# IMAGE CLASSIFICATION: AFRICAN WILDLIFE

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Code: https://github.com/tsengee-s/animal-classification

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# 1. PROBLEM STATEMENT

A deep-learning model for animal detection can serve as a useful tool for nature reserves and national parks in Africa, to aid with continuous surveillance and the protection of wildlife.

The objective of this project is to develop an image classification model based on the following categories present in the training dataset: buffalo, cheetah, elephant, hyena, rhino, and zebra.

It is especially significant to able to correctly identify endangered animals, such as rhinos, as they are frequently targeted by poachers.

# 2. ASSUMPTIONS & HYPOTHESES

Data Sources:

- Kaggle: cheetahs and hyenas
- Kaggle: buffalo, elephants, rhinos and zebras
- The data contains 1000 different images of each animal (category)

Assumptions:

- The dataset is representative and sufficiently diverse with variations within each category
- The images in the dataset are of good quality, properly labeled, and contain the necessary information for accurate classification

Hypotheses:

- Convolutional Neural Networks (CNNs) will be effective for extracting relevant features from the images and achieving high classification accuracy
- Data augmentation techniques, such as random translations and flipping, will help improve the model's ability to generalize and handle variations in the test data
- Zebras would probably be the easiest to classify since they have a very distinct look

# 3. EXPLORATORY DATA ANALYSIS

The cheetah and hyena images were originally in separate train and validation folders, but I re-merged them so that the data can be split into train, validation and test sets along with the other categories.

I browsed through the data to check the quality of the images and found some anomalies within the "buffalo" folder. The first picture below shows what an African Buffalo actually looks like (good quality), and the following two are examples of images found in the data that are clearly not of the same species.

*Figure 1*

*Figure 2*

*Figure 3 (wildebeest)*

# EDA (continued)

Let's visualize some sample images from the other categories to gain insights into the nature of the dataset:





The dataset contains images of varying dimensions, such as (400, 400), (400, 300), (400, 225), etc.

- ➢ everything needs to be resized

After the anomalies have been manually removed, the buffalo folder contains 832 images

- ➢ the dataset now has a slight class imbalance (all other categories have 1000 images)

# 4. FEATURE ENGINEERING & TRANSFORMATIONS

Preprocessing steps:

- Oversampling
  - Randomly duplicate existing samples for the imbalanced category (buffalo) to match the number of samples (1000) in the majority classes
- Resize all images to a consistent size to ensure compatibility with the chosen model architecture: target_size = (200, 200)
- Apply data augmentation techniques, such as shear transformations, zooming and flipping, to increase the diversity of the training dataset and improve the model's ability to generalize

Split data into train, validation and test sets using the ratio: 0.8, 0.1, 0.1

- Use the "ImageDataGenerator()" class from keras.processing.image to build out instances for "train_datagen" and "validation_datagen"
- Then build the training, validation and test sets by using the method ".flow_from_directory()"

# 5. PROPOSED APPROACHES

Convolutional Neural Networks (CNNs)

- ➢ CNNs are the most widely used approach for image classification tasks, including animal classification

Transfer Learning

- ➢ Transfer learning can be particularly useful for relatively small datasets
- ➢ Can take advantage of pre-trained models trained on large-scale image datasets like ImageNet

Ensemble Learning

- ➢ Can combine multiple models to make predictions

Check for overfitting/underfitting with:

- Training and Validation Loss/Accuracy
    - For instance, if the training loss continues to decrease while the validation loss starts to increase or remains high, it can indicate overfitting
- Evaluation Metrics, such as precision, recall, or F1 score

**Chosen Model: CNN**

# 6. PROPOSED SOLUTION

Build a CNN model using the Keras library:

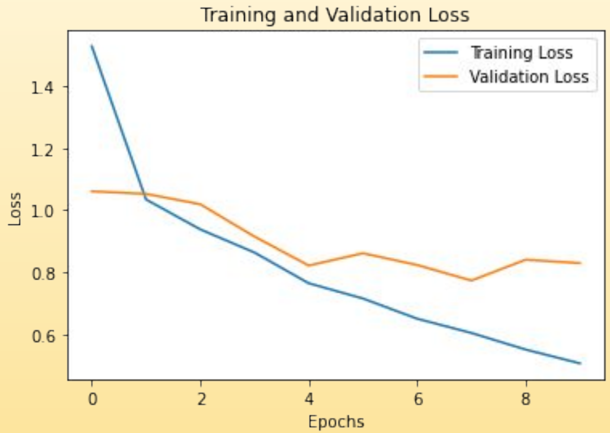
- With a sequence of convolutional layers with ReLU activation, followed by max pooling layers to reduce the spatial dimensions
- Flatten final feature maps and pass through fully connected (dense) layers with ReLU activation
- Softmax activation for the last dense layer to output the predicted probabilities for each class
- Add more layers as needed to improve model performance
- Compile with the Adam optimizer, categorical cross-entropy loss, and accuracy as the evaluation metric

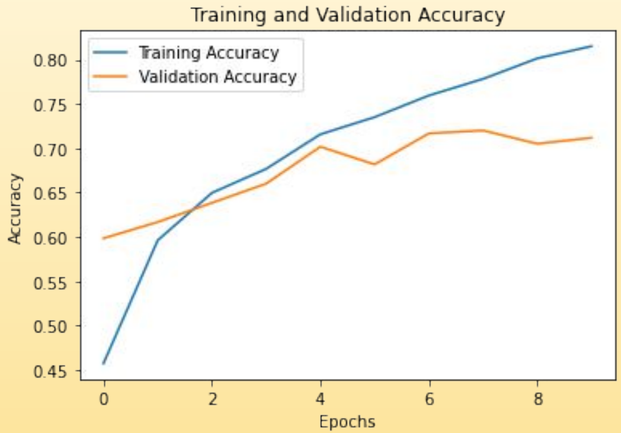
Additionally,

➢ Monitor training and validation loss/accuracy curves to ensure the model is not underfitting or overfitting
  - Add a dropout layer to help prevent overfitting

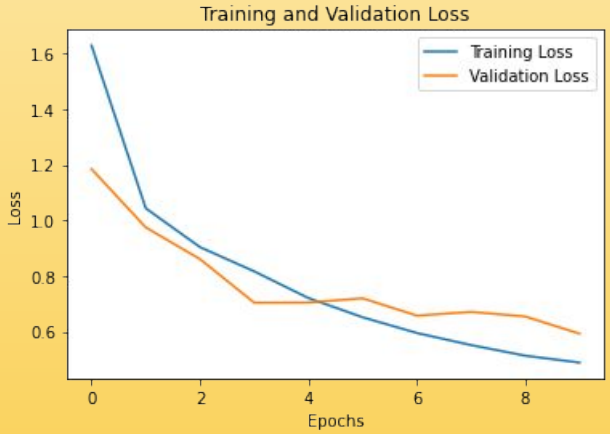
➢ Experiment with different number of epochs

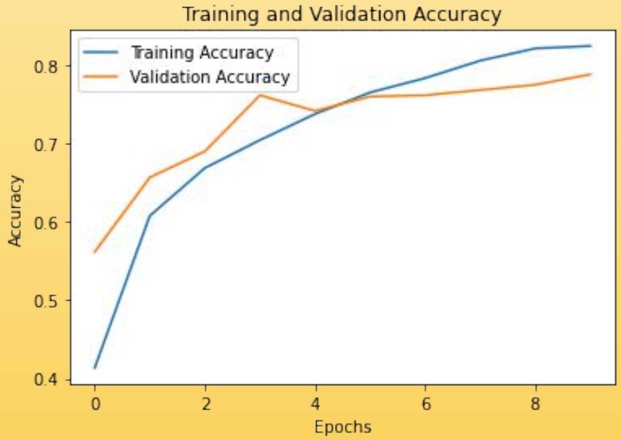
## Before adding dropout to the baseline model:




## After adding dropout (regularization):



# 7. RESULTS & LEARNINGS

- Adding dropout, and more convolutional and pooling layers helped improve overall model performance
- As hypothesized, zebras were indeed the easiest to correctly classify compared to the other animals
- In the final model, the precision for class 4 (cheetah) is 0.87 and recall is 0.92
  - This is an important category to be able to classify fairly well, since cheetahs are the the most endangered big cat in the world, with only around 7000 of them remaining in the wild
- The classification metrics for rhinos and elephants are not bad, but could use some improvement in the future
- Both the baseline and final models were unable to adequately classify the images of hyenas in the test set

| | Baseline | Final |
|---|---|---|
| Training Accuracy | 0.824 | 0.897 |
| Validation Accuracy | 0.788 | 0.880 |
| Overall Test Accuracy | 0.672 | 0.735 |

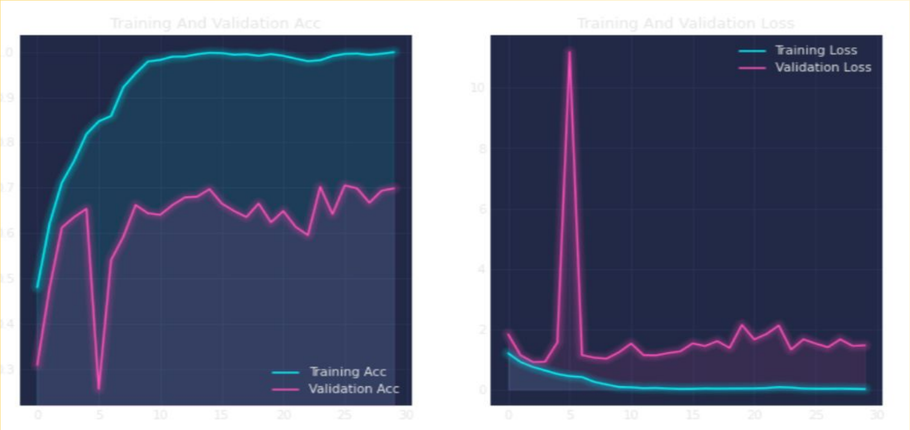
| Test Accuracy Breakdown: | Baseline | Final |
|---|---|---|
| Category 0 "buffalo" | 0.60 | 0.61 |
| Category 1 "elephant" | 0.57 | 0.78 |
| Category 2 "rhino" | 0.52 | 0.76 |
| Category 3 "zebra" | 0.98 | 1.00 |
| Category 4 "cheetah" | 0.91 | 0.92 |
| Category 5 "hyena" | 0.45 | 0.34 |

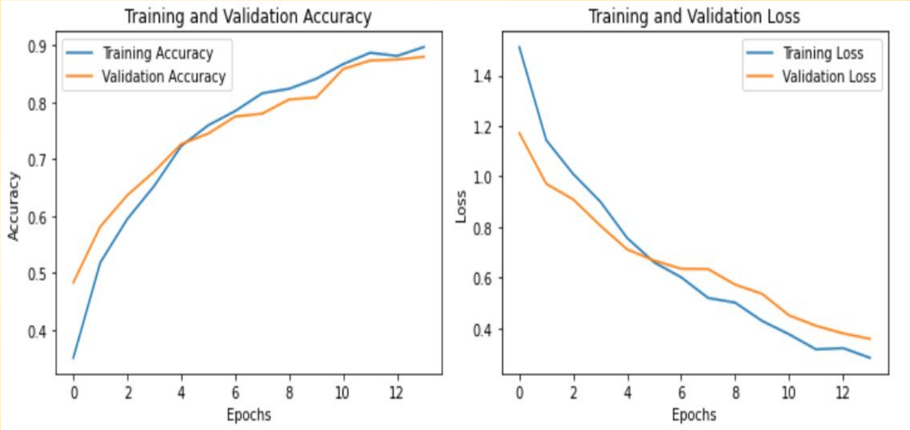
Classification Report (final model)

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| 0 (buffalo) | 0.85 | 0.61 | 0.71 | 100 |
| 1 (elephant) | 0.59 | 0.78 | 0.67 | 100 |
| 2 (rhino) | 0.66 | 0.76 | 0.71 | 100 |
| 3 (zebra) | 0.74 | 1.00 | 0.85 | 100 |
| 4 (cheetah) | 0.87 | 0.92 | 0.89 | 100 |
| 5 (hyena) | 0.87 | 0.34 | 0.49 | 100 |
| | | | | |
| accuracy | | | 0.73 | 600 |
| macro avg | 0.76 | 0.73 | 0.72 | 600 |
| weighted avg | 0.76 | 0.73 | 0.72 | 600 |

There is an existing image classification notebook on Kaggle that also used the dataset containing buffalo, elephant, rhino and zebra images (no cheetah or hyena), but the model performance was not as good.

We can see from the comparison below that there was evidence of overfitting in the Kaggle model (on the left).




The Kaggle model was run for 30 epochs (too many), resulting in training accuracy of 0.9993 and validation accuracy of 0.6983. And, it was not tested on unseen data. Although the train accuracy of this model is higher than mine (0.897), I highly doubt that it would have generalized well to test data due to overfitting issues.

Reference: [https://www.kaggle.com/code/jiaowoguanren/animal-classification-tensorflow](https://www.kaggle.com/code/jiaowoguanren/animal-classification-tensorflow)

# 8. FUTURE WORK

- Train the model with larger and more diverse datasets
  - with at least 5000 images per class
  - incorporate more animals/categories into the classification problem
- Augment the dataset with images of poachers
- Improve image quality (especially for hyenas)
- Experiment with other classification models and approaches, such as transfer learning and pre-trained models
- Combine the image classification model with location data (real-time)
  - Keep track of where all the different animals are within the nature reserve/park (especially the endangered and/or vulnerable ones)
  - Vision: be able to dispatch quick and efficient help to the exact location of an animal in trouble

# Thank You

Source: Animal Drawings