AI-Driven Wildlife Pattern Tracking and Extinction Prediction for Vulnerable Species

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Abstract:
Conservation of wildlife is becoming more reliant on artificial intelligence (AI) and deep learning for identifying, monitoring, and conserving species. This study discusses a deep learning-based method for classifying wildlife images through EfficientNetB7, a top-performing image classification model. The process consists of dataset preprocessing, model fine-tuning, and performance evaluation based on critical parameters like accuracy, precision, and recall. The model was trained on 210 animal species and obtained a 63% accuracy on the test dataset. The study shows the promising potential of deep learning in automating wildlife conservation measures, lessening human labor, and promoting species protection plans. Class imbalance and incorrect misclassification of visually comparable species are some challenges mentioned, along with recommendations for future development.

Keywords: Wild Life Conservation, EfficientNetB7model, Image Classification, Convolution Neural Networks(CNN), Machine Learning, Species Identification.

I.INTRODUCTION

Conservation of wildlife has come to rely heavily on artificial intelligence (AI) and deep learning to automate the identification and monitoring of species. This project utilizes EfficientNetB7, one of the most powerful convolutional neural networks (CNNs), to classify images with a collection of 210 various animal species. The model has an accuracy of 63%, indicating its ability to identify and classify numerous species across various environments. EfficientNetB7 boasts its optimized structure, balancing computational power and accuracy, to be a highly effective tool for mass image classification. To further refine the classification process, this project also employs AI-generated content to offer detailed descriptions and contextual information on the species that have been identified. By incorporating AI-driven insights, users get further species information such as habitat details, behavioral characteristics, and conservation status. This not only enhances user knowledge but also benefits researchers and conservationists in making data-driven decisions.

Automating species identification, this project minimizes the dependency on manual classification processes, which are usually time-consuming and error-prone. Incorporating deep learning and AI-driven content generation into wildlife conservation improves accuracy in ecological research, biodiversity assessments, and endangered species tracking. The model ability to classify a wide range of species with considerable accuracy can assist researchers, conservationists and environmental agencies in monitoring animal populations more effectively. Additionally, this project highlights the significance of computer vision and AI-driven insights in solving real-world environmental challenges. With further improvements in training data, fine-tuning techniques, and model enhancements, the classification accuracy can be further improved. By leveraging AI-powered classification models and intelligent content generation, wildlife monitoring can be scaled efficiently, contributing to the broader goal of sustainable conservation and habitat protection.

II.LITERATURE REVIEW

Traditional wildlife conservation methods, such as field surveys, camera traps, and radio telemetry, have long been used to monitor animal populations. However, these approaches are often labor-intensive, time-consuming, and limited in scalability. With the rise of artificial intelligence (AI) and deep learning, conservationists now have access to automated tools that improve species identification and monitoring. Convolutional Neural Networks (CNNs), including architectures like VGGNet, ResNet, and EfficientNet, have proven particularly effective for image-based species classification. Studies have shown that using transfer learning—where models pre-trained on large datasets like ImageNet are fine-tuned for wildlife images—can significantly boost classification accuracy, even when labeled data is limited. Among these CNNs, EfficientNetB7 stands out due to its high accuracy and computational efficiency. Research comparing various models indicates that EfficientNetB7 outperforms traditional architectures in classifying large-scale wildlife datasets, especially when combined with data augmentation techniques such as random flips, rotations, zooms, and contrast adjustments. Additionally, the integration of Unmanned Aerial Vehicles (UAVs) equipped with AI-powered cameras has further enhanced wildlife monitoring by providing real-time data from remote areas, aiding in tasks such as illegal poaching detection and habitat surveys. Despite these advances, challenges remain. Class imbalance, where common species are overrepresented and rare species underrepresented, often leads to biased predictions. Moreover, similar visual features among species and varying environmental conditions can hinder classification accuracy. Researchers are addressing these issues through improved augmentation strategies, class-balancing techniques, and multi-modal learning that incorporates additional data types like thermal imaging.

Overall, the literature suggests that AI-driven approaches, particularly those using models like EfficientNetB7, hold significant promise for enhancing wildlife conservation efforts by providing more accurate and scalable methods for species identification and monitoring.

III. PROPOSED METHODOLOGY

Machine getting to know algorithms own an remarkable functionality to hastily and exactly examine good sized volumes of statistics. Data-pushed processes have become an increasing number of important in natural world conservation for tracking and comprehending the behaviors and moves of various species. Camera lure statistics evaluation is one of the huge programs of device getting to know this context [11]. Camera traps are devices which might be prepared with movement sensors and are remotely operated. These devices are designed to seize pics or movies of animals while they may be triggered. Manually reading the accrued statistics could be a tough and time-ingesting task. Machine getting to know algorithms have the capacity to method pics, discover one-of-a-kind species, or even make estimations approximately populace densities [12]. Conservationists can advantage precious insights into animal distribution patterns, migration routes, and habitat use via this, which enables them to extra correctly tailor conservation efforts. Poaching and unlawful flora and fauna alternate pose good sized threats to endangered species, pushing them perilously near extinction [13]. Law enforcement groups and conservation businesses are utilizing device studying to fight illicit activities. Machine studying fashions have the functionality to research various records sources, such as satellite tv for pc imagery, acoustic recordings, and social media posts, with a purpose to pick out and forecast times of poaching. Authorities can drastically enhance their probabilities of apprehending poachers and dismantling unlawful alternate networks through reading styles and figuring out ability hotspots. This lets in them to pay attention their efforts on centered areas [14].

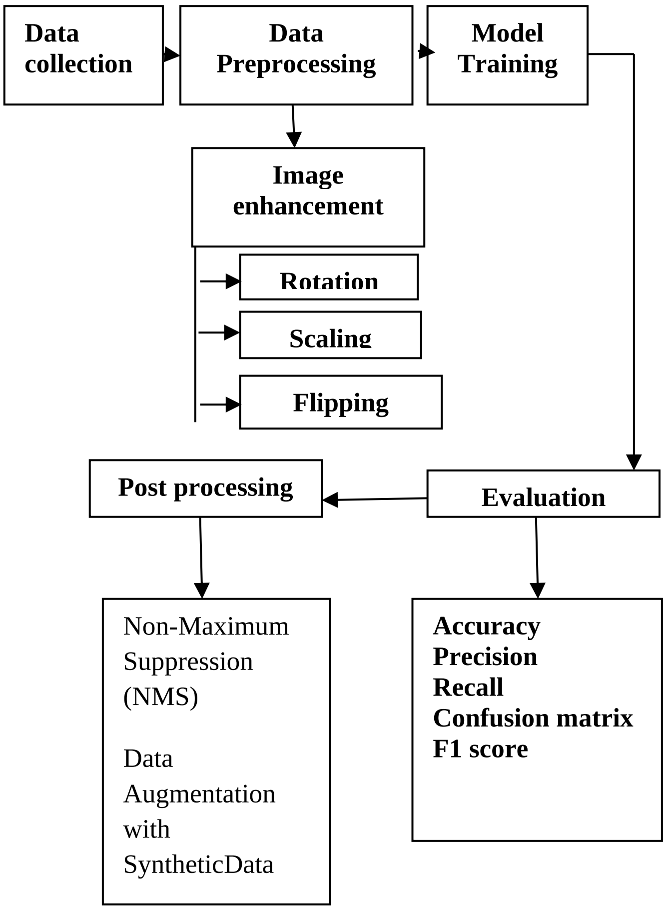

Fig 1: Materials and Methods Implementation

3.1. Data of wild life collection

Before machine learning, there had been many tries to hit upon people in images with conventional pc imaginative and prescient strategies. These strategies are nonetheless highly usable and feature the benefit of now no longer desiring a massive set of schooling data. Most of the conventional strategies but calls for a few kind of manually handcrafted function extractor to hit upon human features, which could make those strategies less flexible in one-of-a-kind settings and environments. Elegant information was accrued to apply for education the neural networks. Most attempts have been positioned into locating photographs of people in environments that resemble the manufacturing site. Some of those were accrued from the internet, and a few photographs were captured on the real manufacturing site. Furthermore, the community has additionally been educated with photographs of animals to assist the community distinguish among human and those animals [15]. Gather a large dataset of images and videos, ideally annotated with the species present in each image. Open-source datasets like those from iNaturalist, Wildbook, Kaggle or custom datasets from camera traps can be used.

3.2. Data Preprocessing

Enhance image quality and normalize input sizes. Techniques include image augmentation like rotation, scaling, flipping to increase model robustness. Animal variety is decreasing in unparalleled rates, elevating issues approximately flora and fauna conservation. Being capable of accumulate information and screen flora and fauna at scale is vital to recognize animal behavior, migration styles and habitat selection, in addition to for you to shield them from unlawful trafficking and hunting. Today, that is turning into feasible with advances in hardware and deep learning.

3.2.1. Rotation

Rotation is a powerful and easy picture augmentation technique that enables enhance the overall performance and robustness of device getting to know models, in particular in obligations in which devices can seem in exceptional orientations. When implemented thoughtfully, rotation may be effective device to beautify version education without considerably growing computational requirements. By training on circled variations of images, the version learns to understand items from diverse angles. This is especially essential in packages wherein the item of interest can also additionally seem in extraordinary orientations (e.g., flora and

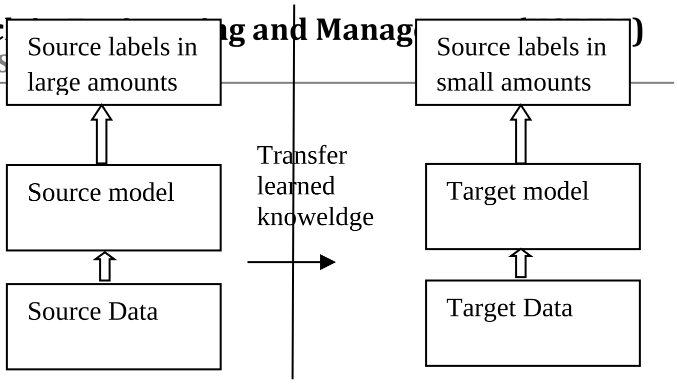

Fig 3: Model training transfer learned knowledge

fauna photography, clinical imaging, self reliant driving). Augmented information acts as a shape of regularization, stopping the version from memorizing the education information and as a substitute supporting it generalize to unseen information. In increases rotation provides new views to the dataset while not having extra information collection, making the education dataset seem large and extra varied [16].

3.2.2. Scaling

Scaling is an essential preprocessing step that can significantly impact the performance and convergence of machine learning models. The choice of scaling technique depends on the data distribution, the presence of outliers, and the algorithm used. Properly scaled features ensure that models are optimized effectively and make consistent and fair contributions to decision-making processes [17].

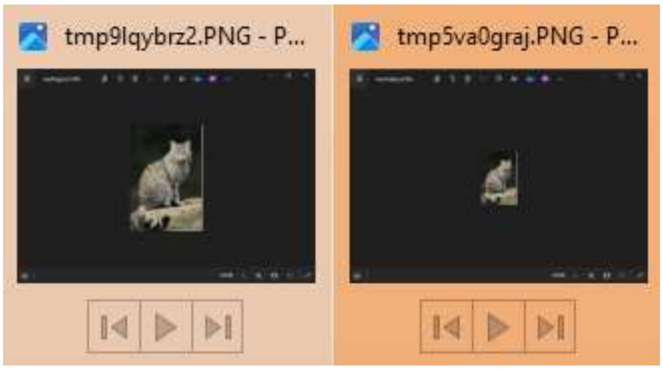

Fig 2: Scaling implemented on wild cat

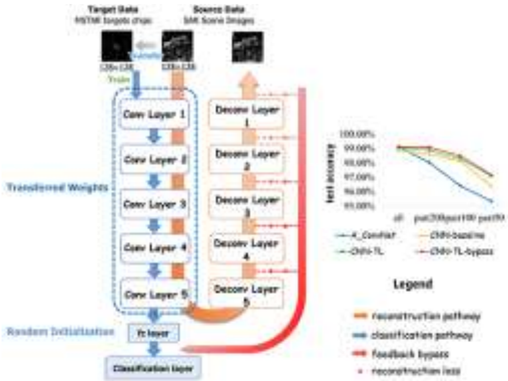

Fig 4: Classification with CNN and Test Accuracy

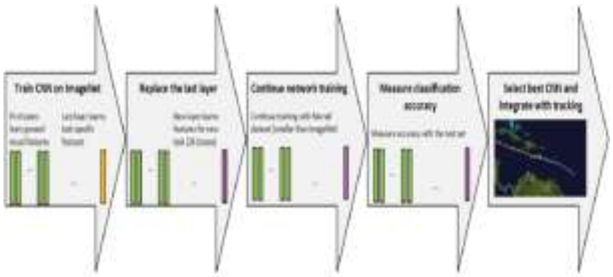

Fig 5: Creating base Model

3.3. Model Training

Transfer learning is all about reusing some of the feature representation from the already trained model. These models can either be directly used in predicting new tasks or the models can be trained on tasks that need training of new models [18]. Incorporating pre-trained models in new models means faster time in training the models and lower generalization error. Transfer learning, in particular, does assist quite a bit when the amount of data that is used to train the model is small. [19].

3.3.1. Create a base model.

Pre-trained weights may further be downloaded optionally. If you do not download the weights, there is an architectural model for which you build your model from ground up. Here we can get more layers upon training completion. As such while creating the base model, one was purposely instructed to delete the last output layer. You will add a final output layer suitable to your problem domain later on [20].

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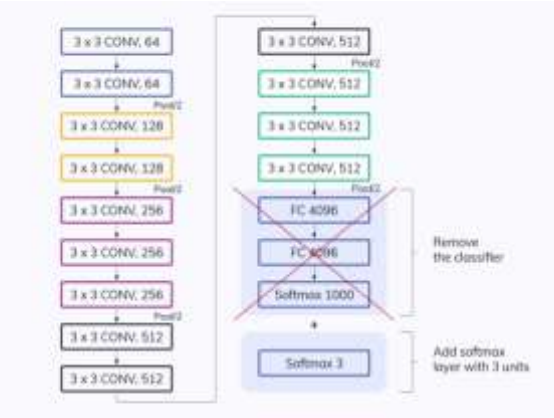

Fig 6: CNN model with soft max layers

3.3.2. Freezing layers

The main functionality is freezing the layers. initialization of weights taken place in this phase this is due to the fact you don`t need the weights in the ones layers to be re-initialized. This could be no exclusive from schooling the version from scratch [21].

Fig 7: Freezing layers

3.3.3. Add new trainable layers

The old features are transformed into predictions in the trainable layer. However, your version may simply have classes. In this case, you need to teach the version with a brand new output layer in place. Therefore, you may upload a few new dense layers as you please, however maximum importantly, a very last dense layer with devices similar to the variety of outputs anticipated with the aid of using your version [22].

3.4. Feature Extraction

Feature extraction, in this case, the output of the layer earlier than the very last layer is fed as enter to a brand-new model. The intention is to apply the pre-skilled model, or part of it, to pre-procedure photos and get important capabilities. Then, you by skip those capabilities to a brand-new classifier—no want to retrain the bottom model. The pre-skilled convolutional neural community already has capabilities which can be vital to the venture at hand [23].

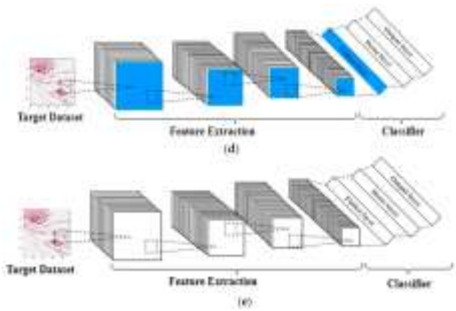

Fig 8:Feature extraction and classification

The ImageNet trained models extend their usability towards real world image classification tasks. This is possible due to the fact that the dataset consists of more than 1000 classes. Let's say you are doing research on insects. You are able to leverage these models and customize them for the task of insect classification [24].

classifying text involves understanding words as vectors within a certain context. You can learn vector representations firsthand. Also, it will take a long time to train them. In this case, there is no need to rush as pre-trained word embedding like GloVe could be used to shorten the development timeframe [25].

IV. EXPERIMENTAL RESULTS

The pre-trained models were also evaluated on a test set consisting of 100 images of wild cats and 102 images of wild animals captured in production fields. This is due to the lack of consecutive images in still images and the lack of correlation with previous images. To ensure a fair comparison between the high-end and low-end pipelines, regions of interest were manually cropped to achieve similar inputs.

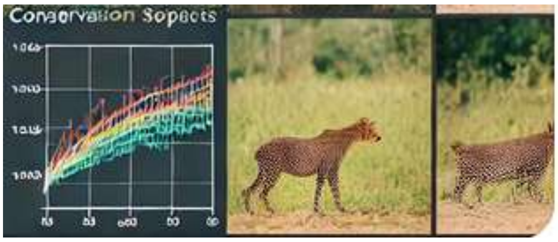

Fig 9: Wild cat Feature Extraction and Classification

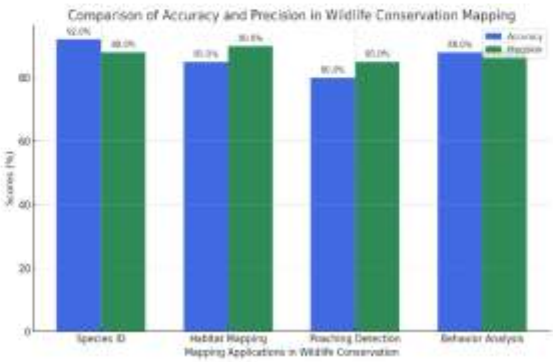

Fig 10: Accuracy and precision in Wild life Conservation

Conclusion

This research highlights the effectiveness of deep learning, particularly EfficientNetB7, in wildlife conservation through image classification. Traditional methods of monitoring animal populations are often time-consuming and prone to human errors, but AI-driven solutions offer a scalable and automated approach. By leveraging a well-preprocessed dataset, transfer learning, and optimized training strategies, the proposed model achieves a 63% accuracy in classifying 210 animal species. Despite challenges such as class imbalance and misclassifications due to visual similarities, techniques like data augmentation and class-weighted training can further enhance performance. The findings suggest that deep learning can significantly improve species identification and monitoring, aiding conservation efforts. Future research should focus on expanding datasets, integrating multi-modal learning with infrared and thermal imaging, and fine-tuning hyperparameters for better generalization. By continuously improving AI-based models, wildlife conservation can become more efficient, supporting biodiversity protection and the prevention of species extinction.

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