Image classification

Georg F.K. Höhn

Ironhack

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Overview

Introduction

Introduction

- Animals-10
  - dataset of 26179 images of animals in 10 classes
  - https://www.kaggle.com/datasets/alessiocorrado99/animals10/data

Aims

Build image classification models for the 10 classes in the dataset

1) "manually" setting up convolutional neural networks from scratch
2) transfer learning from pre-trained models
3) compare performance metrics

Data challenges

- category names encoded by folder structure
- no predetermined train-validation-test sets
- unbalanced category sizes

Animal	Count
butterfly	2112
cat	1668
chicken	3098
cow	1866
dog	4863
elephant	1446
horse	2623
sheep	1820
spider	4821
squirrel	1862

Formats

- some variation in formats
- some images with 4 channels (+ 1 with 1 channel)

Format	Channels	Count
jpeg	3	24209
jpg	1	1
	3	1917
	4	1
png	3	2
	4	49

Sizes

- lots of variation

width

- 283 distinct values
- most common:
  - `300`: 19942 times
  - `640`: 1765 times
  - `225`: 496 times

height

- 454 distinct values
- most common:
  - `300`: 4870 times
  - `225`: 4401 times
  - `200`: 3295 times

Summary of challenges

- normalising image formats and sizes
- applying train-validation-test-split
- translating category titles and create labeling

Methodological considerations

General project structure

- 3 distinct notebooks
  1. preprocessing
  2. convolutional neural networks
  3. transfer learning
- `auxiliary.py`: helper functions for notebooks 2 and 3
- export of (some) models to separate folder
- (later) export of training graphics to assets folder

Preprocessing notebook

Function for cataloguing

- extract and save metainformation in a table about all images in a folder
  - filepath
  - category
    - extracted from folder name, translate to English when reading the raw dataset
    - if *not* working on raw data, apply sklearn.preprocessing.LabelEncoder to generate column with numerical labels
  - format
  - width, height, mode, channels
  - table saved as DataFrame and exported as csv

- catalogue raw dataset for inspection
- reformat and save processed images in different folder
- catalogue normalised/cleaned dataset

Image reformatting

- use `Pillow` library
- apply to all images:
  - reformat to RGB (3 channels)
  - rescale to 224x224 pixel size
  - save as jpg with 90% compression

Regarding train-val-test-split

- applied to dataframes
  - filepaths later used to load images
- `train_df, intermed_df = train_test_split(clean_df, stratify=clean_df['category'], test_size=0.3, random_state=5)`
- `val_df, test_df = train_test_split(intermed_df, stratify=intermed_df['category'], test_size=1/3, random_state=5)`

Dealing with unbalanced dataset

- tested 3 versions
  - downsampling: to size of smallest category (1012)
  - upsampling: to size of largest category (3404)
  - “mid”-sampling: to mean category size (1832)
- eventually used mid-sampled training set for all remaining model training, best balance of size and doubling
- aside: tried running best performing model with upsampled dataset $\Rightarrow$ first ever kernel crash

Relevant auxiliary function

`sample_to_n(df,n)`

- use `sklearn.utils.resample` to sample a dataframe to desired size
- only applied to training dataframe, val and test remain unmodified (and unbalanced)

Feeding data to the model

- data are fed to models as `tensorflow.Datasets`
  - shuffling and augmentation for training dataset(s), but not for validation or training
- augmentation helps ensuring upsampling does not lead to plain duplicates

Relevant auxiliary function

```
mk_tf_dataset(df, shuffle=True, augment=False,
preprocess_fn=None)
```

- make a tf.Dataset from a dataframe
  - loads images based on the filepath
  - applies preprocessing, augmentation, shuffling as desired
- augmentations using `tf.image`, e.g. zooming, shifting, flipping, brightness, saturation etc.

Some more auxiliary functions

- function for model evaluation
  - print results
  - logging core data to csv
- function for training and evaluating
  - more robust reuse
  - simpler internal changes
  - but: painful to deploy midway (and changes to interface also difficult)
- plot accuracy/loss over training epochs
  - implemented rather late
  - useful for identifying where training stops yielding results

CNNs from scratch

- variation in
  - 3-5 convolutional layers
  - pool: one pooling layer at (3,3) instead of (2,2)
  - decreasing size of convolutional layers
  - increasing size of convolutional layers (`inv`)
  - more than one ReLU dense layer
- mostly trained with mid-sampled training set (exceptions: `up`)

Insights

- 4 and 5 convolutional layers performed best
- "inverted" order (i.e. increasing size of conv layers) performed best
- slightly larger dense layer led to improvement in some cases

Excerpt of results

model_id	lrate	epochs	acc_train	accuracy
conv4invto128-dense256-up	0.00050	80	0.87568	0.71963
conv5invto128-dense1	0.00050	80	0.82495	0.71390
conv4invto128-dense1	0.00050	80	0.82991	0.71085
conv4invto128-dense256	0.00050	80	0.83657	0.70283
conv5invto128-dense256-up	0.00020	80	0.86639	0.70092
conv4invto128-pool-dense256-up	0.00050	80	0.83117	0.68373
conv4lesspoll-dense1	0.00050	35	0.74039	0.66883
conv3-dense1	0.00050	35	0.70912	0.66348
conv3invert-dense1	0.00050	35	0.71676	0.65050
conv4small-dense1	0.00070	30	0.68788	0.64629
conv4lesspoll-dense1	0.00050	80	0.67980	0.64591
conv4inv8to128-dense96	0.00010	80	0.72860	0.64553
conv5small-dense1	0.00070	30	0.67757	0.64286
conv4inv128-pool-dense256	0.00010	80	0.75704	0.63904
base-upsamp-augment+	0.00070	15	0.59175	0.56684
base-meansamp-augment+	0.00070	15	0.58133	0.54240
base-downsamp-augment+	0.00070	15	0.51018	0.52597

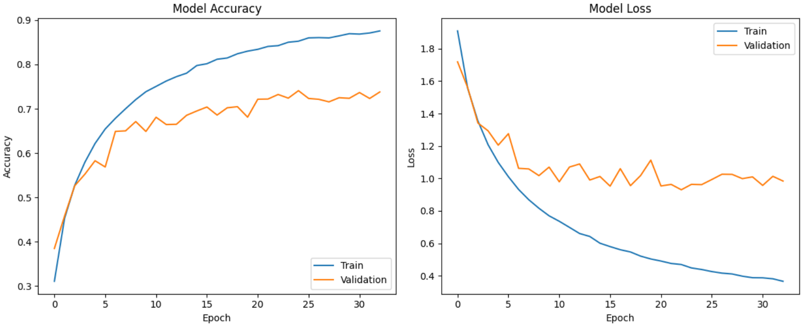
Strongest CNN

Layer Type	Output Shape	Param #
Conv2D	(None, 222, 222, 16)	448
MaxPooling2D	(None, 111, 111, 16)	0
Conv2D	(None, 109, 109, 32)	4,640
MaxPooling2D	(None, 54, 54, 32)	0
Conv2D	(None, 52, 52, 64)	18,496
MaxPooling2D	(None, 26, 26, 64)	0
Conv2D	(None, 24, 24, 128)	73,856
MaxPooling2D	(None, 12, 12, 128)	0
Flatten	(None, 18432)	0
Dense	(None, 256)	4,718,848
Dropout	(None, 256)	0
Dense	(None, 10)	2,570
Total params		14,456,580 (55.15 MB)
Trainable params		4,818,858 (18.38 MB)
Non-trainable params		0 (0.00 B)

Table 3: Model summary for ‘conv4invto128_dense256_upsamp‘

- upsampled training set

Training progression for `conv4invto128-dense256-upsamp`



Second-best performing CNN

Layer Type	Output Shape	Param #
Conv2D	(None, 222, 222, 8)	224
MaxPooling2D	(None, 111, 111, 8)	0
Conv2D	(None, 109, 109, 16)	1,168
MaxPooling2D	(None, 54, 54, 16)	0
Conv2D	(None, 52, 52, 32)	4,640
MaxPooling2D	(None, 26, 26, 32)	0
Conv2D	(None, 24, 24, 64)	18,496
MaxPooling2D	(None, 12, 12, 64)	0
Conv2D	(None, 10, 10, 128)	73,856
MaxPooling2D	(None, 5, 5, 128)	0
Flatten	(None, 3200)	0
Dense	(None, 128)	409,728
Dropout	(None, 128)	0
Dense	(None, 10)	1,290
Total params		1,528,212 (5.83 MB)
Trainable params		509,402 (1.94 MB)
Non-trainable params		0 (0.00 B)

Table 4: Model summary for ‘conv5invto128_dense1‘

Transfer learning

- all training on mid-sampled training set

Pre-trained models used

- MobileNet-V2
- ResNet-V2
- EfficientNetV2S

Insights

- adding dense layers provided no noticable benefit
- increasing dense layer neurons to 256 slightly improved results(?)
- slight benefits from fine-tuning, but diminishing returns (or different strategy)

Results overview

model_id	lrate	epochs	acc_train	accuracy
effnet2S-small-finetune	0.00001	35	0.98826	0.97670
effnet2S-small	0.00050	12	0.97413	0.97479
mobnet2-dense256-finetune	0.00001	30	0.96692	0.96562
mobnet2-dense256	0.00050	13	0.95770	0.96142
mobnet2-small-tune20	0.00010	15	0.96588	0.96028
resnet2-small-finetune	0.00001	30	0.99383	0.95913
mobnet2-small-tune20	0.00010	5	0.96043	0.95760
mobnet2-small-tune20	0.00001	5	0.95360	0.95684
mobnet2-dense256	0.00050	13	0.96141	0.95607
mobnet2-2dense	0.00050	15	0.94110	0.95493
mobnet2-small	0.00070	15	0.95628	0.95302
mobnet2-3dense	0.00050	15	0.91332	0.95187
resnet2-small-finetune	0.00010	30	0.98957	0.94958
resnet2-small	0.00070	15	0.95448	0.94576

Best performing transfer learning (and overall)

Layer Type	Output Shape	Param #
Functional	(None, 7, 7, 1280)	20,331,360
global_average_pooling2d	(None, 1280)	0
Dense	(None, 256)	327,936
Dense	(None, 10)	2,570
Total params	25,211,268 (96.17 MB)	
Trainable params	2,274,698 (8.68 MB)	
Non-trainable params	18,387,168 (70.14 MB)	

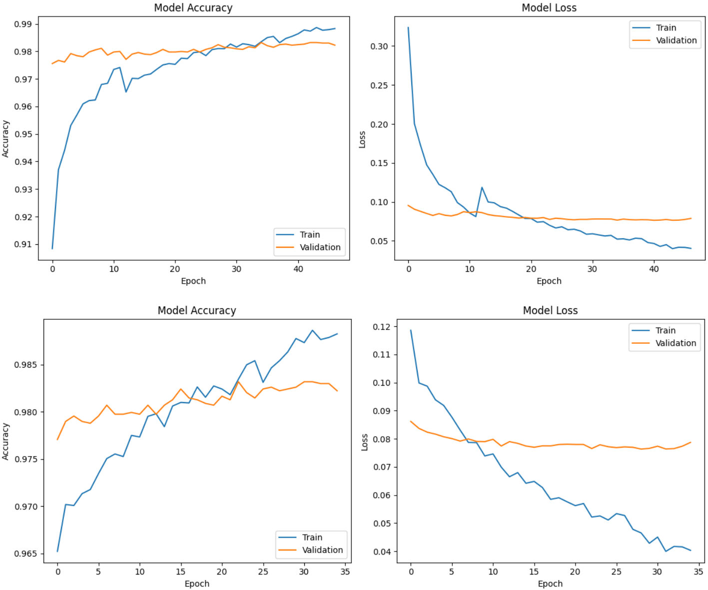
Table 5: Model summary for ‘effnet2s_small‘

Runner-up

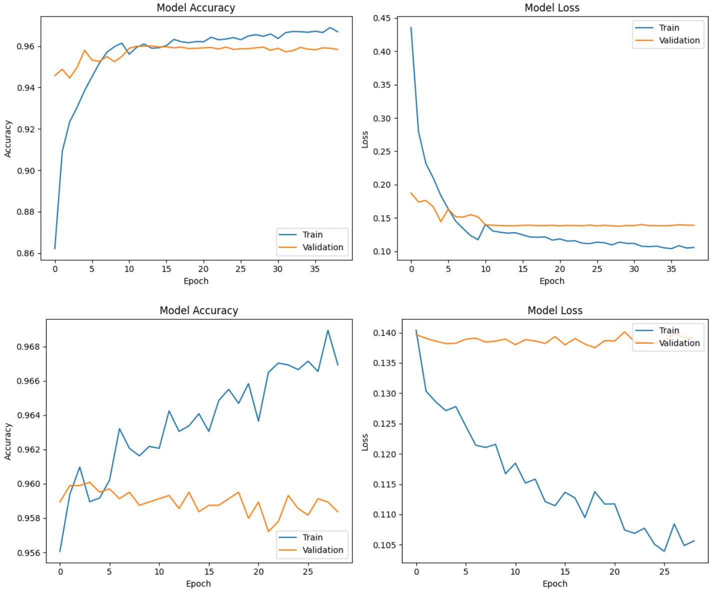
Layer Type	Output Shape	Param #
mobilenetv2_1.00_224	(None, 7, 7, 1280)	2,257,984
global_average_pooling2d	(None, 1280)	0
Dense	(None, 256)	327,936
Dense	(None, 10)	2,570
Total params		3,249,508 (12.40 MB)
Trainable params		330,506 (1.26 MB)
Non-trainable params		2,257,984 (8.61 MB)

Table 6: Model summary for ‘mobnet2_dense256‘

Training plots `effnet2S-small`



Training plots `mobnet2_dense256`



Trade-offs

effnet2S-small (EfficientNetV2S)

- accuracy: 0.9767 (after finetuning)
- size: 20,661,866 parameters (78.82 MB)
- training time: ca. 6min + 14min

mobnet2-dense256 (MobileNet-V2)

- accuracy: 0.96692 (after finetuning)
- size: 3,249,508 (12.40 MB)
- training time: 2min 14s + 6min 9s

Conclusion

Manual CNNs

- 4 and 5 convolutional layers performed best
- “inverted” order (increasing size of conv layers) performed best
- slightly larger dense layer led to improvement in some cases

Transfer Learning

- adding dense layers provided no noticable benefit
- increasing dense layer neurons to 256 slightly improved results(?)
- slight benefits from fine-tuning, but diminishing returns (or different strategy)

- use `sparse-categorical-crossentropy` loss function for label encoding and `sparse-categorical-crossentropy` for one-hot-encoding (check here)
- adding function definitions mid-project is time-consuming
  - same for modifications influencing the interfaces (changes to arguments or return values)
  - good to take decisions to outsource to functions (and separate file) early, otherwise it can be hard to get rid of dependencies/global variables etc.
- writing log to csv file is useful
  - clear plan of what exactly to log, too (see above)

Thanks for your attention!