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Carnivorous Animal Detection Using AI & ML

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Abstract: Carnivorous Animal Detection Project explores the application of deep Learning models, Specifically ResNet-50, for detection and classification of carnivorous animals in diverse ecological for the detection and classification of carnivorous animals in diverse ecological environments. Utilizing advanced computer vision techniques, the system automates the identification of species and their dietary habits, offering an efficient, scalable solution for wildlife monitoring and conservation. By leveraging large datasets of animal images, the model is trained to accurately distinguish between carnivorous and non-carnivorous species, enhancing the understanding of predator-prey dynamics. The system's real-time detection capability provides immediate insights, supporting conservation efforts, ecological research, and mitigating human-wildlife conflicts. Future improvements aim to expand the model's scope to include more species, refine detection accuracy, and integrate additional data modalities such as acoustic and thermal imaging. This project highlights the potential of AI-driven solutions to advance wildlife conservation, offering a robust tool for researchers and environmental organizations.

I. INTRODUCTION

A. Background

Wildlife observation in the natural habitat is the core of ecology. The rapid growth of human population and the boundless quest for economic advancement are causing excessive utilization of natural resources, causing sudden, new and severe modifications to Earth's ecosystems. An increasing section of land surface has been altered with the help of human activity, modifying wildlife population, habitat and behavior.

More critically, most species of wildlife on the Earth have been led to extinction, and numerous species are introduced into new regions where they can destabilize nature as well as human system. Following wild animals, thus, is imperative since it provides researchers with evidences to guide conservation and administration decisions in order to ensure diverse, balanced and sustainable ecosystems despite those changes. Several recent technologies have occurred developed for wild animal listening, such as radio tracking ,wireless sensor network tracking, satellite and global positioning system (GPS) tracking, and monitoring by motion sensitive camera traps. Motion sensor remote cameras or "camera traps" are a rapidly

gaining popular instrument for wildlife monitoring, thanks to their new features outfitted, broader commercial availability, and its deployment and usage ease. After being well loaded, a camera can take millenaries of consecutive records, delivering a large quantity of data. Such needs make camera trapsan effective instrument for ecologists because they can record each aspect of wildlife.

B. Objective

Camera trapping is coming to be accepted quickly for being monitored due to innovations in digital technology that yield more recent camera traps on the occasion of automation of system components but reduced cost of acquisition; the work of dealing with huge collections of camera trap images, nonetheless, has occurred accompanied by hand. Although human visual form can handle images with ease and quickly, handle individual a vast amount of images manually is much costly. For instance, up to date, the Snapshot Serengeti project1 gathered 3.2 ton images using 225 camera traps in the Serengeti National Park, Tanzania during 2010–2013 .Another same project, Wildlife Spotter2, gathered lots photos of being trapped in tropical rainforests and dry rangelands of Australia. Sadly, due to auto trap camera snapping mechanism, the extensive majority of captured images is challenging to process even for human. A limited number of images are in good condition only. In addition, many images are grayscale since they were captured every night with shade that looks like, and aa great number of representations contains no animal (75% of the Snapshot Serengeti and 32.26% of Wildlife Spotter marked concepts were classified as top-secret as "no animal"), whereas in others power conduct different objects belonging to different variety

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II. LITERATURE REVIEW

Some prediction systems already existed, and the Authors have researched successfully and proposed the pr The Literature Related to "Animal Detection in Man-made Environments" is discussed in this paper that is authored by Abhijeet Singh, Marcin Pietrasik, Gabriell Natha, Nehla Ghouaiel, Ken Brizel,Nilanjan Ray. This research paper solves the above-said problem using deep learning techniques inherited from various fields of computer vision, like object detection, segmentation, tracking, and edge detection. Importantly, insightful results into the use of transfer learning are revealed as the authors transfer models that have been trained on standardized data to real world use in practical implementation. Towards Automatic Wild Animal Detection in Low Quality Camera-Trap Images Using Two Channelled Perceiving Residual Pyramid Networks" this paper by Chunbiao Zhu; Thomas H. Li; Ge Li in which introduce a new method named Two-Channel Perceiving Residual Pyramid Networks (TPRPN)specifically for object detection in camera-trap photos. The TPRPN model is carefully designed to deliver high-resolution and high-quality detection results. To guarantee rich local information is captured, we derive depth cues from the original images and use a two-channel perceiving model as input when training networks. Importantly, our new architecture uses three-layer residual blocks that successfully combine all accessible information and produce complete detection results at full size. Moreover, we create a new and high-quality dataset in cooperation with Wildlife Thailand's Community and e Mammal Organization. Empirical tests performed on our dataset confirm the excellence of our method over current object detection methods.

III. METHODOLOGY

A. *Architecture Of Proposed Work*

1) Dataset – Offer a dataset for deep learning that does not see data the same way that provide do, the data acquired should be made standard the inrelligble. The dataset is divided between train the test groups at a ratio 80:20. The Video dataset that was used in this study is collection of images of diverse animals.
2) Pre-processing - Because real-world data frequently contains noise, missing values, and sometimes even an unusable format that makes it impossible for machine learning models to use directly, pre-processing is required. Pre-processing of the data is required to make it clean and get it ready for a machine learning model, which also increases the efficacy and accuracy of the model.
3) Feature Extraction - Feature extraction attempts to reduce the number of features in a dataset by creating new features from the old ones (and then removing the original features). After that, most of the information in the initial feature collection should be able to be summed up by this new, more condensed feature set.
4) Classification -The Classification, a computer learns from the dataset or observations that are provided and subsequently divides fresh observations into several classes or groups, Classification method used supervised learning to categorize observations in light of training data

a) Collection of data is the first step of the process for this project. We had collected data set from Kaggle, it is available, it is open source
b) Next task after data collection is data pre- processing. Then they are cleansed in this phase of data and unnecessary values are eliminated. It also takes out the None/ null/ corrupted values.
c) The next step is to split the Data after cleansing the data, we split the data into balanced two sets Training data and test data. We need to work with these missing entries before we go back to build the training model. And from training data we construct a prediction model.
d) We use Random Forest as it is accurate and efficient. Now, we have to calculate the accuracy of the model.
e) The final Step is Classification.

B. *System Architeure*

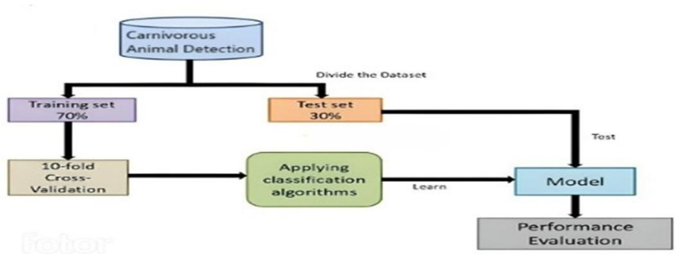

Figure: 1. System Architectural Model

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1) Carnivorous Animal Detection Dataset is the input, dataset is divide into 70%(training) and 30 (test)
2) The test and train set is used to test the final model trained on the training data
3) The Trained models performance is evaluated using the test dat
4) This step includes matrices like accuracy, precision, recall,F1-score,etc.

C. Implemention

This project was implemented using Python, a high-level programming language that is widely used due to its versatility and extensive libraries. Python automates tasks efficiently and is ideal for data analysis and machine learning projects. Below are the steps and tools used:

Installing Python: The first step is to install Python. After installation, the following libraries are imported:

NumPy: NumPy is used for working with multi-dimensional arrays. It performs element-wise operations and provides various methods for processing arrays efficiently.

Pandas: Pandas is a popular Python library for data manipulation and analysis. It offers high-performance tools for handling and analyzing data, making the process fast and easy.

Sklearn: Sklearn (Scikit-learn) is an essential library for building machine learning models. It provides efficient tools for tasks such as classification, regression, and clustering.

Dataset Splitting: After importing the necessary libraries, the dataset is divided into training and testing sets. In this project, 90% of the dataset is used for training the model, and the remaining 10% is used for testing its performance.

Performance Metrics Analysis

Accuracy:

Accuracy measures the overall correctness of the model's predictions. It is calculated as the ratio of correctly predicted values (both positive and negative) to the total number of predictions:

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}}$$

Precision:

Precision indicates how often the model's positive predictions are correct. It is calculated as the ratio of true positives to the total predicted positives:

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Recall:

Recall measures the model's ability to identify actual positive values. It is the ratio of true positives to the total actual positives:

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

F1Score:

The F1 score combines both precision and recall into a single metric. It is particularly useful when the balance between precision and recall is important. The F1 score is the harmonic mean of precision and recall:

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

These metrics are used to evaluate the performance of the machine learning model and ensure its effectiveness in predicting outcomes.

D. Machine Learning Algorithms

Random Forest: Random Forest is a popular machine learning algorithm that belongs to the supervised learning technique. It can be used for both Classification and Regression problems in ML. It is based on the concept of ensemble learning, which is a process of combining multiple classifiers to solve a complex problem and to improve the performance of the model. As the name suggests,

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"Random Forest is a classifier that contains a number of decision trees on various subsets of the given dataset and takes the average to improve the predictive accuracy of that dataset."

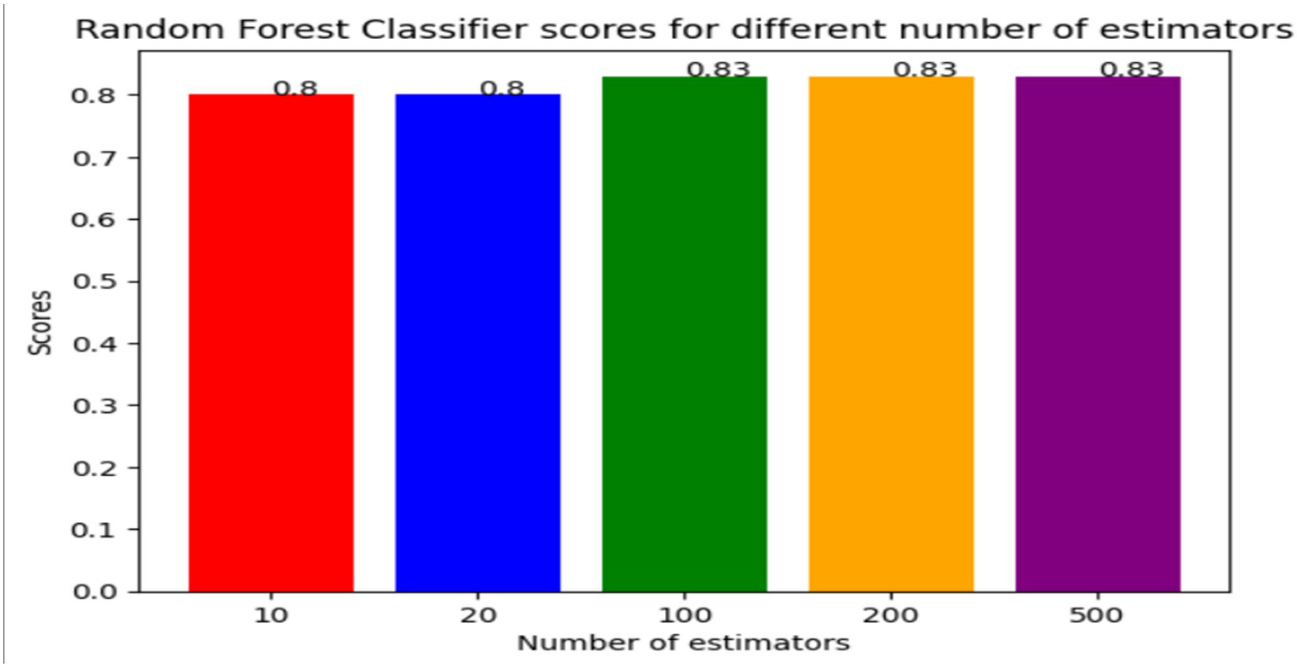

Figure 2: shows accuracy of Random Forest

1) VVG16:- This misclassification highlights a major limitation of the VGG16 model. Although VGG16 performs well for general image classification, it struggles with fine-grained tasks like identifying an animal's diet. Its architecture is relatively shallow and lacks the depth to capture complex semantic features. The model relies more on basic textures and shapes, which can lead to confusion when animals have similar appearances. This example clearly shows that VGG16 has limited generalization ability, and more advanced or fine-tuned models are required for better accuracy.

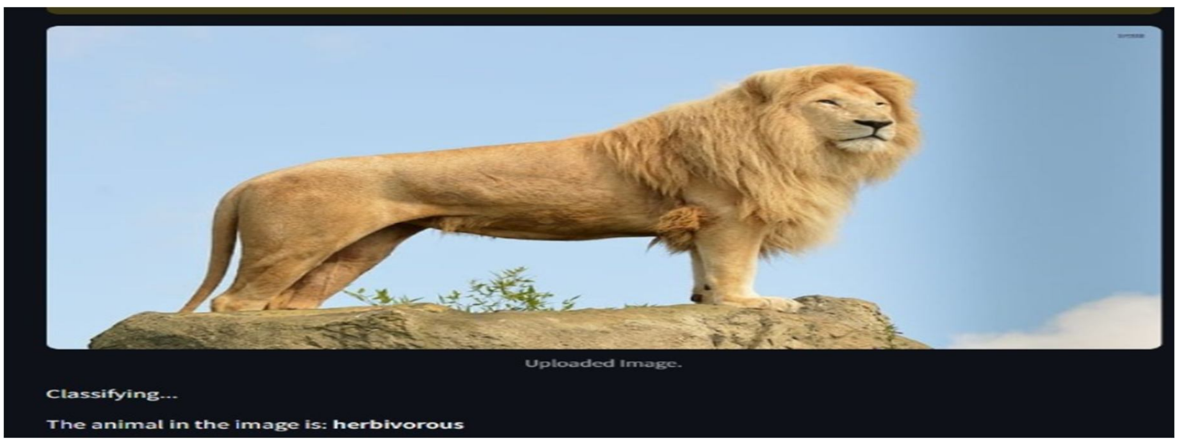

Figure 3: Output of VVG16

2) MobilNet: The model identified the animal as an elephant with a herbivore diet, but with a low confidence of 54.59%. This low confidence suggests that the MobileNet model struggles in real-world scenarios, especially when the background is complex or when multiple animals are present. MobileNet is a lightweight model optimized for speed and low-resource devices, but it lacks the deep feature extraction capabilities of larger models like ResNet50. As a result, it may produce inaccurate or uncertain classifications in such conditions. This highlights the need for further fine-tuning with a more diverse and high-quality dataset to improve its performance.

Figure 4: Output of Mobile Net

3) ResNet50: ResNet50 (Residual Network) is a deep convolutional neural network with 50 layers, known for its high accuracy in image classification tasks. It introduces skip connections (residual learning), which solve the vanishing gradient problem and allow deeper models to be trained efficiently. In the Carnivorous Animal Detection project, ResNet50 is ideal because it can capture complex features from animal images, such as texture, shape, and fine details — critical for distinguishing between carnivorous and non-carnivorous species.

IV. RESULTS

```
# Example usage
image_path = r"C:\Users\Aniket\OneDrive\Desktop\imagesAnimals\e.jpg"# Replace with your image path
predicted_class, accuracy_percentage, predicted_diet = predict_image(image_path)
print(f"The model predicts: {predicted_class} with {accuracy_percentage:.2f}% confidence.")
print(f"This animal is a {predicted_diet}.")
```

```
C:\Users\Aniket\anaconda3\Lib\site-packages\torchvision\models\_utils.py:208: UserWarning: The parameter 'pretrained' is deprecated since 0.13 and may b
e removed in the future, please use 'weights' instead.
  warnings.warn(
C:\Users\Aniket\anaconda3\Lib\site-packages\torchvision\models\_utils.py:223: UserWarning: Arguments other than a weight enum or `None` for 'weights' ar
e deprecated since 0.13 and may be removed in the future. The current behavior is equivalent to passing `weights=None`.
  warnings.warn(msg)
The model predicts: eagle with 92.91% confidence.
This animal is a carnivore.
```

V. CONCLUSION

The image above outlines a structured approach for the carnivorous animal detection project using machine & deep learning pipeline. It begins with dataset division into training and testing set, Classification algorithms are applied to learn distinguishing features of carnivorous animals. The trained model is tasted on unseen data to evaluate its performance. This process ensures reliable and accurate detection of carnivorous animals, making the system effective for real-time or automated wildlife monitoring applications.

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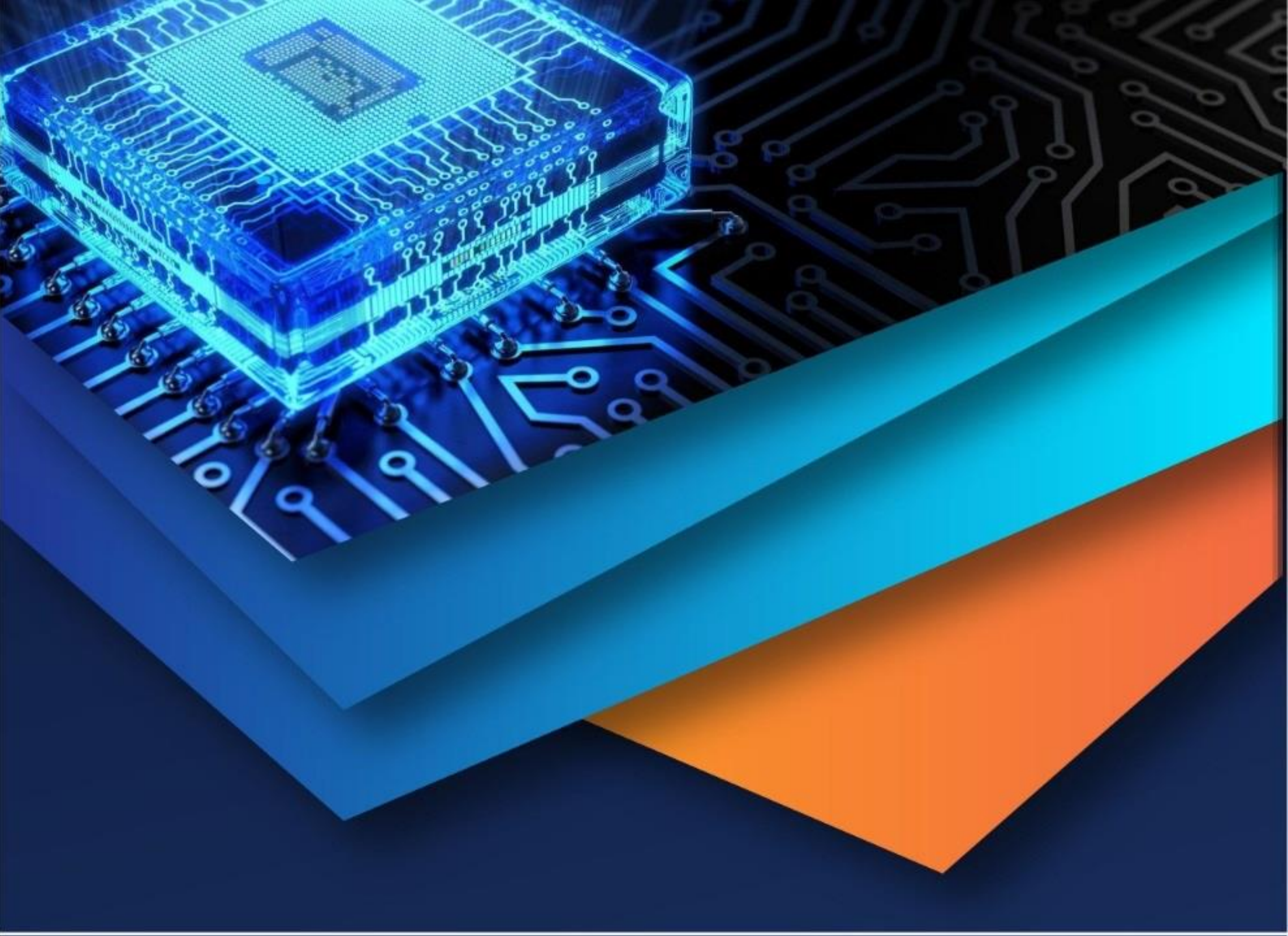

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