Image Classification for African Wildlife Conservation Using DenseNet

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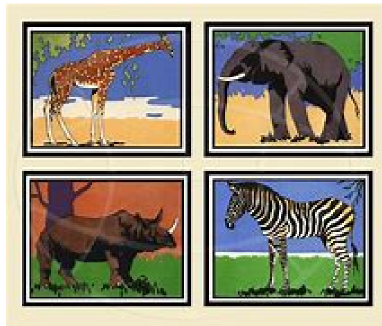

Figure 1: African Wildlife: A portrayal of the biodiversity of the African savannah.

ABSTRACT

Image classification is an essential component of computer vision with significant implications for biodiversity conservation. In this study, we focus on the classification of images from the African Wildlife dataset, comprising buffalo, elephant, rhino, and zebra categories. We employ DenseNet, known for its efficiency and performance in deep learning, to develop a robust classifier. This architecture's dense connectivity enhances gradient flow and feature reuse, which is crucial for learning distinctive features from high-variance wildlife images. Our methodology is a strategic training approach leveraging transfer learning from pre-trained DenseNet weights. We achieve a final test accuracy of approximately 68%, a promising result for applications in wildlife monitoring and conservation efforts. The model's deployment on Streamlit demonstrates its practicality for real-world applications.

Keywords: Image Classification, DenseNet, African wildlife, Computer Vision, Deep Learning.

1 INTRODUCTION

The decline in wildlife populations globally accentuates the need for innovative conservation strategies [4]. Image classification in computer vision offers a potent tool for biodiversity monitoring, enabling automated identification and tracking of animal species in their natural habitats. This paper explores the application of DenseNet [3] , a convolutional neural network (CNN), for classifying species in the African wildlife dataset [2]. DenseNet's architecture promotes feature reuse and mitigates the vanishing-gradient problem, making it uniquely suited for this task[6].

2 RELATED WORK

The intersection of deep learning and wildlife conservation has seen considerable interest. Previous works have applied various CNN architectures for species recognition [6], but the DenseNet model, with its efficient parameter utilization and improved feature propagation, offers avenues for exploration. We build upon the foundational work by Huang et al. [3].

3 DATASET AND PREPROCESSING

Our research employed the African Wildlife dataset, enriched with balanced classes including buffalo, elephant, rhino, and zebra. The dataset was methodically split into training and testing subsets using an 80-20 ratio, ensuring a comprehensive evaluation framework. We adopted rigorous preprocessing steps to bolster our model's performance: each image was resized to 64x64 pixels and normalized to a [0,1] scale to enhance the model's robustness and generalization capabilities. The code for the preprocessing was adapted from those published in the LearnPyTorch course material [1].These preprocessing steps were vital in preparing the dataset for effective deep learning model training.

4 METHODOLOGY

The crux of our methodology lay in leveraging DenseNet201, chosen for its efficient feature propagation and reduced parameter necessity compared to other architectures. We initialized our model with pre-trained weights obtained from torchvision, adapting it to our specific task while freezing the feature-extraction layers to conserve computational resources and focus training on the classification layers. Our training approach was meticulously structured, incorporating Adam optimizer with a learning rate of 0.001 and a CrossEntropy loss function, reflecting our objective to fine-tune the model for multi-class classification. We implemented batch processing and data loaders for efficient memory usage, enabling seamless model training and evaluation. As with the preprocessing step, we customised code from the course material[1]. Through this rigorous methodology, we aimed to optimize our model's performance on the African Wildlife classification task, underscoring our commitment to contributing meaningfully to the fields of computer vision and wildlife conservation.

5 EXPERIMENTAL RESULTS

We present the results of our model's performance, including training and validation accuracy over epochs, demonstrated through

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graphs for clarity. Figures showcasing training and validation losses help illustrate the model's convergence behavior.

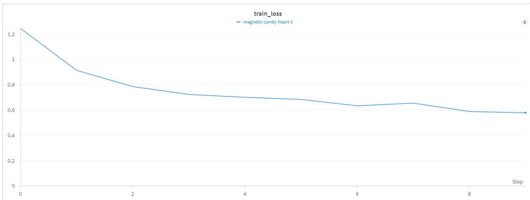

Figure 2: Training Loss: A graphical representation of the decrease in training loss over epochs, indicating the model's learning progress.

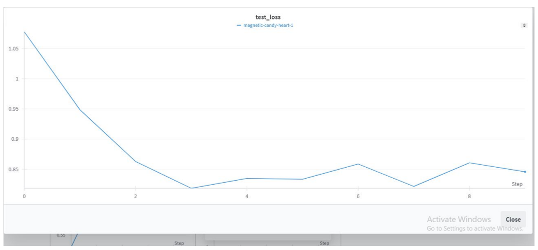

Figure 3: Validation Loss: Illustration of the model's performance on the validation set over time, highlighting generalization capabilities.

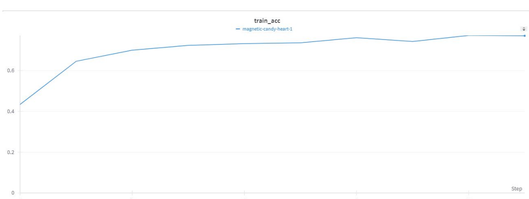

Figure 4: Training Accuracy: The increase in accuracy on the training set across epochs, reflecting the model's improving classification skills.

6 Discussion

Our analysis revealed a test accuracy of 68%, which, while indicative of substantial learning, suggests room for improvement. Notably, the deployed model on Streamlit demonstrated a higher success rate in correctly classifying images of the animals, particularly those that closely resembled the training images sourced from the internet. This phenomenon underscores a critical limitation of our current model: its potential overfitting to the training data, which could restrict its generalization capabilities to new, unseen images of other sources like smartphones.

Moreover, the consistent trends observed in loss and accuracy during the training phase, validated through comprehensive logging via Weights & Biases (wandb), attest to the methodological soundness of our approach. Yet, the variance between laboratory accuracy and field performance accentuates the necessity for a broader and more diversified dataset to enhance the model's applicability and resilience against overfitting.

7 Conclusion and Future Work

Our investigation underscores the viability of DenseNet for classifying images within the domain of wildlife conservation, marking a significant contribution to the ongoing efforts in biodiversity preservation. By leveraging DenseNet, we not only streamline the identification process for various animal species but also pave the way for more nuanced and expansive applications of machine learning in environmental science.

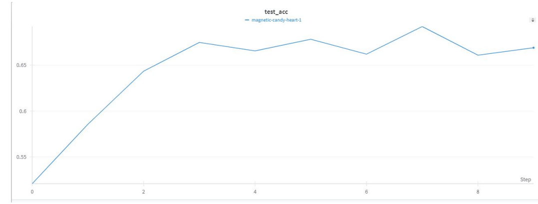

Figure 5: Validation Accuracy: Trends in accuracy on the validation set, showcasing the model's effectiveness in generalizing to new data.

In addition to developing the model, we have deployed a live application for real-world testing and user interaction. The deployed model can be accessed and evaluated through our Streamlit application, available at https://wildlifeclassify.streamlit.app/. This interactive platform [5] allows users to upload images and receive immediate classification results, demonstrating the practical applicability and efficiency of our wildlife classification model.

Looking ahead, we envision several avenues for future research. Expanding the scope of our dataset to include a wider array of animal species, coupled with the integration of location data and temporal analysis, could dramatically improve the model's utility and accuracy. Such enhancements would enable more precise tracking and monitoring of wildlife, facilitating targeted conservation strategies and interventions.

Moreover, addressing the limitations highlighted in this study, particularly regarding data diversity and model generalization, will be crucial. By adopting advanced data augmentation techniques and exploring more sophisticated training regimes, future iterations of our work could achieve greater robustness and applicability across a variety of conservation scenarios. Ultimately, our ongoing research aims to harness the full potential of deep learning to foster a more sustainable and informed approach to wildlife conservation.

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