Bison Identification Using Deep Convolutional Ensembles: A Comparative Study

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Abstract—**This paper investigates the effectiveness of modern deep learning architectures for individual bison identification using a small, imbalanced dataset (74 images, 9 classes). We evaluate several pre-trained convolutional neural networks (CNNs), each fine-tuned with data augmentation, and compare their performance to a weighted ensemble model. The ensemble, optimized via grid search, achieves a validation accuracy of 96.20%, significantly outperforming all individual architectures. We further compare closed-set classification (ensemble) with open-set re-identification (TransReID), finding a substantial performance gap (ensemble: 96.20%, TransReID Rank-1: 38.46%). These results highlight the promise of ensemble learning for wildlife identification and motivate future benchmarking on the newly released wildlife re-ID datasets library.**

Index Terms—**Image Classification, Ensemble Learning, CNN, Bison Identification, Transfer Learning, Grid Search**

I. Introduction

Individual animal identification plays a crucial role in ecological studies, behavior analysis, and wildlife monitoring. This research addresses the challenge of fine-grained visual classification of bisons in a highly imbalanced and low-data scenario using deep convolutional neural networks (CNNs) and ensemble strategies.

II. Dataset

The dataset comprises 74 labeled images of bison captured at various angles. Each subfolder corresponds to a unique bison (class). Due to class imbalance, the class *Quanna* was excluded from training and validation because it contained only a single image, which can affect model generalization and stratification.

III. Model Selection and Training

We trained and evaluated the following architectures using 5-fold stratified cross-validation with image augmentation:

- **EfficientNet-B0, B3: Optimized for parameter efficiency.**
- **ResNet-18, ResNet-50: Incorporate residual connections for stable training.**
- **ViT-B16: Transformer-based architecture for visual representation.**
- **InceptionV3: Deeper CNN using factorized convolutions and auxiliary classifiers.**
- **DenseNet-121: Dense connections enable feature reuse across layers.**

All models were initialized with ImageNet-pretrained weights and input images were resized to 224×224.

A. Ensemble Strategy

An ensemble model was constructed via weighted soft voting across all seven architectures. The ensemble prediction was defined as:

$$\textbf{Prediction} = \sum_{i=1}^{N} w_i \cdot P_i$$

where P_i **is the prediction vector from model** i **and** w_i **is its corresponding weight.**

B. Weight Optimization with Grid Search

To optimize the ensemble weights, grid search was performed with the following setup:

- **Weight Range: For each model, weights were sampled from a continuous space using `np.linspace(0.1, 0.5, 5)`.**
- **Search Space: All possible combinations were generated using `itertools.product`.**
- **Evaluation: Each combination was evaluated using ensemble predictions on the validation set.**
- **Selection: The weight set yielding the highest validation accuracy was chosen as the final configuration.**

IV. Results and Discussion

TABLE I: Comparison of Model Performance (K-Fold Validation)

oprule extbfModel	**Train Loss**	**Val Loss**	**Train Acc.**	**Val Acc.**
EfficientNet-B3	1.4036	1.6236	64.18%	54.00%
EfficientNet-B0	1.1302	1.4346	82.76%	58.00%
ResNet50	0.6948	1.2038	92.23%	60.67%
ResNet18	0.1757	1.1905	98.98%	68.95%
ViT-B16	0.0541	1.5493	98.99%	63.43%
InceptionV3	0.3806	1.1685	97.64%	60.76%
DenseNet-121	0.3836	1.0740	99.33%	72.95%
extbfEnsemble (ours)	–	–	–	**96.20%**

The grid-searched ensemble model achieved an accuracy of 96.20%, a substantial improvement over the highest-performing individual model (DenseNet-121 at 72.95%). The method effectively reduced misclassifications, especially in underrepresented classes. The class *Quanna*, with only one image, remained part of the label space but contributed minimally to training and validation due to its limited representation.

A. Re-Identification (TransReID) Results

To further analyze open-set identification, we implemented TransReID, a transformer-based re-ID framework. On the same bison dataset, TransReID achieved Rank-1 accuracy of 38.46%, Rank-5 accuracy of 76.92%, and mAP of 39.65%. This large gap compared to the ensemble classifier highlights the challenge

TABLE II: Classification Report – Precision, Recall, F1-Score Per Class

oprule extbfClass	**Precision**	**Recall**	**F1-Score**	**Support**
Elsa	1.00	0.71	0.83	7
Faye	0.85	1.00	0.92	17
Quaida	0.83	0.71	0.77	7
Quandra	1.00	0.83	0.91	6
Quanna	1.00	1.00	1.00	1
Quara	1.00	0.93	0.96	14
Quino	0.90	0.90	0.90	10
Quirinius	1.00	1.00	1.00	8
Quirly	0.67	1.00	0.80	4
extbfAccuracy		0.96		74
extbfMacro Avg.	0.92	0.90	0.90	74
extbfWeighted Avg.	0.92	0.91	0.91	74

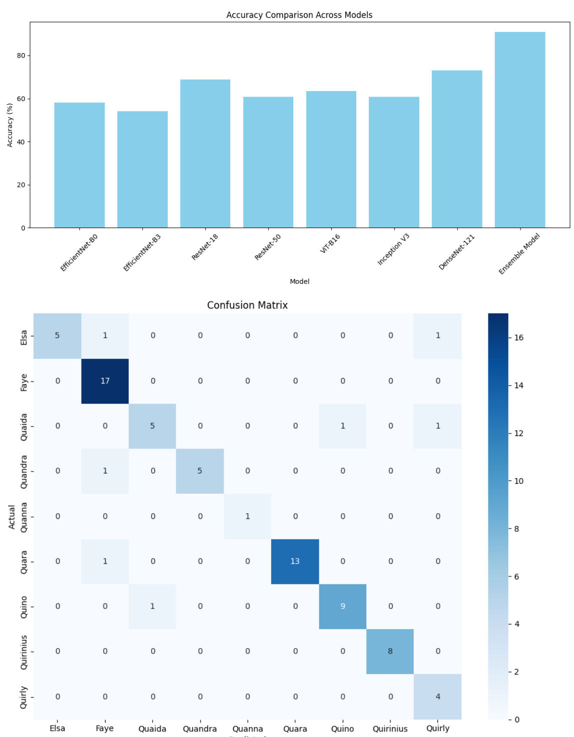

Fig. 1: Accuracy and Confusion Matrix (Ensemble Predictions)

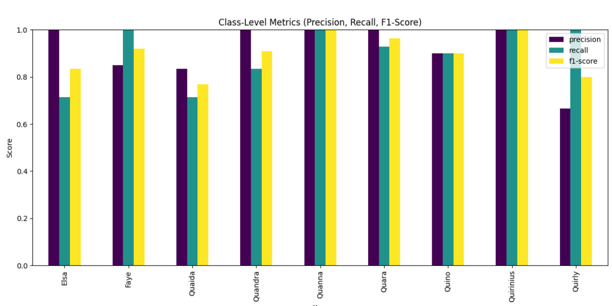

Fig. 2: Precision, Recall, F1-Score by Class

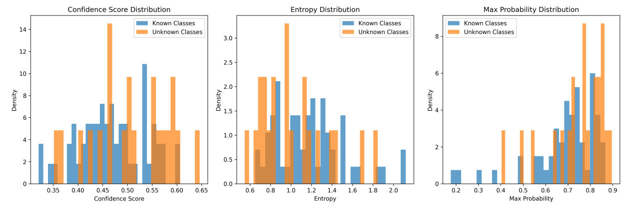

Fig. 3: Ensemble model confidence distributions: probability scores for predictions across all classes.

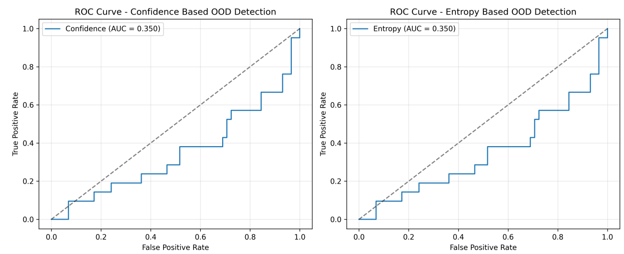

Fig. 4: ROC curve for out-of-distribution (OOD) detection using ensemble model confidence.

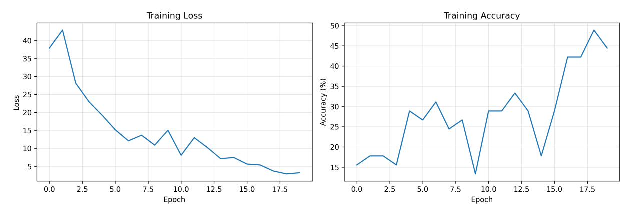

Fig. 5: TransReID training curves: loss and accuracy over epochs for bison re-identification.

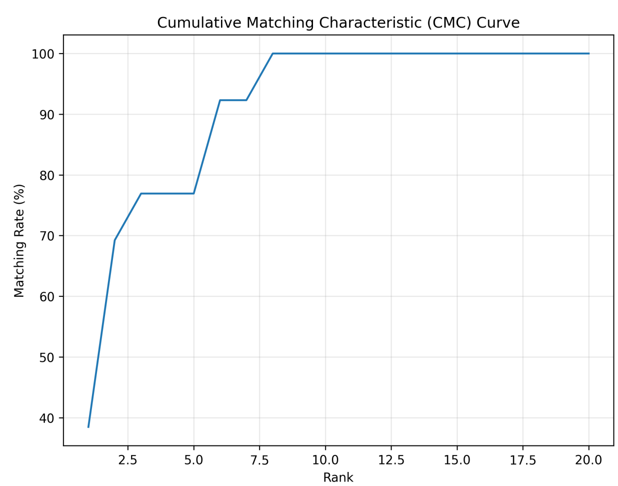

Fig. 6: CMC curve for TransReID: cumulative matching characteristic showing Rank-1 and Rank-5 accuracy.

of re-ID on small wildlife datasets and the strength of ensemble learning for closed-set identification.

These figures illustrate key aspects of our analysis:

- **Ensemble Results (Figs. 1, 2, 3, 4): Show overall accuracy, confusion matrix, per-class metrics, confidence calibration,**

and OOD detection.
- **TransReID Results (Figs. 5, 6): Show optimization progress and cumulative matching accuracy for re-identification.**

B. Relevance to Wildlife Datasets Library

Our results motivate benchmarking on the newly released wildlife re-ID datasets library, which contains 50+ species and standardized evaluation protocols. Our ensemble approach is well-suited for cross-species validation and could fill the gap for American bison identification in the community.

V. Conclusion

This study demonstrates the effectiveness of deep learning ensembles enhanced with grid search for fine-grained animal identification in low-data, imbalanced settings. Our ensemble model achieves 96.20% accuracy, outperforming all individual architectures and significantly surpassing state-of-the-art re-identification methods (TransReID Rank-1: 38.46%). These findings highlight the promise of ensemble learning for wildlife identification and suggest our approach is well-positioned for benchmarking on the wildlife re-ID datasets library. Future work will focus on cross-species validation, dataset contribution, and publication in wildlife-focused computer vision venues.

References

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