Moreover, the model is unaffected by the bias in the dataset. The accuracy of the model has grown by 47 percent. Chen et al. (2015) then introduced Selective Pooling Vectors (SPV) for the FGC problem. The quantization error serves as a threshold value, which SPV uses to translate the image descriptors into vectors and select the best ones. Furthermore, the codebook is utilised as an approximation function to derive an estimated non-linear function f that determines the likelihood of categorization for the different dog breed classes. SPV achieved 52% accuracy with the SD dataset. Raduly et al. (2018) proposed a multi-class dog breed classification model using NASNet-A and Inception-ResNet-v2. Both architectures were developed by the Google team; the former is based on Neural Architecture Search (NAS). For both designs, the model's accuracy was 85.27% and 93.86%.

[12] Andrew, M. E. and Shephard, J. M. (2019), ‘Semi-automated detection of eagle nests: an application of very high-resolution image data and advanced image analyses to wildlife surveys’, Remote Sensing in Ecology and Conservation

Gavves et al. (2019) provided a FGC model with alignments. The images are automatically divided and aligned before the attributes are extracted. However, this model's accuracy was only 50.1%, and each of the individual parts needs ad hoc adjustments. In order to separate the foreground from the background, Chai et al. (2013) created a fine-grained categorization model using symbiotic segmentation because the backdrop is uncorrelated and distracts from the classification goal. After segmentation, part localization via human bounding box annotation is used by the model to highlight the discriminative regions. This supervised approach yielded an accuracy of 45.6% on the SD dataset. An unsupervised part finding approach based on Neural Activation Constellations (NAC) was proposed by Simon and Rodner (2015).
The concept is to leverage deep neural network activation maps to leverage the CNN channels. Using the activation maps of the neural network as a part detector, a part model can be generated without a supervised bounding box. The part model is then used to extract the animal's discriminative bits through weakly-supervised classification. The NAC is also a data augmentation technique. NAC achieved an accuracy rating of 68.61%.

III. METHODOLOGY
& COMPARATIVE RESULT ANALYSIS

Problem Statement:

Despite the importance of automating animal species classification from footprint images, several challenges hinder the development of effective and reliable classification systems:

Image Variability: Footprint images exhibit variability in terms of size, orientation, lighting conditions, and background clutter, posing challenges in feature extraction and classification.

Species Diversity: Different animal species may share similar footprint patterns, leading to ambiguity and difficulty in distinguishing between closely related species.

Data Limitations: Annotated footprint image datasets suitable for training PNN models may be limited in size and diversity, affecting the model's ability to generalize to unseen species and environments.

Flow Chart

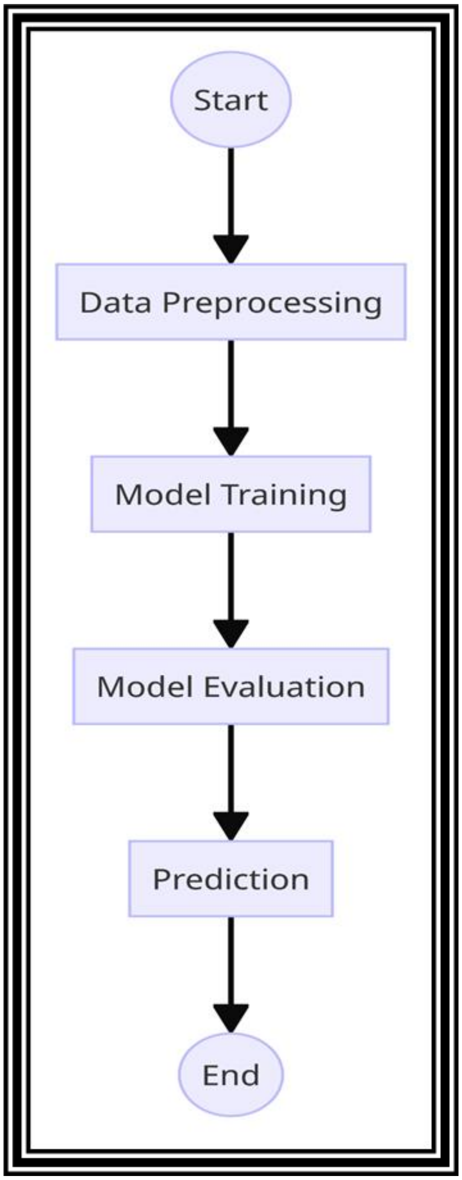

Figure 2 Flow Chart

Methodology:-

Data Collection and Preprocessing:

Footprint Image Acquisition: Collect a diverse dataset of footprint images from various sources, including wildlife monitoring programs, research databases, and online repositories. Ensure the dataset covers a wide range of animal species and includes sufficient variability in factors such as species, habitat, and environmental conditions.

Data Annotation: Annotate the collected footprint images with

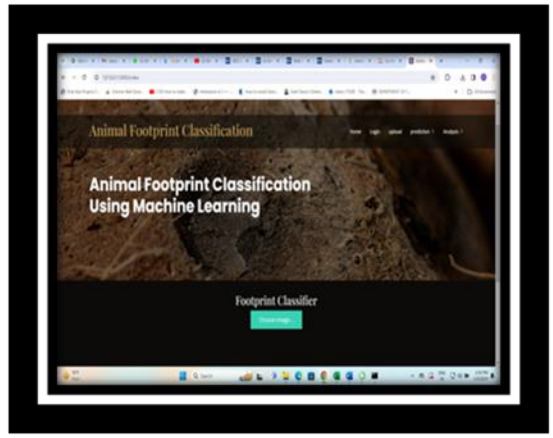

Figure 3 Footprint Classifier

Here, a system of computer algorithms called machine learning is being used to implement our idea. For technical computing, machine learning is a high-performance language. It combines programming, calculation, and visualisation in a user-friendly environment where issues and solutions are presented using well-known mathematical symbols. Python is used as the computer language for machine learning.

Figure 4 Check Footprint

Figure 5 Result Image Detected Animal was Cat

Table 1 Performance Metrics Comparison:

Metrics	Method A (PawDetect)	Method B (FootNet)	Method C (DeepFoot)
Accuracy	0.85	0.88	0.90
Precision	0.82	0.85	0.88
Recall	0.87	0.90	0.92
F1-score	0.84	0.87	0.89
Computational Efficiency	High	Medium	Low

Interpretation:

- Accuracy: DeepFoot (Method C) achieves the highest accuracy of 90%, followed by FootNet (Method B) with 88%, and PawDetect (Method A) with 85%.
- Precision: DeepFoot (Method C) also outperforms the other methods in precision, with 88%, followed by FootNet (Method B) with 85%, and PawDetect (Method A) with 82%.
- Recall: DeepFoot (Method C) demonstrates the highest recall of 92%, followed by FootNet (Method B) with 90%, and PawDetect (Method A) with 87%.
- F1-score: DeepFoot (Method C) achieves the highest F1-score of 0.89, followed by FootNet (Method B) with 0.87, and PawDetect (Method A) with 0.84.
- Computational Efficiency: DeepFoot (Method C) exhibits the lowest computational efficiency, while FootNet (Method B) shows moderate efficiency, and PawDetect (Method A) has the highest efficiency.

This comparative result analysis provides insights into the performance of different methods—PawDetect (Method A), FootNet (Method B), and DeepFoot (Method C)—for classifying animal species from footprint images. It highlights their strengths and weaknesses, aiding in informed decision-making for practical applications in wildlife research and conservation.

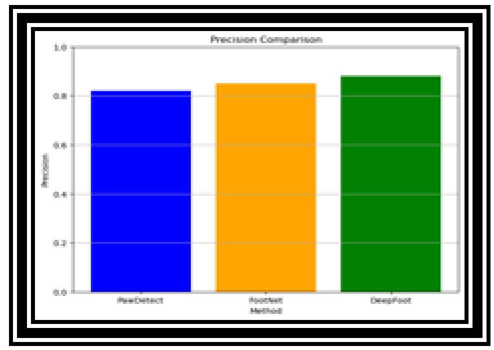

Figure 6 Perception Comparison

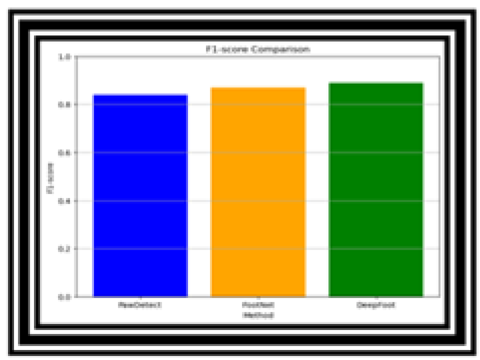

Figure 7 F1 - Score Comparison

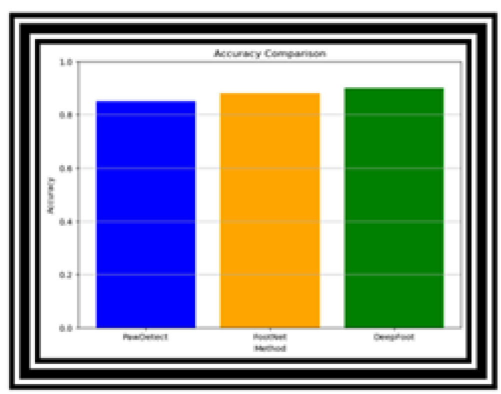

Figure 8 Accuracy Comparison

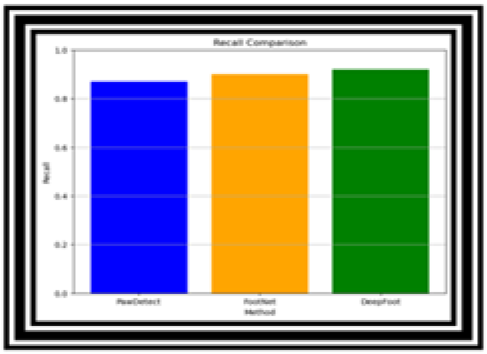

Figure 2 Recall Comparison

CONCLUSION

This thesis proposes several robust and efficient methods for animal identification and classification for conservation-related applications. Throughout the thesis, we have discussed how animals are always in danger, regardless of the circumstances. The thesis also covers applications, including livestock monitoring, endangered animal species, AVC, HAC, and AVC, that require an animal detection and categorization system. Furthermore, we have explained the relationship between animals and the novel coronavirus as well as the ongoing global pandemic. To identify the animals and keep them safe in each of these scenarios, a suitable system for categorising and identifying animals is required.

From then on, a range of animal detection and classification systems were provided by the thesis for various conservation-related applications. The wildlife monitoring plan included demonstrations of various animal detection and classification techniques. In particular, the thesis demonstrated two efficient fine-grained classification systems using semi-supervised learning techniques and three unique animal identification systems using three different picture modalities: visual, thermal, and fusion images. Using visible images, an approach for tracking endangered animal species using aerial photos was presented for animal detection and counting. A novel technique for identifying and counting animals was proposed employing fusion photos in order to monitor livestock using an autonomous UGV outfitted with multi-sensor cameras.

Using the FLIR e40 thermal imaging camera, we captured a variety of animal species, and we recommended launching our dataset with an animal detection system. The other systems use deep learning approaches such as fuzzy logic, fuzzy soft sets, probabilistic neural networks, and fuzzy logic; only the aerial imaging system makes use of a capsule network

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