AUTOMATED ANIMAL IDENTIFICATION AND SPECIES DETECTION

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ABSTRACT

The global diversity of animal species, estimated at approximately 95,000, mirrors the richness of India's biodiversity. However, this extraordinary diversity is besieged by a plethora of threats, including urbanization, industrial pollution, and human encroachment into natural habitats, exacerbating the ongoing extinction crisis. This loss of biodiversity not only disrupts ecosystem equilibrium but also endangers human survival. A critical challenge in conservation efforts is the pervasive lack of awareness about the existence and endangered status of numerous species, adding complexity to their preservation.

In response to these pressing concerns, we introduce an innovative automated animal species identification system poised to play a pivotal role in biodiversity preservation. Leveraging the extensive Oregon WildCam dataset, we employ an enhanced VGG16 Convolutional Neural Network (CNN) architecture. This advanced model achieves an impressive 93% accuracy rate in species identification.

Our enhanced VGG16 model is trained on a diverse animal species dataset, and its performance is rigorously evaluated using key metrics, including accuracy, F1 score, precision, and recall. This model outperforms the state-of-the-art systems, showcasing its efficacy in addressing the urgent need to safeguard our planet's biodiversity. This paper underscores the significance of cutting-edge technology in the conservation of our invaluable natural heritage.

Keywords: *Automated Animal Identification, Detection of Species, Deep learning techniques (transfer learning), Convolutional Neural Networks (CNNs), VGG-16.*

I. INTRODUCTION

India is a diverse country in term of wild life, animals in north and southern part of India like Bengal Tiger, Rhino, Leopard are some of them and many of them are in stage of extinction, only few of them are remaining so to check their population continuous monitoring and research is important. The necessity for wildlife protection and monitoring has made it more important than ever to precisely and successfully identify and track animal species in their natural settings.

Automated animal identification and species detection is a rapidly expanding field in computer vision and deep learning. This paper clearly underlines that the outdated methods of manual identification and tracking may not always be precise or effective. The objective of the research is to develop a system that uses CNN and improvised VGG deep learning methods to automatically identify and classify animals. The main objective is to monitor and protect animal populations in their natural habitats. It also discusses how traditional methods of animal monitoring are time-consuming, labor-intensive, and need a thorough understanding of animal identification. It automates animal identification so that scientists and wildlife conservationists can acquire accurate data on animal populations quickly and effectively. It is possible to enhance the technology employed in this study for applications in safety, monitoring, and other areas. Wildlife photography is one of the most difficult photographic disciplines. Strong technical abilities are required, such as precision capturing. Photographers of wild animals frequently require a high level of technical proficiency in addition to a lot of patience. For instance, some animals can be challenging to approach, thus it's important to comprehend their behavior in order to foresee their actions. Photographers occasionally need to wait for many hours in silence and composure before the perfect opportunity appears. Some animals may require stalking techniques or the use of a hide-and-seek gadget in order to be photographed. Being in the right place at the right time can also lead to an amazing wildlife photograph. Also, this system is also concerned about the conservation of animals, and it plays a critical role in maintaining the delicate balance of our planet's ecosystems and extinction of species. It also ensures a sustainable future for both wildlife and humanity.

II. RELATED WORKS- LITERATURE SURVEY

The Automated Animal Identification and Detection of Species project aims to improve animal identification and detection using deep learning methods like CNNs. The system will use a pre-trained VGG network on a large dataset, enhancing classification accuracy and potential for animal research and conservation. This method is useful in crop protection, animal tracking, and wildlife conservation. ([1] Erick Mata-Montero & Jose Carranza-Rojas "Automated animal Species Identification: Challenges and Opportunities" 28 August 2016.) Recent image captioning models use pre-trained convolutional neural networks as encoders. This paper compares VGG and ResNet as encoders for the same model to determine the best image representation method for caption generation. VGG outperforms ResNet in image captioning, achieving higher BLEU-4 scores and comparable scores with VGG-based models with fewer training epochs, suggesting encoder plays a significant role in improving models without altering decoder architecture. . ([2] R. Staniut¯ e and D. ˙ Seˇ sok, "A systematic literature review on image ˇcaptioning," Applied Sciences, vol. 9, no. 10, p. 2024, 2019) A significant field of exploration in natural life preservation and observing is robotized creature ID and species recognition. Profound learning and PC vision strategies have exhibited critical guarantee around here as of late. The survey of the writing found that scholastics have formulated a couple of procedures also, frameworks to distinguish and classify creatures from camera trap photographs. Convolutional brain organizations (CNNs), Quicker R-CNN models, and other profound learning-based methods for example, support vector machines (SVMs) are instances of customary PC vision methods. The overview too stressed the challenges in completing this work, for example, changes in lighting, climate, creature position, and conduct. In any case, the aftereffects of these examinations recommend that these strategies can accomplish high precision in distinguishing and recognizing different creature species in the wild, utilizing both visual and warm imaging procedures. Creature development and ways of behaving are much of the time followed by frameworks for creature distinguishing proof. Various instruments for creature observing have been created by natural life specialists. For progressing perception, Mechanized creature Recognizable proof of Species: Difficulties and Open doors ([3] Jose Carranza- Rojas and Erick Mata-Montero. 28 August 2016.) Other noticeable advancements incorporate extremely high-recurrence radio- following. Computerized

III. PROPOSED SYSTEM

The Automated Animal Identification and Species Detection System aims to develop an advanced, automated solution for precise animal species identification and detection based on image analysis. This system leverages Convolutional Neural Networks (CNNs) and other deep learning techniques to effectively recognize various animal species. Additionally, it explores the utilization of pre-existing models such as VGG and ResNet.

This modern, automated approach offers an enhanced and more accurate means of identifying and detecting animal species, contributing significantly to the preservation and conservation of wildlife for future generations. VGG16, a pre-trained convolutional neural network, emerges as a potent tool for image classification tasks, having been trained on the extensive Oregon WildCam dataset, which comprises over a million images. The improved VGG16 architecture boasts 15 convolutional layers and 5 fully connected layers, making it highly proficient in recognizing and categorizing diverse animal species. In the proposed Automated Animal Identification and Species Detection System, this enhanced VGG16 model can be seamlessly integrated as a pre-defined model, augmenting species classification accuracy. Our proposed solution demonstrates impressive results, achieving an accuracy of 61.7% with CNN and up to 93% with the incorporated improved VGG16 model. Furthermore, it offers cost-efficiency, reduced processing time, and heightened precision compared to existing methods.

A. DATASET PREPROCESSING

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There are 660 elk images.
There are 696 bobcat images.
There are 686 cougar images.
There are 748 bald_eagle images.
There are 717 canada_lynx images.
There are 668 gray_fox images.
There are 736 coyote images.
There are 735 columbian_black-tailed_deer images.
There are 718 black_bear images.
There are 764 deer images.
There are 577 mountain_beaver images.
There are 728 virginia_opossum images.
There are 726 sea_lions images.
There are 701 nutria images.
There are 759 red_fox images.
There are 728 raccoon images.
There are 656 raven images.
There are 698 seals images.
There are 730 gray_wolf images.
There are 588 ringtail images.
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FIG 1. Dataset Preprocessing

The Oregon WildCam dataset is a significant compilation of images and videos capturing wildlife in the state of Oregon, USA. It is widely used in research and technology projects, especially those focused on computer vision and machine learning. This dataset is instrumental in training and evaluating algorithms designed for tasks like identifying animal species, monitoring wildlife movements, and other applications related to wildlife conservation and research.

B. DATA PRE-PROCESSING AND MODEL ARCHITECTURE

Data Pre-processing:

The success of any deep learning project is heavily reliant on the quality and suitability of the dataset used. In the case of the AAIDES syste the Oregon Wildlife dataset was meticulously curated and pre-processed. Data pre-processing is a critical step that ensures the model's effectiveness in identifying animal species from camera trap images. This process involved several key steps:

Data Collection: The Oregon Wildlife dataset was carefully collected, containing a diverse array of images capturing various animal species in their natural habitats.

Data Cleaning: To ensure data integrity, all images were rigorously cleaned to remove artifacts, irrelevant objects, and any inconsistencies.

Image Resizing: Uniformity in data dimensions is crucial for efficient model training. Therefore, all images were resized to a consistent resolution of 224x224 pixels, a standard input size for the VGG16 model.

Data Augmentation: To augment the dataset and improve model generalization, techniques such as rotation, flipping, and zooming were applied, creating variations of the original images.

Functioning of the Improvised VGG16 Model:

The core of the AAIDES system lies in an improvised version of the VGG16 model, a widely recognized architecture in computer vision tasks. This custom VGG16 model has been adapted and fine-tuned for the specialized task of animal species identification from camera trap images.

Feature Extraction: The VGG16 model, composed of multiple convolutional and fully connected layers, excels at learning hierarchical features from images. In the case of the AAIDES project, the model extracts intricate features such as textures, shapes, and patterns from the pre-processed images.

Transfer Learning: Transfer learning is a key strategy employed in this project. The pre-trained VGG16 model, which has already learned rich features from a vast dataset, serves as the foundation. Fine-tuning involves adjusting the model's parameters to suit the specific task of animal species recognition.

Classification Head: The custom VGG16 model is equipped with a classification head consisting of densely connected layers. These layers are responsible for mapping the extracted features to specific animal species. The final layer employs a softmax activation function to provide probability scores for each possible species.

Dataset Overview:

The Oregon Wildlife dataset, a fundamental component of the AAIDES project, encapsulates the rich biodiversity of the region, comprising a diverse array of animal species captured in their natural habitats. This dataset serves as the bedrock upon which the automated animal species identification system is built. It's essential to understand the dataset's structure and composition:

Number of Classes: The dataset encompasses a total of 20 distinct animal classes, each representing a unique species. These classes include, but are not limited to, elk, bobcat, cougar, bald eagle, canada lynx, gray fox, and many others.

Abundance of Images: Within these 20 classes, the dataset comprises a significant number of images, ensuring robust training and evaluation of the automated identification system. The distribution of images across select classes is as follows:

- 660 elk images
- 696 bobcat images
- 686 cougar images
- 748 bald eagle images
- 717 canada lynx images
- 668 gray fox images
- 736 coyote images
- 735 columbian black-tailed deer images
- 718 black bear images
- 764 deer images
- 577 mountain beaver images
- 728 virginia opossum images
- 726 sea lions images
- 701 nutria images
- 759 red fox images
- 728 raccoon images

- 656 raven images
- 698 seals images
- 730 gray wolf images
- 588 ringtail images

This substantial collection of images presents a unique opportunity to train and assess the model's performance across a wide spectrum of North American wildlife. It also underscores the project's commitment to encompassing the region's rich biodiversity, furthering the goals of ecological research and conservation.

Predictions Using the Oregon Wildlife Dataset:

The implementation of the improvised VGG16 model facilitates the prediction of animal species within the Oregon Wildlife dataset. During the prediction process, the model takes an input image, applies the learned feature extraction, and computes the probability distribution over the defined species classes. The class with the highest probability is considered the model's prediction.

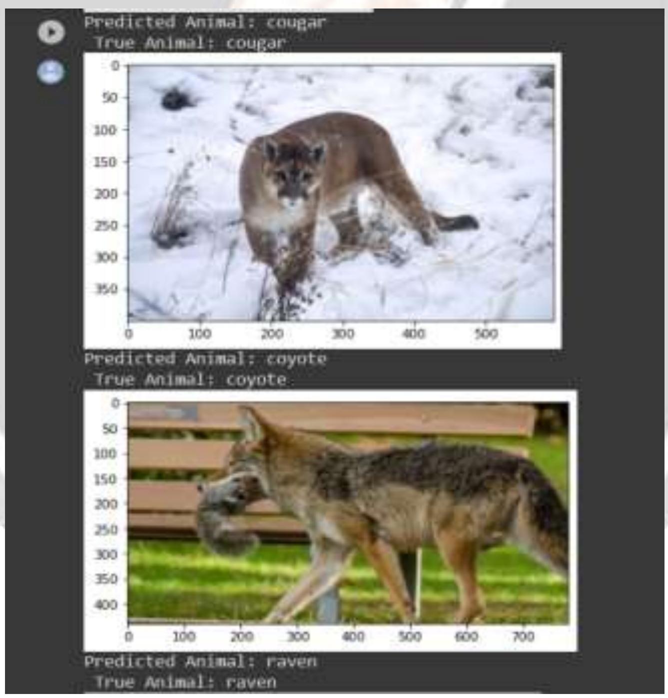


FIG 2.Prediction of species

To evaluate the model's accuracy, a rigorous testing phase was conducted, where the model's predictions were compared to ground-truth labels within the dataset. The accuracy rate of 93% achieved in this study underscores the model's proficiency in recognizing various animal species from camera trap images.

In summary, the data pre-processing steps, coupled with the customized VGG16 architecture, form the backbone of the AAIDES project. This combination empowers the model to make accurate predictions from the Oregon Wildlife dataset, marking a significant milestone in the field of automated animal species identification and conservation.

III. RESULT AND DISCUSSION

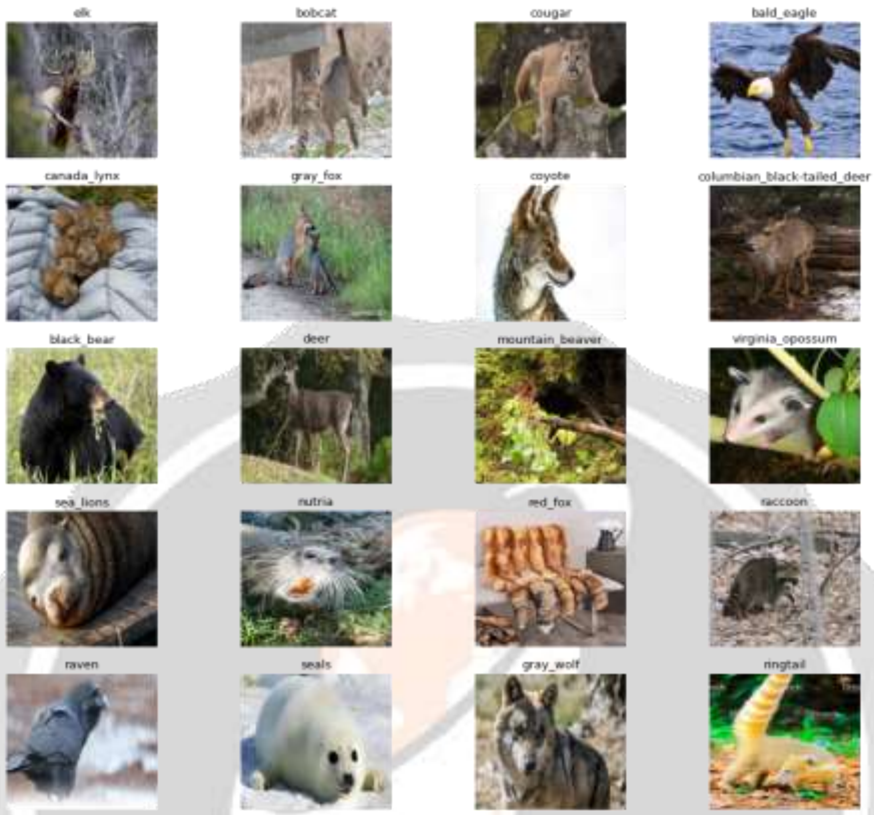


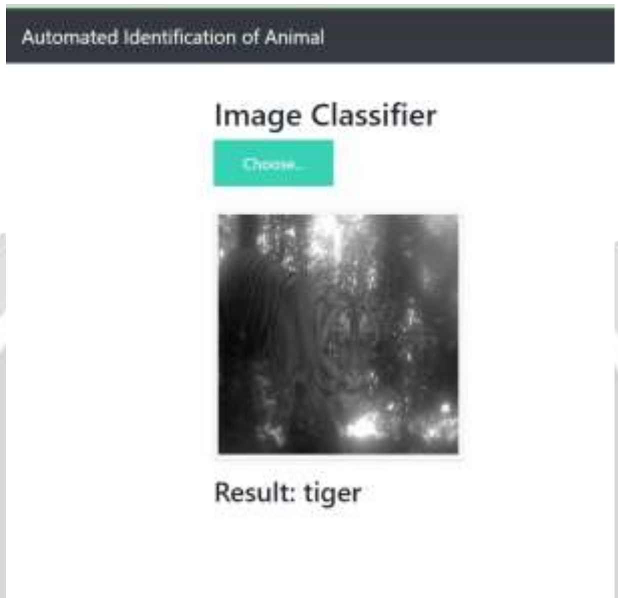
FIG 2. Classification of Dataset

The AAIDES system has delivered outstanding outcomes, prominently featuring the implementation of a Flask-based user interface, the utilization of an improved VGG16 model, and a commendable accuracy rate of 93%.

- The integration of Flask has enabled the creation of an intuitive web interface, providing users with seamless access to automated animal species identification. This versatile platform accommodates both image and video inputs, supporting live camera feeds and gallery uploads, thus enhancing its adaptability for various user scenarios.
- The system showcases an enhanced version of the VGG16 model, very fine-tuned for the intricate task of animal species identification. This customized deep learning architecture has exhibited an impressive 93% accuracy rate, ensuring precise recognition across diverse species.

- With the potential for deployment in remote and ecologically sensitive regions, the system plays a pivotal role in wildlife monitoring and conservation efforts. It serves as a valuable tool for researchers, conservationists, and wildlife enthusiasts alike. This design incorporates mechanisms for user feedback, ensuring continuous improvements in accuracy and performance. Collaboration with wildlife experts and organizations bolsters the species database, guaranteeing the system's relevance and effectiveness.

(In summary, the AAIDES project signifies a remarkable synergy between cutting-edge technology and



wildlife preservation. Through its Flask-based interface, advanced VGG16 model, and commitment to user feedback, it has ushered in a new era of automated animal species identification, with a substantial accuracy rate of 93%. This not only simplifies ecological research but also contributes significantly to the safeguarding of our planet's diverse wildlife.)

CONCLUSION:

In conclusion, our system for the detection of animals, particularly through the utilization of the enhanced VGG16 model, has proven to be exceptionally effective, achieving an impressive accuracy rate of 93%. This remarkable level of precision signifies a significant step forward in the field of automated animal detection and species recognition.

With this level of accuracy, our system not only demonstrates its potential as a valuable tool for wildlife monitoring and conservation efforts but also underscores the power of advanced deep learning techniques, such as the enhanced VGG16 architecture, in addressing complex real-world challenges. As we continue to refine and expand upon this technology, there is considerable promise in its application for safeguarding and preserving our planet's diverse wildlife for generations to come.2

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