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Title: Hybrid Deep Learning Framework for Automated Classification of Wildlife Camera Trap Images

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OVERVIEW

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Introduction

- **Motivation**: Increasing use of camera traps necessitates efficient wildlife image classification.
- **Challenges**: Manual analysis is time-consuming, error-prone, and not scalable.
- **Solution**: Deep learning automates classification, accelerates analysis, and enhances conservation efforts.
- **Scope**: Developing a Hybrid Object Classification Model (HOCM) for robust species identification.
- **Objectives**: Enhancing dataset quality, optimizing species detection, improving model performance, validating with log loss, and enabling real-world deployment.

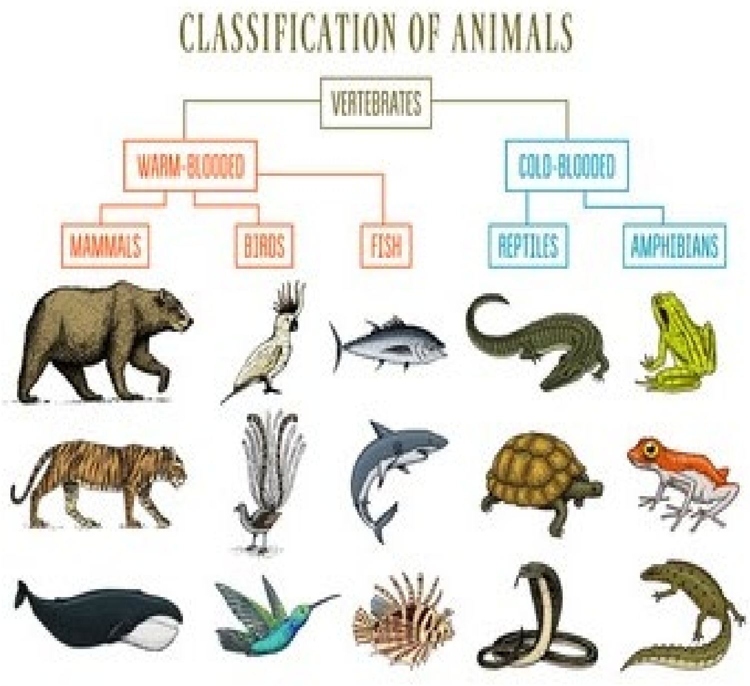


Fig. 1 classification of animals(example)

Methodology Overview

Objective: Develop a Hybrid Object Classification Model (HOCM) for wildlife image classification.

Phases:

1. Data Collection and Exploration
2. Model Development
3. Ensemble Approach
4. Model Evaluation

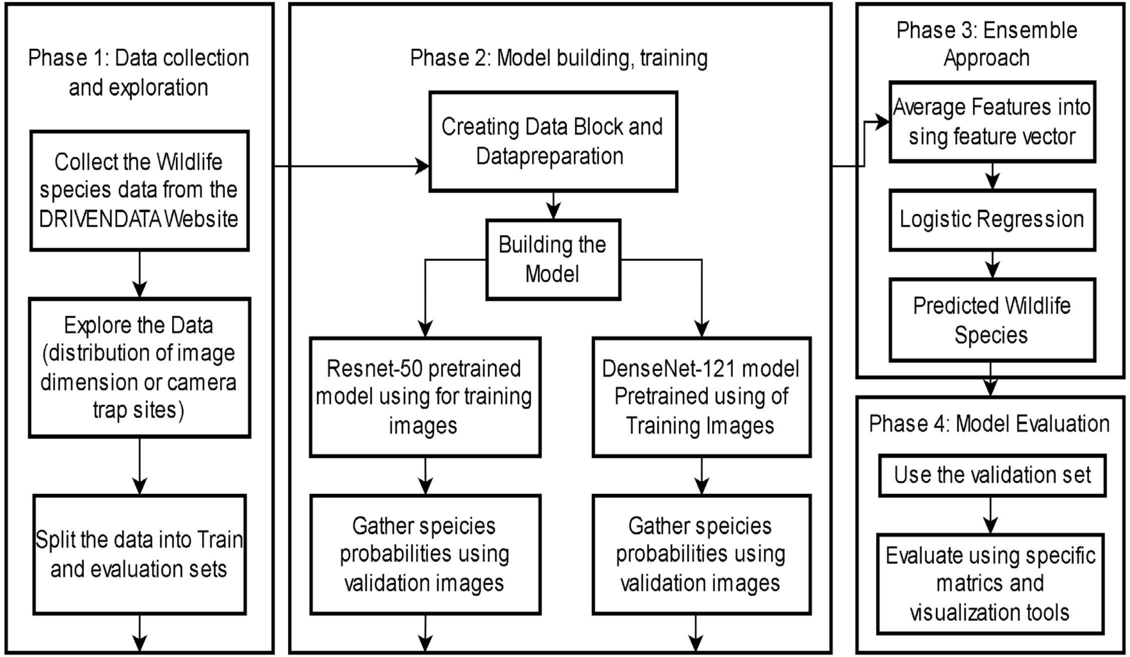


Fig. 2 Block Diagram of the Methodology

Data Preparation

Source: "CLIMATE Conser-vision Practice Area: Image Classification" competition on DrivenData.

Content: 20,950 images (16,487 training, 4,463 testing).

Categories: Antelope_duiker, bird, civet_genet, hog, leopard, monkey_prosimian, rodent, blank.

Distinct Sites: Ensures model generalizability across different environments.

Tools: Python, Fastai, PyTorch.

Metadata Handling: Efficient access and merging of data for classification.

Distribution: Balanced representation of species for unbiased model training.

Transformations: Resize, random crop, flip, brightness, contrast adjustments, and normalization.

Fig. 3 Sample Images used for training

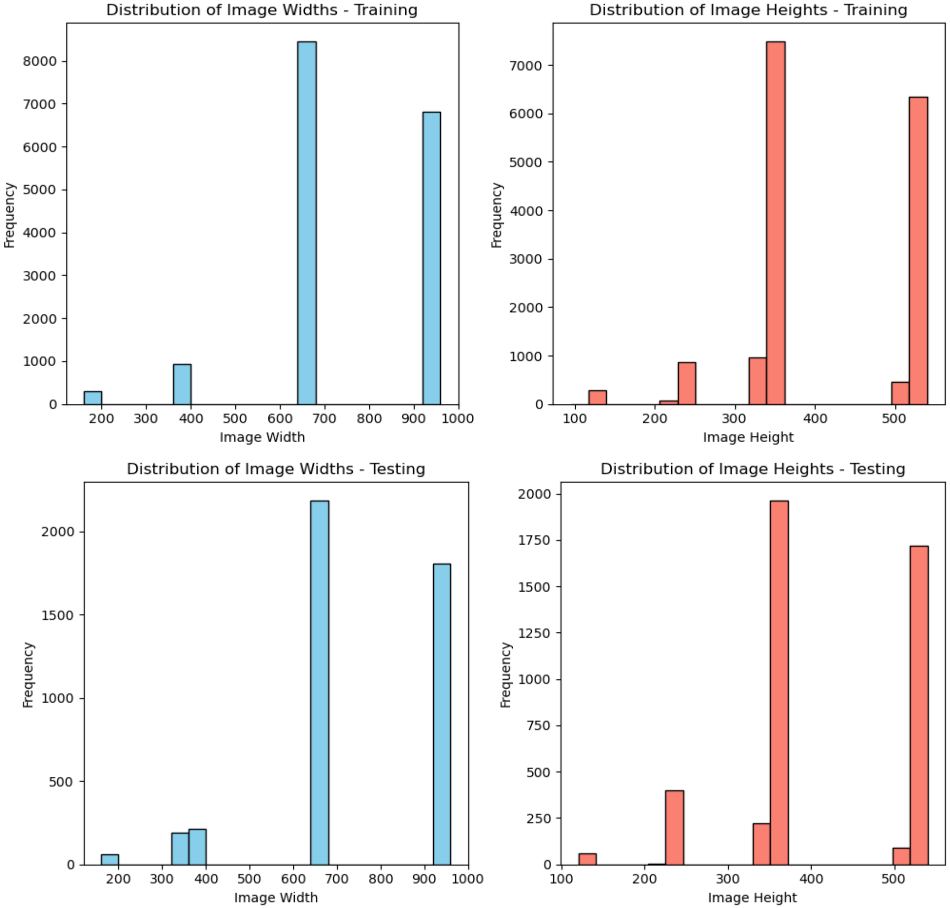


Fig.4 Distribution of Image width and height

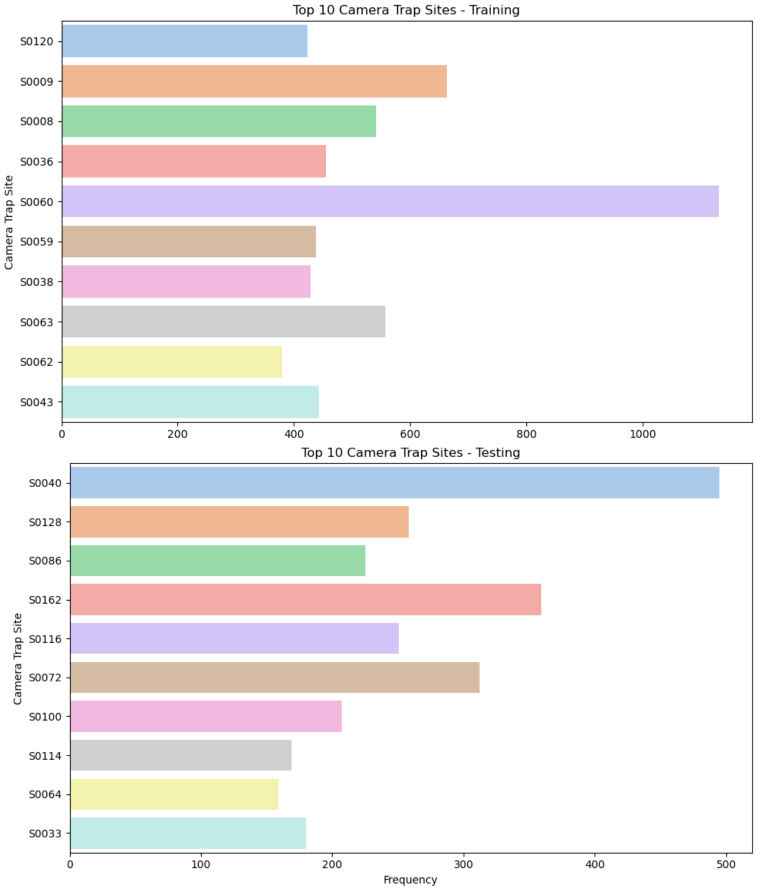


Fig.5 Distribution of camera trap sites

Model Development

Model Selection:

- DenseNet121 and ResNet50: Pre-trained on ImageNet, chosen for their high accuracy in image classification tasks.
- Fine-tuning: Adjust final layers for specific wildlife classification.

Learning Rate Optimization:

- Objective: Find optimal learning rates to ensure stable and efficient model training.

Ensemble Model Creation:

- Combining Models: Use logistic regression to combine predictions from DenseNet121 and ResNet50.
- Ensemble Advantage: Leverages complementary strengths of both models for better performance.

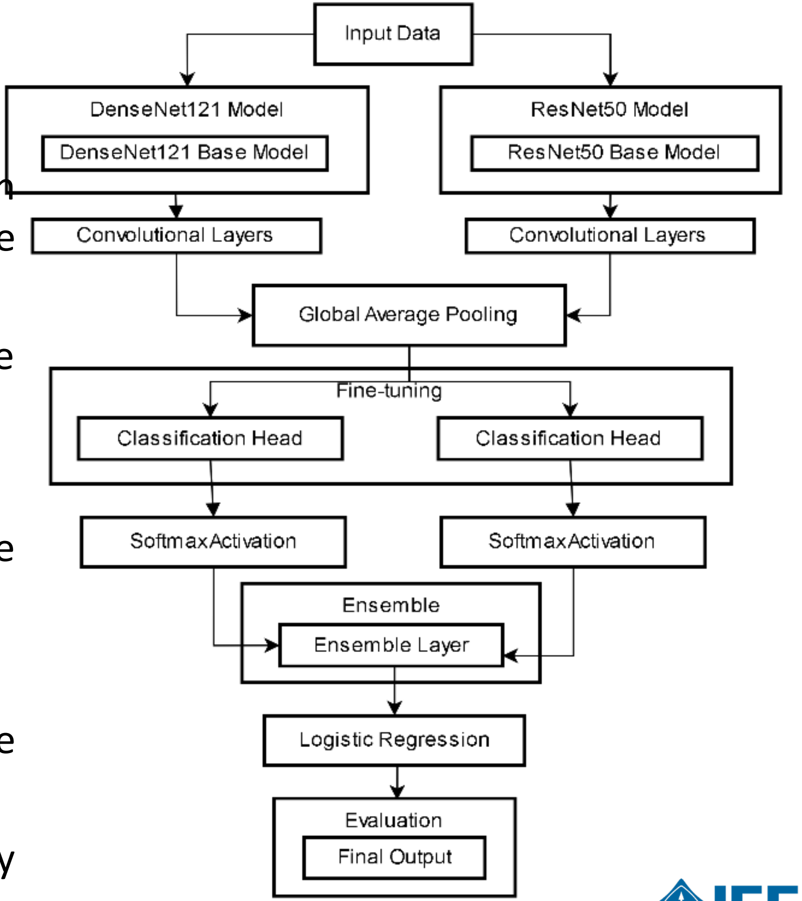


Fig. 6 Model Architecture

Model Evaluation

Separate Validation Set: Ensures the mode generalizability.

Performance Metrics: Accuracy, error rate.

Confusion Matrix:

- Purpose: Visualize correct and incorrect classifications.
- Insights: Identify areas for model improvement.

Log Loss:

- Measurement: Quantifies prediction accuracy.

$$loss = -\frac{1}{N} \cdot \sum_{i=1}^{N} \sum_{j=1}^{M} y_{ij} \log p_{ij}$$

Fig. 7 Log loss matric formula

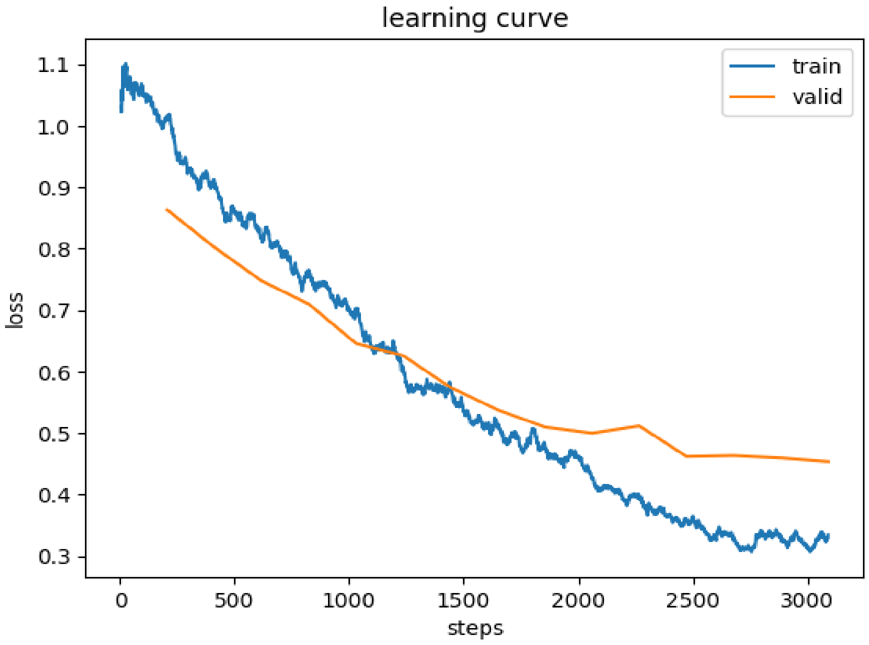
Variables:

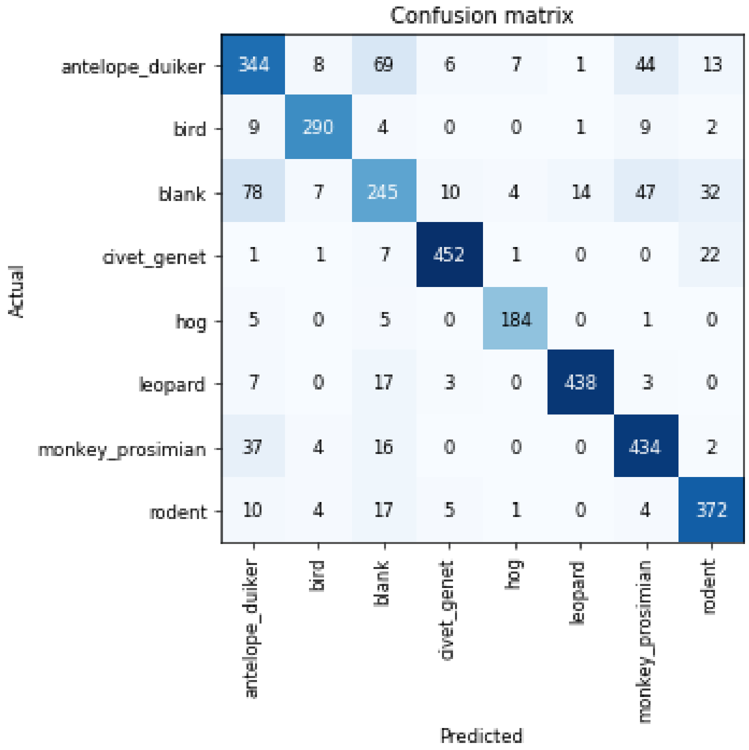
- N: Number of observations
- M: Number of classes
- yij: Binary indicator (correct class)
- Pij: Predicted probability for class j

Results: Baseline Models (ResNet-50)

- **Parameters:**
  - **Model**: ResNet-50,
  - **Learning Rate (lr_max)**: 4e-03, **Weight Decay (wd)**: 1e-05, **Epochs**: 15
- **Results:**
- **Validation Loss**: Started at 0.985, reduced to 0.454,
- **Error Rate**: Decreased from 35.34% to 15.20%,
- **Training Time**: ~1 minute 18 seconds per epoch.
- **Training Dynamics:**
- Effective reduction in validation loss and error rate over epochs.
- Efficient training with consistent performance improvements.

Results: Baseline Models (ResNet-50)



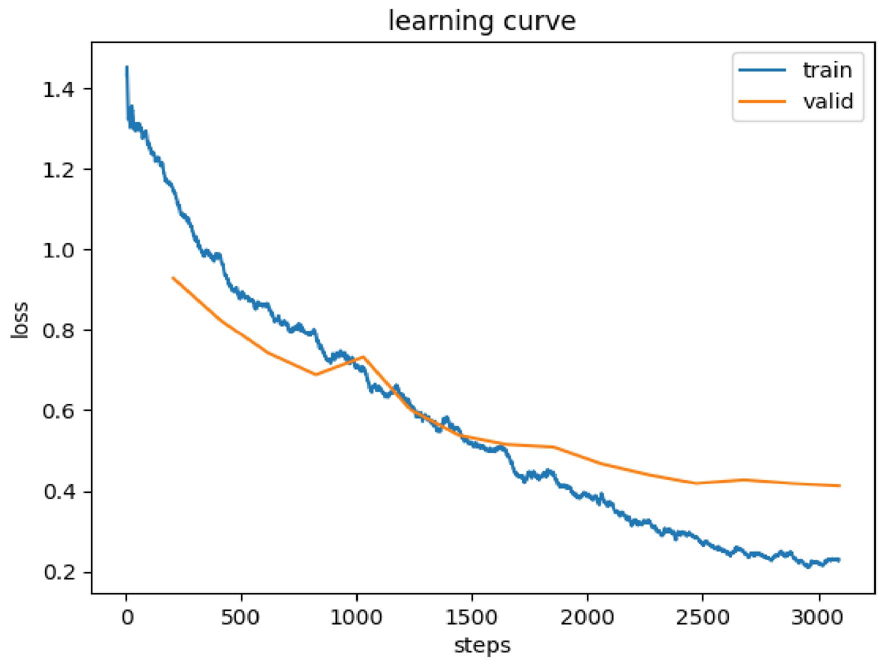


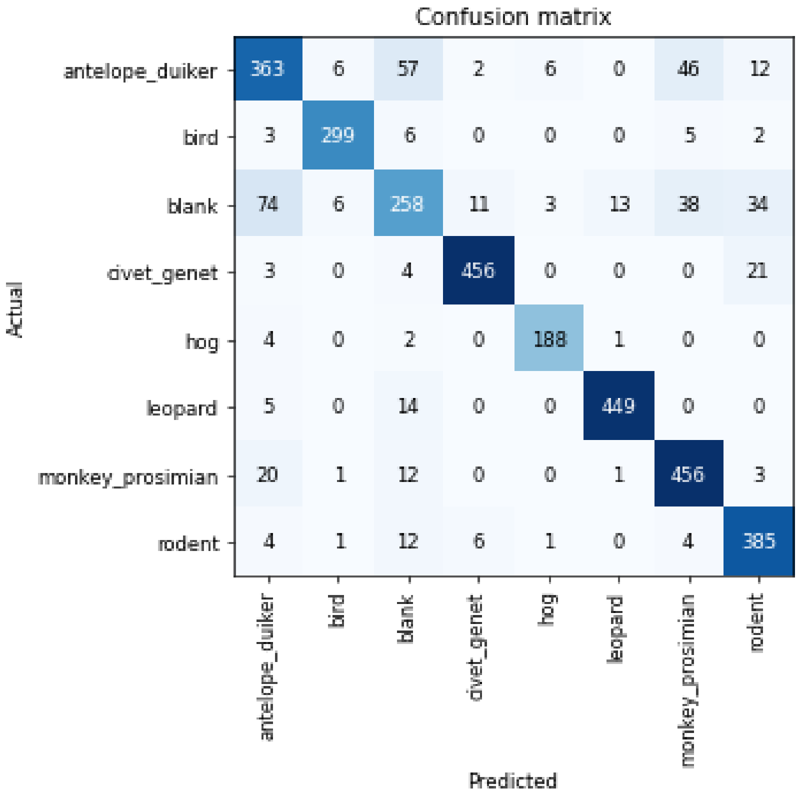
Results: Baseline Models (DenseNet-121)

- **Parameters: Model**: ResNet-50, **Learning Rate (lr_max)**: 4e-03, **Weight Decay (wd)**: 1e-05, **Epochs**: 15
- **Results:**
  - **Validation Loss:** Started at 1.213, reduced to 0.412,
  - **Error Rate:** Decreased from 43.62% to 13.44%,
  - **Training Time:** ~1 minute 38 seconds per epoch
- **Training Dynamics:**

- Effective reduction in validation loss and error rate over epochs.
- Efficient training with consistent performance improvements.

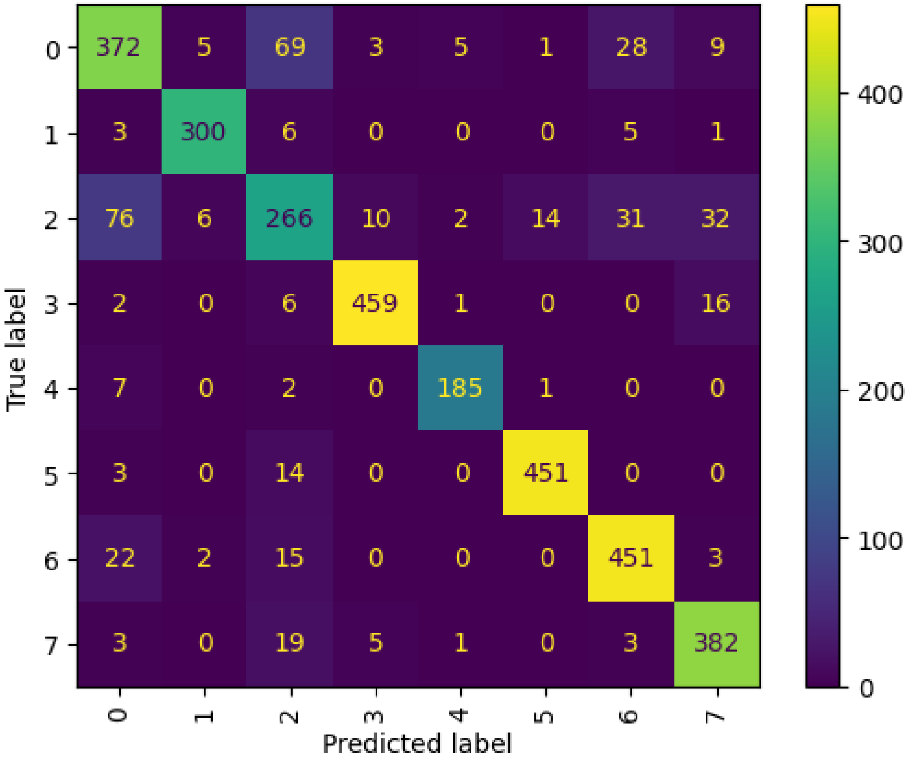
Results: Baseline Models (DenseNet-121)





Results: Baseline Models (Ensemble Model)

- **Metrics:**
- **Log Loss**: 0.3983
- **Accuracy**: 0.8693
- **Model Training:**
- **Classifier**: Logistic Regression
- **Maximum Iterations**: 1000
- **Confusion Matrix:**
- Visual representation of model performance on validation data.



Conclusion

- Demonstrated effectiveness of deep learning and ensemble learning for wildlife species identification.
- Fine-tuned DenseNet121 and ResNet50 models showed promising results.
- Ensemble approach with logistic regression leveraged strengths of both models.
- Future work includes:
    1. Optimizing ensemble architectures and hyperparameters.
    2. Improving data preprocessing techniques.
    3. Exploring other CNN architectures through transfer learning.
    4. Integrating R-CNN or YOLO for better classification.
    5. Developing real-time systems with physical sensors.
- Commitment to continuous updates and advancements to support ecological research and conservation.

References

1. A. Swanson et al., "Making the most of our time: distinguishing behavior in camera trap studies," Methods Ecol. Evol., vol. 7, no. 4, pp. 464-473, 2016.
2. M. S. Norouzzadeh et al., "Automatically identifying, counting, and describing wild animals in camera-trap images with deep learning," Proc. Nat. Acad. Sci., vol. 115, no. 25, pp. E5716-E5725, 2018.
3. M. Ibraheam, F. Gebali, K. F. Li, and L. Sielecki, "Animal Species Recognition Using Deep Learning," in Proc. IEEE Int. Conf. Image Processing (ICIP), 2020, pp. 827-831.
4. K. He et al., "Deep residual learning for image recognition," in Proc. IEEE Conf. Comput. Vision Pattern Recognit. (CVPR), 2016, pp. 770-778.
5. G. Huang et al., "Densely connected convolutional networks," in Proc. IEEE Conf. Comput. Vision Pattern Recognit. (CVPR), 2017, pp. 4700-4708.
6. X. Wu, J. Huang, J. Yang, and X. Han, "Identification and classification of wild animals from video sequences using hybrid deep residual convolutional neural network," Int. J. Comput. Vision Image Process. (IJCVIP), vol. 10, no. 3, pp. 45-60, 2020.
7. M. Amodio, M. Battini, M. Giorgi, F. Micheli, and F. Pascucci, "Animal species recognition using deep learning," IEEE Access, vol. 9, pp. 51921-51932, 2021.
8. Hamoye, A. (2020). Animal species detection using deep learning. Journal of Computational Vision and Imaging Systems, 2(1), 27-35. DOI: 10.14355/cviss.2020.0201.04
9. Tabak, M. A., Norouzzadeh, M. S., Wolfson, D. W., Sweeney, S. J., Vercauteren, K. C., Snow, N. P., & et al. (2018). Machine learning to classify animal species in camera trap images: Applications in ecology. Methods in Ecology and Evolution, 9(4), 678-688. DOI: 10.1111/2041-210X.12997

References

10. Norouzzadeh, M. S., Morris, D., Beery, S., Joshi, N., Jojic, N., & Clune, J. (2020, September). A deep active learning system for species identification and counting in camera trap images. Proceedings of the IEEE International Conference on Computer Vision Workshops (pp. 137-146). DOI: 10.1109/ICCVW51393.2021.00021
11. Zhang, Y., Xiang, T., Hospedales, T. M., & Lu, H. (2019). Deep mutual learning. Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (pp. 4320-4328). DOI: 10.1109/CVPR.2019.00445
12. Dutta, J., Samanta, S. K., & Sa, P. K. (2023). Hybrid deep learning models for improved wildlife classification. Traitement du Signal, 40(5), 1467-1476. DOI: 10.18280/ts.402521
13. B. H. Curtin and S. J. Matthews, "Deep Learning for Inexpensive Image Classification of Wildlife on the Raspberry Pi," Department of Electrical Engineering & Computer Science, U.S. Military Academy, West Point, NY, USA.
14. S. S. Khan, N. V. Doohan, M. Gupta, S. Jaffari, A. Chourasia, K. Joshi, and B. Panchal, "Hybrid Deep Learning Approach for Enhanced Animal Breed Classification and Prediction," Traitement du Signal, vol. 40, no. 5, pp. 2087-2099, 2023.
15. P. Rajendra and S. Latifi, "Prediction of diabetes using logistic regression and ensemble techniques," Journal Name, vol. 10, no. 5, pp. 26938, Mar. 2024.
16. N. Behar and M. Shrivastava, "ResNet50-Based Effective Model for Breast Cancer Classification Using Histopathology Images," Research Article, vol. 10, no. 5, E26938, Mar. 15, 2024
17. DrivenData. (n.d.). Competition: Conser-vision Practice Area: Image Classification.

THANK YOU