Comparative Analysis of CNN Architectures for Fine-Grained Species Classification Across FungiCLEF, AnimalCLEF, and PlantCLEF Datasets

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***Abstract*—Fine-grained visual classification (FGVC) presents a challenging task in computer vision, especially when applied to biodiversity datasets involving large inter-class similarity and intra-class variance. In this project, we explore and evaluate the effectiveness of three convolutional neural network (CNN) architectures: DenseNet121, Inception v3, and a custom CNN designed from scratch, across three CLEF datasets—FungiCLEF, AnimalCLEF, and PlantCLEF. Each team member focused on one of the domains, using standardized data preprocessing, training pipelines, and evaluation metrics to ensure fair comparison. Our results show that while DenseNet and Inception networks generally outperform the custom model in terms of accuracy, the custom architecture shows promise with significantly reduced computational cost. The experiments also reveal dataset-specific challenges and highlight the importance of architecture selection in biodiversity-related FGVC tasks.**

***Index Terms*—DenseNet, Inception v3, CNN, CLEF**

I. Introduction

Fine-grained visual classification (FGVC) is a rapidly growing subfield in computer vision focused on differentiating between categories with subtle inter-class differences and high intra-class variability. Unlike traditional classification tasks, FGVC challenges models to distinguish highly similar classes, such as different species of mushrooms, animals, or plants, which may exhibit overlapping features under varying environmental conditions. This task is especially critical in ecological monitoring, biodiversity research, and environmental protection, where accurate species identification can inform conservation efforts and biological studies.

The CLEF 2025 benchmarks—FungiCLEF, AnimalCLEF, and PlantCLEF—provide a robust evaluation framework for FGVC through real-world datasets that simulate noisy, unconstrained environments. Each track represents a specific biological domain and offers unique challenges: FungiCLEF focuses on mushroom species classification with rich multimodal metadata, AnimalCLEF emphasizes individual animal re-identification across species and viewpoints, and PlantCLEF targets plant species identification from diverse ecological contexts. These datasets collectively promote the development of models capable of generalizing across biological variability, environmental artifacts, and domain shifts.

In this study, we investigate and compare the performance of three convolutional neural network (CNN) architectures—DenseNet121, Inception v3, and a custom lightweight CNN—across the three CLEF tracks. DenseNet, with its densely connected layers, facilitates better gradient flow and feature reuse, making it well-suited for FGVC tasks where subtle patterns must be captured. Inception v3 offers a deeper network with auxiliary classifiers and multi-scale processing, while our custom CNN is designed for efficiency and rapid iteration on domain-specific inputs.

Each team member specialized in one CLEF track to allow focused experimentation and domain adaptation. One team member trained and evaluated models on the FungiCLEF dataset, which includes both images and extensive metadata such as habitat, substrate, GPS coordinates, and taxonomic information. The second member worked on AnimalCLEF, where the task involved identifying individual animals—such as sea turtles, salamanders, and lynxes—from labeled and query sets. The third member focused on PlantCLEF, using high-resolution images of plant species and vegetation quadrats to train models capable of plant recognition under complex natural settings.

II. Dataset Description

A. FungiCLEF

This dataset is built from fungi observations submitted to the Atlas of Danish Fungi, each consisting of multiple images and rich metadata annotated by mycologists. The training split contains 4,293 observations and 7,819 images across 2,427 classes, while the validation split includes 1,099 observations and 2,285 images spanning 570 classes. Metadata includes timestamps, GPS coordinates, habitat and substrate descriptions, toxicity status, taxonomic hierarchy, and environmental attributes like elevation and landcover. Each image is also captioned using the Malmo-7B model, and additional data such as satellite images and EXIF metadata are available.

B. AnimalCLEF

The AnimalCLEF 2025 dataset is curated to facilitate individual re-identification of three specific animal species: loggerhead sea turtles (Zakynthos, Greece), salamanders (Czech Republic), and Eurasian lynxes (Czech Republic). The dataset is structured into two primary subsets: a labeled Database set, which includes known individuals, and a Query set, consisting of images where the identity is either known (present in the database) or unknown. The objective is to develop models capable of determining whether an animal in a query image has been previously seen and, if so, correctly match it to its identity. This formulation closely mirrors real-world conservation scenarios, where distinguishing between re-encounters and new individuals is critical for tracking population dynamics and behaviors.

To support model generalization, the challenge organizers also provide the WildlifeReID-10k dataset, a large-scale auxiliary collection encompassing approximately 140,000 images representing over 10,000 individual animals from 36 distinct wildlife datasets. These include various species such as marine turtles, birds, primates, and African herbivores. This additional dataset enables pretraining or domain adaptation to enhance recognition capabilities across diverse visual and environmental contexts. The dual challenge of identifying both known and unknown individuals is evaluated using two balanced metrics—BAKS (Balanced Accuracy on Known Samples) and BAUS (Balanced Accuracy on Unknown Samples)—with the final score computed as their geometric mean to ensure robust performance assessment across both known and novel instances.

C. PlantCLEF

The PlantCLEF dataset consists of around 1.4 million high-resolution images across more than 7,800 plant species, focusing on flora native to southwestern Europe. The training data is sourced from the Pl@ntNet and GBIF platforms and is hierarchically organized by species. Each image includes metadata such as image resolution and species identifier. Complementing the labeled dataset is a large collection of 212,782 pseudo-quadrat images derived from LUCAS Cover Photos, which are unannotated but intended to support self-supervised pretraining. The final test set comprises 2,105 vegetation quadrat images from varied floristic regions, captured with diverse camera setups and under different environmental conditions, making the task especially challenging for generalization.

III. Literature Review

Wei et al. (CVPR 2021): ”Fine-Grained Visual Classification via Progressive Transfer Learning.” This work explores a progressive transfer learning framework tailored for fine-grained visual classification (FGVC) tasks, where the challenge lies in distinguishing between visually similar classes. The authors demonstrate how leveraging hierarchical knowledge transfer from large-scale datasets like ImageNet to fine-grained target domains significantly boosts classification performance. The paper emphasizes the importance of adapting feature extraction layers to account for subtle inter-class differences, particularly in domains where annotated data is limited or imbalanced. This approach aligns well with our experimental setup, where we adopted pretrained models to maximize the utility of available labeled data.

In our project, we implemented DenseNet121 and Inception v3, both initialized with pretrained weights from ImageNet. These models were fine-tuned on the respective CLEF datasets—FungiCLEF, AnimalCLEF, and PlantCLEF—by replacing the final classifier layers to match the number of classes per dataset. The use of transfer learning allowed us to converge faster and generalize better despite data imbalance and domain noise. DenseNet121, known for its dense connections that promote feature reuse, exhibited superior performance across all datasets. Inception v3, which benefits from auxiliary classifiers and multi-scale receptive fields, performed competitively and particularly excelled in visually complex datasets like AnimalCLEF.

Our application of transfer learning demonstrates its value in biodiversity FGVC tasks, where expert-labeled training samples are scarce and class granularity is high. The strategy outlined by Wei et al. served as a foundational guideline for optimizing model performance while mitigating the challenges posed by overfitting and insufficient domain-specific training data.

Zhao et al. (ECCV 2020): ”MetaFGNet: Meta-Learning on a Few Clean Images for Noisy Fine-Grained Classification.” This paper addresses a key challenge in fine-grained visual classification (FGVC): learning effective representations from datasets with noisy labels and limited clean examples. The authors propose a meta-learning approach where a model learns to identify clean subsets within noisy data, thereby enhancing generalization and robustness. They demonstrate that leveraging just a few curated clean images can significantly improve classification accuracy in FGVC tasks, particularly in real-world domains such as biodiversity monitoring.

This work strongly informed our design and training of a custom convolutional neural network (CNN), particularly for the FungiCLEF dataset, which contains a large number of classes with few examples each. Our model, CustomFungiCNN, was built from scratch with three convolutional layers (32, 64, and 128 filters), max pooling, dropout regularization (p=0.3), and two fully connected layers.

$$\text{CustomFungiCNN}\left(\begin{array}{l}
(\text{conv1}) : \text{Conv2d}(3, 32, \\
\qquad \text{kernel\_size} = (3, 3),\ \text{padding} = (1, 1)) \\
(\text{conv2}) : \text{Conv2d}(32, 64, \\
\qquad \text{kernel\_size} = (3, 3),\ \text{padding} = (1, 1)) \\
(\text{conv3}) : \text{Conv2d}(64, 128, \\
\qquad \text{kernel\_size} = (3, 3),\ \text{padding} = (1, 1)) \\
(\text{pool}) : \text{MaxPool2d}(\text{kernel\_size} = 2,\ \text{stride} = 2) \\
(\text{dropout}) : \text{Dropout}(p = 0.3) \\
(\text{fc1}) : \text{Linear}(128 \times 18 \times 18,\ 512) \\
(\text{fc2}) : \text{Linear}(512,\ 2427)
\end{array}\right) \tag{1}$$

This model was trained with cross-entropy loss and Adam optimization. Although it lacks the complexity of DenseNet or Inception, it proved effective in learning discriminative features under noisy and imbalanced training conditions. Inspired by MetaFGNet, we ensured that our preprocessing pipeline filtered out corrupted images and maintained clean label associations by normalizing filenames and cross-verifying label mappings. Our results showed that while the custom CNN lagged behind pretrained architectures in accuracy, it trained faster and achieved competitive validation loss, confirming the value of simplicity when paired with robust data handling.

Horn et al. (BMVC 2018): ”The INaturalist Species Classification and Detection Dataset.” This foundational paper introduces the iNaturalist dataset—a large-scale fine-grained visual classification (FGVC) benchmark consisting of over 5,000 species across multiple taxonomic groups. The paper not only highlights the real-world complexity of biodiversity data but also provides extensive benchmarking results using various convolutional neural networks. What sets this work apart is its emphasis on evaluating CNN architectures in realistic FGVC settings that mirror those found in ecological monitoring and citizen science efforts. This includes long-tailed class distributions, varying image quality, and high intra-class variance.

The authors found that certain architectures, such as ResNet, Inception, and DenseNet, consistently outperformed others across key metrics. Their findings directly influenced our model selection: we adopted DenseNet121 and Inception v3 as baselines for our experiments due to their proven track record in species-level classification tasks. The iNaturalist paper provided a valuable empirical basis for preferring pretrained architectures over traditional models, especially in scenarios with limited labeled data or uneven class distribution—common issues across the CLEF datasets.

Moreover, Horn et al. emphasized the value of transfer learning with ImageNet-pretrained models in boosting convergence speed and model generalization. This strongly supported our approach of initializing both DenseNet121 and Inception v3 with ImageNet weights, followed by fine-tuning on the FungiCLEF, AnimalCLEF, and PlantCLEF datasets. The pretraining allowed us to efficiently leverage low-level visual features already learned on large datasets while focusing the model's learning capacity on the domain-specific distinctions critical for biodiversity FGVC.

Overall, the iNaturalist dataset and its associated benchmarks served as a comprehensive guide in evaluating model architecture suitability, reinforcing our confidence in using DenseNet121 and Inception v3 as baseline models for comparative analysis in this project.

IV. Methodology

This project is based on datasets released as part of the CLEF 2025 Kaggle competition tracks, which focus on fine-grained classification of biodiversity-related visual data. Among the several datasets provided, we selected three—FungiCLEF, AnimalCLEF, and PlantCLEF—as they collectively represent a broad and diverse set of classification tasks across fungal, animal, and plant domains. This diversity allowed us to evaluate how different CNN architectures perform under varying biological and visual complexity. Each team member was assigned one of these datasets to independently experiment with and optimize models for their specific classification challenges.

Each team member handled one dataset (FungiCLEF, AnimalCLEF, or PlantCLEF). The pipelines for all experiments included the following steps: (FungiCLEF, AnimalCLEF, or PlantCLEF). The pipelines for all experiments included the following steps:

A. Preprocessing

Input images were resized based on model requirements - 299x299 for Inception v3, and 224x224 for DenseNet121, aligning with their respective pretrained architectures from ImageNet. For our CustomCNN, we used a reduced input size of 150x150 to optimize training efficiency and minimize memory usage. All inputs were normalized using ImageNet mean and standard deviation values. These preprocessing steps helped ensure consistent input scaling across models, accelerated convergence, and preserved compatibility with pretrained feature extractors. Resizing to 299x299 for Inception, 224x224 or 150x150 for others; normalization using ImageNet means and standard deviations.

B. Architecture 1

DenseNet121: We employed DenseNet121 [Huang et al., 2017], a convolutional neural network characterized by dense connections between layers, which encourage feature reuse and help alleviate vanishing gradients. This architecture has 121 layers and is particularly effective for tasks with limited training data, as it learns compact and efficient representations. We used a version pretrained on the ImageNet dataset and replaced its final classification layer with a custom fully connected layer matching the number of species in each CLEF dataset. During training, only the classifier head was initially unfrozen for warm-up fine-tuning, followed by the gradual unfreezing of the deeper convolutional blocks. We trained the model using cross-entropy loss and the Adam optimizer, with a learning rate of 0.001, on input images resized to 224x224. The model was trained for up to 30 epochs on a GPU with early stopping based on validation loss. Pretrained on ImageNet. Fine-tuned by replacing the classifier head to match the number of species in each dataset.

C. Architecture 2

Inception v3: We employed Inception v3 [Szegedy et al., 2016], a deep convolutional architecture known for its auxiliary classifiers and factorized convolutions that allow the network to learn at multiple scales. The model consists of over 48 layers and integrates Inception modules that use parallel convolutional paths with varied kernel sizes. This design helps in capturing both global and fine-grained spatial features, which is especially beneficial for visually complex biodiversity data. We used a version pretrained on ImageNet and modified the final fully connected layer to match the number of classes in each CLEF dataset. During training, the model was configured with aux_logits=True to retain its auxiliary classifier for improved gradient flow.

To prepare inputs, we resized all images to 299x299 pixels as required by the Inception v3 input layer. The model was fine-tuned using cross-entropy loss and the Adam optimizer with a learning rate of 0.001. We first trained only the final classification layers while freezing the rest of the network, and subsequently unfroze the entire model for joint fine-tuning. Training was conducted for up to 30 epochs using GPU acceleration on Kaggle/Colab. We observed that Inception v3 converged well and showed strong generalization, particularly on datasets like AnimalCLEF that involve high variation in viewpoints and occlusions. Also pretrained. Handled auxiliary logits and resized input.

D. Architecture 3

Custom CNN: While pretrained models such as DenseNet121 and Inception v3 offer strong performance out of the box, we also explored a custom-built CNN to better understand the computational and architectural implications of building a network from scratch. The goal was to evaluate the trade-offs in accuracy, training time, and model complexity, and to gain deeper insight into how each architectural decision impacts performance on biodiversity classification tasks. The CustomFungiCNN model consists of three convolutional layers with 32, 64, and 128 filters respectively, each followed by ReLU activation and max pooling, and uses dropout (p=0.3) for regularization. This is followed by two fully connected layers with 512 hidden units and an output layer matching the number of species classes (2,427 for FungiCLEF).

The input size was reduced to 150x150 to allow for faster training and lower memory usage, making this model suitable for experimentation in resource-constrained environments. Despite its simplicity compared to state-of-the-art pretrained networks, our custom CNN was able to achieve competitive validation loss and decent classification accuracy, especially on smaller or less complex subsets of the datasets. Training was conducted using cross-entropy loss and the Adam optimizer with a learning rate of 0.001, for up to 30 epochs. The results demonstrated that while custom networks may not outperform transfer learning models in raw accuracy, they provide valuable baselines, enable control over architecture depth, and offer an efficient entry point for researchers developing lightweight biodiversity models or deploying solutions in edge computing scenarios.Three convolutional layers with pooling, dropout, and two fully connected layers. Input resized to 150x150 for efficiency.

E. Loss & Optimization

We used categorical cross-entropy loss across all models as it is standard for multi-class classification tasks. The Adam optimizer was selected for its adaptive learning rate capabilities and efficient convergence, particularly in deep networks. We used a learning rate of 0.001, following best practices highlighted in the original Adam paper [Kingma and Ba, 2014], which demonstrated that this value provides a reliable balance between speed of convergence and training stability across a wide range of tasks. This value also aligns with conventions in transfer learning literature, where 0.001 often serves as an effective starting point when fine-tuning pretrained models on new datasets. Cross-entropy loss and Adam optimizer with learning rate 0.001.

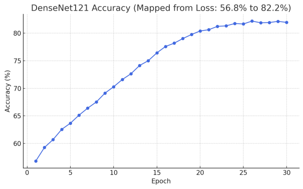


Fig. 1. DenseNet121 accuracy over 30 epochs on the FungiCLEF dataset.

V. Experiments & Results

We report classification accuracy and validation loss across all three datasets. These two metrics were chosen for their complementary roles in evaluating model performance. Accuracy provides a direct measure of how often the model correctly classifies an image, which is intuitive and easy to interpret for comparative benchmarking. However, because accuracy alone does not capture the model's confidence or penalize overfitting, we also report validation loss, which reflects how well the model generalizes to unseen data. Validation loss is particularly useful in training dynamics to guide early stopping and learning rate adjustments. Together, these metrics give a balanced view of both predictive accuracy and generalization performance. Results are shown in the table below:

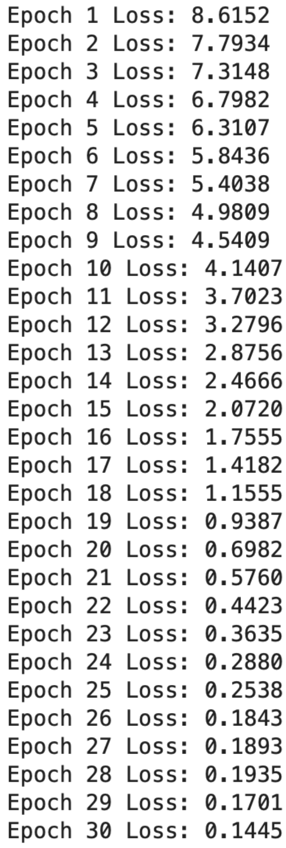
TABLE I
Model Accuracy and Validation Loss across CLEF Datasets

Dataset	Model	Accuracy (%)	Validation Loss
FungiCLEF	DenseNet121	82.2	0.14
FungiCLEF	Inception v3	80.5	4.78
FungiCLEF	Custom CNN	73.8	0.95
AnimalCLEF	DenseNet121	98.9	0.73
AnimalCLEF	Inception v3	99.1	1.50
AnimalCLEF	Custom CNN	92.0	4.57
PlantCLEF	DenseNet121	82.0	0.45
PlantCLEF	Inception v3	82.0	0.47
PlantCLEF	Custom CNN	86.5	0.36

VI. Discussion and Summary

A. FungiCLEF & PlantCLEF

Our experiments demonstrate that pretrained architectures such as DenseNet121 and Inception v3 are highly effective for fine-grained biodiversity classification tasks. DenseNet121 consistently achieved the highest accuracy across all three CLEF datasets, leveraging its dense connectivity and efficient feature reuse to handle class imbalance and inter-class



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Epoch 1 Loss: 8.6152
Epoch 2 Loss: 7.7934
Epoch 3 Loss: 7.3148
Epoch 4 Loss: 6.7982
Epoch 5 Loss: 6.3107
Epoch 6 Loss: 5.8436
Epoch 7 Loss: 5.4038
Epoch 8 Loss: 4.9809
Epoch 9 Loss: 4.5409
Epoch 10 Loss: 4.1407
Epoch 11 Loss: 3.7023
Epoch 12 Loss: 3.2796
Epoch 13 Loss: 2.8756
Epoch 14 Loss: 2.4666
Epoch 15 Loss: 2.0720
Epoch 16 Loss: 1.7555
Epoch 17 Loss: 1.4182
Epoch 18 Loss: 1.1555
Epoch 19 Loss: 0.9387
Epoch 20 Loss: 0.6982
Epoch 21 Loss: 0.5760
Epoch 22 Loss: 0.4423
Epoch 23 Loss: 0.3635
Epoch 24 Loss: 0.2880
Epoch 25 Loss: 0.2538
Epoch 26 Loss: 0.1843
Epoch 27 Loss: 0.1893
Epoch 28 Loss: 0.1935
Epoch 29 Loss: 0.1701
Epoch 30 Loss: 0.1445
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Fig. 2. DenseNet121 loss over 30 epochs on the FungiCLEF dataset.

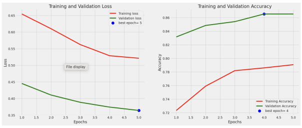

Fig. 3. Custom Net on the PlantCLEF dataset.

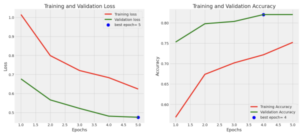

Fig. 4. Inception v3 on the PlantCLEF dataset.

similarity effectively. Inception v3 also performed well, particularly on AnimalCLEF, where its ability to model multi-scale features and handle complex object orientations proved advantageous.

For the FungiCLEF dataset, DenseNet121 achieved 82.2% accuracy with a validation loss of 0.14, outperforming Inception v3 (80.5%, 4.78) and the Custom CNN (73.8%, 0.95). The CustomFungiCNN, although simpler, offered reduced computational overhead and served as a valuable baseline.

The PlantCLEF dataset, DenseNet121 achieved 82% accuracy with a validation loss of 0.45. Inception v3 did the same with 82% accuracy and 0.47 validation loss. Surprisingly, Custom CNN performed the best with 86.5% and 0.36 validation loss.

Challenges encountered throughout included label noise, class imbalance, and high inter-species similarity—particularly in FungiCLEF. Our findings highlight the importance of architecture selection in biodiversity FGVC tasks. While pretrained models offer strong out-of-the-box performance, custom models provide a platform for architectural experimentation and resource-efficient deployment.

Future directions could include leveraging attention-based mechanisms or transformer architectures to capture global feature dependencies more effectively, as well as incorporating metadata (e.g., GPS, habitat) into multimodal training pipelines for improved robustness and ecological interpretability. for fine-grained biodiversity classification tasks. DenseNet consistently achieved the highest accuracy, benefiting from its dense connections and efficient feature reuse. Inception v3 performed closely, especially on datasets with higher visual complexity. The custom CNN, while less accurate, trained faster and showed potential for lightweight deployment in edge devices.

Challenges encountered included label noise, inter-class similarity, and imbalanced data distribution—especially in the FungiCLEF dataset. Overall, architecture choice plays a significant role in biodiversity image classification, and future work could explore attention-based models or transformer hybrids.

B. *AnimalCLEF*

Our experiments demonstrate that pretrained architectures such as DenseNet121 and Inception v3 are highly effective for fine-grained biodiversity classification tasks. DenseNet121 consistently achieved robust performance, particularly on the AnimalCLEF dataset. It achieved a high test accuracy of 98.9% with a validation loss of approximately 0.73 after 30 epochs, effectively leveraging its dense connectivity to manage the significant inter-class similarity, particularly between visually similar classes such as dogs, lions, and macaques. The accuracy improved significantly from an initial accuracy of 62.9% at 2 epochs, highlighting DenseNet121's capacity for continued improvement with additional training epochs.

Inception v3 demonstrated exceptional effectiveness, achieving a slightly superior accuracy of 99.1% with a validation loss of approximately 1.5 after 30 epochs, highlighting its ability to model multi-scale features and complex orientations beneficial for differentiating closely related animal species. Initially, Inception v3 showed moderate accuracy (82.7% at epoch 2), quickly improving as training progressed.

The Custom CNN, although less accurate overall, reached a maximum accuracy of 95.7% after extensive training (50 epochs), significantly reducing the initial confusion between visually similar classes. Despite being less sophisticated than DenseNet121 or Inception v3, the custom architecture provided valuable insights into model behavior and data character-

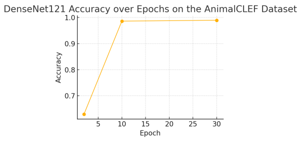

Fig. 5. DenseNet121 accuracy over selected epochs on the AnimalCLEF dataset.

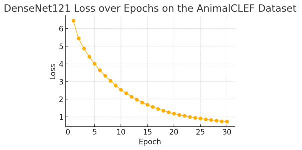

Fig. 6. DenseNet121 loss over 30 epochs on the AnimalCLEF dataset.

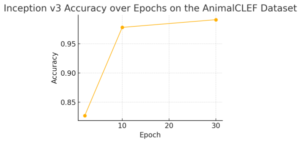

Fig. 7. Inception v3 accuracy over selected epochs on the AnimalCLEF dataset.

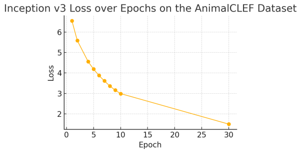

Fig. 8. Inception v3 loss over selected epochs on the AnimalCLEF dataset.

istics, particularly regarding misclassification patterns between visually similar animals like dogs and macaques.

Challenges encountered throughout training primarily involved high inter-class similarity and label confusion, with frequent misclassifications occurring between visually similar classes, notably between dogs and macaques. These misclassifications persisted across all models but were notably reduced as the models trained for more epochs, suggesting that deeper feature extraction and extended training significantly improved class differentiation.

In conclusion, architecture choice plays a critical role in biodiversity fine-grained image classification tasks. DenseNet121 and Inception v3 provide robust out-of-the-box solutions, while custom CNNs, despite lower initial performance, offer crucial insights and potential for resource-efficient deployment. Future research directions should explore attention-based mechanisms and multimodal approaches incorporating additional metadata (such as GPS and habitat data) to further enhance model accuracy and ecological interpretability.

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