HAMOYE

# Animal wildlife classification (supervised image recognition project)

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# Our Team

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# Introduction

Animal wildlife classification using deep learning represents a significant leap forward in biodiversity monitoring and conservation efforts. Traditional methods, which rely on manual identification, are increasingly impractical due to the vast amounts of data generated by modern monitoring tools.

Deep learning, particularly Convolutional Neural Networks (CNNs), automates the classification process by identifying features and patterns in images that indicate specific animal species.

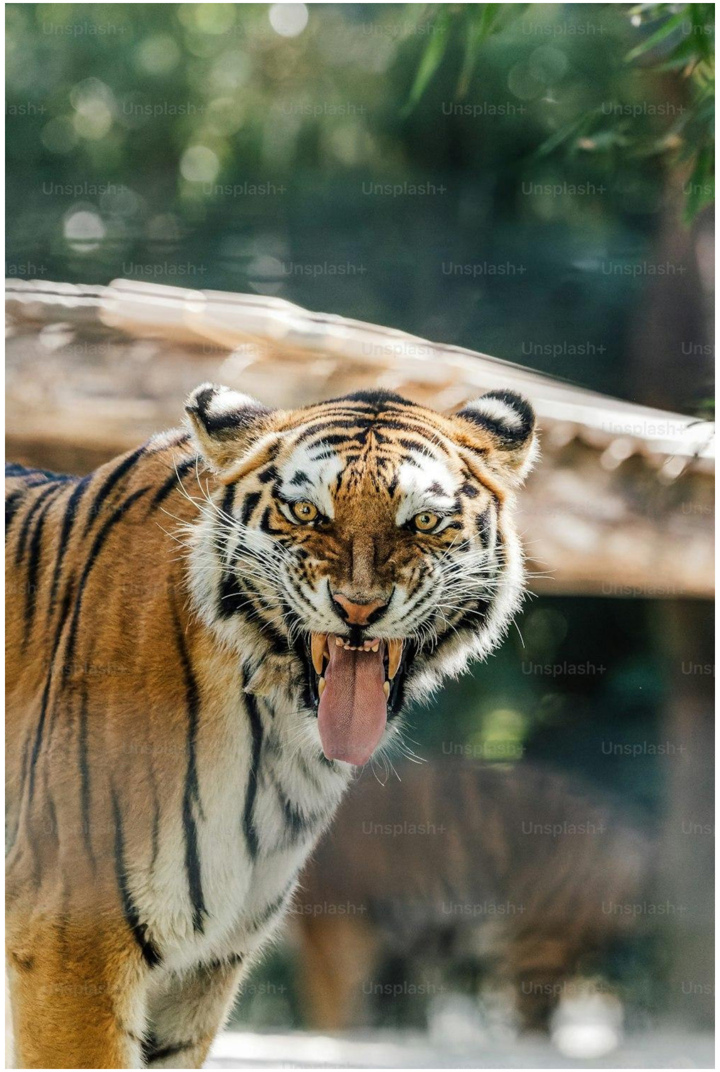
Despite challenges faced with detecting animal species, the integration of deep learning promises to revolutionize wildlife conservation, offering comprehensive monitoring capabilities for protecting global biodiversity.

# Problem Statement

The task of detecting and classifying animal species in images presents a formidable challenge with diverse applications in conservation, ecology, and wildlife management. Traditional methods of species identification often demand extensive manual labor and face limitations stemming from the intricacies of animal environments and appearances.

Deep learning algorithms promise to overcome these challenges by autonomously learning features and patterns from extensive datasets. Nevertheless, significant hurdles remain in creating precise and efficient deep-learning models for animal species detection that can adapt to various environments and species.

Therefore, the central problem revolves around developing deep learning algorithms capable of accurately and efficiently recognizing and categorizing animal species in images, spanning a wide range of environments and species.



# Existing Solutions

Most of the existing research solutions focus on the application of CNN or transfer learning as standalone in the wildlife image classification.

The studies used machine learning techniques to identify animal classes from camera trap images.

The solution proferred here fuses a CNN solution with the transfer learning technique, EfficientNetV2L, for the best model.

# Our Approach

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### *Image Rescaling*

- We rescaled our image pixels to fall between **0 and 1**

### *Data Optimization*

- We performed data optimization to speed up the training process by loading the training data in advance using the prefetch method

### *Preprocessing*

- We performed data augmentation by adjusting the properties of the images to make the model generalize well on the images

### *What we made use of*

- Flip- Left-right,
- Adjust_brightness
- Adjust_constrast.

# Model Selection

Random sampling was performed on the dataset using an argument called **shuffle**. The shuffle argument helps to select random images for training the model

Data Splitting

| Training Set 70% | ⟷ | Validation Set 20% | ⟷ | Testing Set 10% |
|---|---|---|---|---|

```
training_data = image_dataset_from_directory(
    directory=r"/content/images",
    color_mode="rgb",
    batch_size=32,
    image_size=(256, 256),
    shuffle=True,
    validation_split=0.3,
    subset="training",
    seed = 1
)
```

```
[ ] validation_data = image_dataset_from_directory(
        directory = r"/content/images",
        color_mode="rgb",
        batch_size=32,
        image_size=(256, 256),
        shuffle=False,
        validation_split=0.2,
        subset="validation",
        seed = 1
    )
```

*NB: The test data represents the unseen data that the model would be evaluated on. Likewise, training and validation are done simultaneously when training the model.*

# Model Development and Compilation

*We used 2 CNN Models*

- **Sequential Model**: In the sequential model, three(3) convolutional layers were created (inside the convolutional layers were maximum pooling layers) with an activation function called rectified linear unit(Relu).

- Afterwards, a flattened layer was created to flatten out or linearize the convolutional layers. Finally, we created a single layer of neural network.

*Model Compilation*
Optimizer: Adam was used because of its adaptive nature and overall efficiency.

*Loss*
Sparse Categorical Cross entropy

- **Efficient Net V2L**: This model was employed to improve the accuracy/performance of our sequential model. The efficientnetv2l model is a CNN model. For this model, we used the weights from imagenet, include_top = False which means do not include the fully connected layer at the top, and froze all layers to prevent the parameters from learning during training. New layers were added to the top of this model.

*Model Compilation*
Optimizer: Adam (learning rate = **0.01)**

*Loss*
SparseCategoricalCrossentropy

# Model Evaluation

Among the various models tested, EfficientNetV2L stood out, delivering exceptional performance. It achieved an impressive accuracy of 98.67% on the test data, showcasing its robust generalization ability. On the validation set, it attained a high accuracy of 98.33%, showcasing it does not overfit. Even during training, EfficientNetV2L achieved an accuracy of 98.96%.

Note: During training, we ensured that both training and validation loss was reducing simultaneously because if the train loss is reducing and the validation loss isn't reducing then there's the case of overfitting but if both reduce simultaneously, then the model is training properly.

## Performance metrics on the test dataset

### Sequential model

| Accuracy | Loss |
| --- | --- |
| **71.33%** | **1.267** |

### Transfer Learning model (EfficientNetV2L)

| Accuracy | Loss |
| --- | --- |
| 98.67% | **0.038** |

# Conclusion

*Of all the models trained in this project, EfficientNetV2L was able to generalize well on unseen data implying that EfficientNetV2L model can be deployed in real-life scenarios to solve the problem of identification and classification of wildlife animals.*