thesis_main_v6

August 8, 2021

1 The main implementation of thesis project

2 Introduction

In this Python notesbook, we choose the following as baselines and evaluate their performances: - Supervised learning with simple convolutional network (training from scratch) - Supervised learning with MLP (training from scratch) - Supervised learning with ResNet50 - Supervised learning with VGG16 - Supervised learning with MobileNet

We then evaluate our self-supervised contrastive model, which uses InfoNCE, known as NT-Xent (Normalized Temperature-scaled Cross Entropy Loss) in SimCLR and used in other works like MoCo.

The goal of our texture classification model is to train an embedding space constrained by contrastive loss, our model consists of two image augmentation transformers, base encoder, a projection head, and a pure linear regressor with cross-entropy loss as the customised accuracy metric.

We evaluate our proposed model with: - Contrastive learning with simple convolutional network as encoder (training from scratch) - Contrastive learning with VGG16 as encoder - Contrastive learning with Vision Transformer (ViT) as encoder (training from scratch)

3 Importing libraries

[1]:
```
import tensorflow as tf
import tensorflow_addons as tfa
from tensorflow import keras

import numpy as np
import pandas as pd
import os
import sys
import random

import matplotlib.pyplot as plt

# enable GPU on macOS
#import os
#os.environ["KERAS_BACKEND"] = "plaidml.keras.backend"
```

```
#os.environ["RUNFILES_DIR"] = "/usr/local/anaconda3/share/plaidml"
#os.environ["PLAIDML_NATIVE_PATH"] = "/usr/local/anaconda3/lib/libplaidml.dylib"
#import keras
```

4 Setting local library path

Our modules lie in the directory *lib*, we add the path to the library searching path:

[2]:
```
import numpy as np
import pandas as pd
import os
import sys

#libpath = "lib"
#sys.path.append(libpath)
```

5 Configurations

[2]:
```
#image_size = (128, 128)
image_size = (64, 64) #faster for running on laptop

#dataset_root_orig = ""

n_image_channels = 3

#input image shape
image_shape = (*image_size, n_image_channels)


# sample batch size
batch_size = 128
#batch_size = 64


# how many epochs
n_epochs = 20

temperature = 0.2
#temperature = 0.5



#relatively slight augmentation
imgaug_params = {
                  "min_area": 0.75,
                  "brightness": 0.3,
```

```
                  "jitter": 0.1
                }

#relatively strong augmentation
#imgaug_params = {
#                   "min_area": 0.25,
#                   "brightness": 0.6,
#                   "jitter": 0.2
#                 }
```

6 Bootstrapping the dataset

6.1 Image augmentation model for dataset bootstrapping

[345]:
```
from tensorflow.keras.layers.experimental import preprocessing as␣
↪keras_preprocessing_layers


class CustomisedBootstrapImageAugmenter(keras.layers.Layer):
    def __init__(self,
                 target_size = (128, 128),
                 seed = 1121,
                 name = 'boostrap_imgaug_layer',
                 **kwargs):

        self.target_size = target_size
        self.seed = seed

        self.model = keras.Sequential([
              #keras_preprocessing_layers.Rescaling(1.0 / 255),
              #keras_preprocessing_layers.Normalization(),
              keras_preprocessing_layers.RandomFlip(
                                    "horizontal",
                                    seed = self.seed
                                ),
              keras_preprocessing_layers.RandomZoom(
                                    height_factor=0.3,
                                    width_factor=0.3,
                                    seed = self.seed
                                ),
              keras_preprocessing_layers.RandomRotation(
                                    0.5,
                                    seed = self.seed
                                ),
              keras_preprocessing_layers.RandomCrop(
                                    *self.target_size,
                                    seed = self.seed
```

```
                                    )

            ],
            name = "bootstrap_imgaug_model")

        super(CustomisedBootstrapImageAugmenter, self).__init__(name = name,␣
↪**kwargs)

    def get_config(self):
        config = super().get_config()

        config['target_size'] = self.target_size
        config['seed'] = self.seed
        config['model'] = self.model

        return config

    def call(self, images, training = True):
        if training:
            images = self.model(images)

        return images

    @classmethod
    def from_config(cls, config):
        return cls(**config)
```

7 The facilities of operating the original dataset

[19]:
```
import numpy as np
import pandas as pd
import os
import sys


TEXTURE_DS_IMAGE_SIZE = (512, 512)

def get_texture_subdirs():
    dataset_root = "datasets_orig"

    subdirs = [d.path for d in os.scandir(dataset_root)
                        if d.is_dir(follow_symlinks = False) and
                            not d.name.startswith(".") and
                            not d.name.endswith("_npy")]

    subdirs = [s.rsplit(r"/", 1)[1] for s in subdirs]
```

```
    return subdirs
```

[20]:
```
get_texture_subdirs()
```

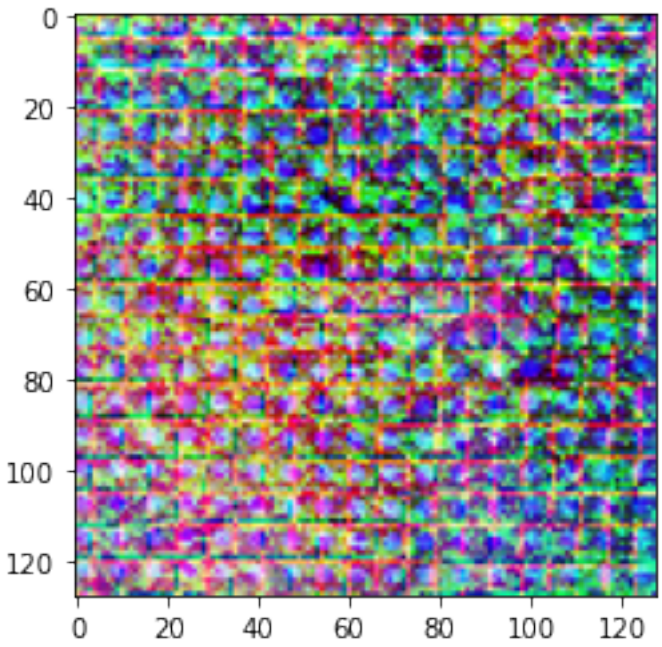
[20]:
```
['Normalised_Brodatz_Texture',
 'Multiband_Brodatz_Texture',
 'Colored_Brodatz_Texture']
```

[23]:
```
def load_texture_dataset_xy(*, image_size = TEXTURE_DS_IMAGE_SIZE,␣
↪dataset_name):

    assert dataset_name  is not None, "The dataset_name must be specified."

    #dataset_path = "datasets_orig" + os.path.sep + "Multiband_Brodatz_Texture"
    dataset_path = "datasets_orig" + os.path.sep + dataset_name

    assert os.path.exists(dataset_path), f"{dataset_path} does not exist."


    print()
    print(f"Loading dataset from path: {dataset_path} ...")
    print("image size: ", image_size)

    X = []
    y = []


    # Get the subdirs for given dataset path

    files = []

    suffixes = (".tif", ".gif", ".png", ".jpg")

    imgfiles = [d.path for d in os.scandir(dataset_path)
                    if d.is_file(follow_symlinks = False) and
                        not d.name.startswith(".") and
                        d.name.lower().endswith(suffixes) ]

    #print(imgfiles)

    for p in sorted(imgfiles):
        #print(p)


        # Loading images and pre-processing images
        img = keras.preprocessing.image.load_img( path = p,
```

```
                        grayscale = False,
                        color_mode='rgb',
                        target_size = image_size)

        # Converting images into numpy arraries.
        img = keras.preprocessing.image.img_to_array(
                        img = img,
                        data_format = "channels_last",
                        dtype = np.double)


        filename, file_extension = os.path.splitext(p)

        label = os.path.basename(filename)

        #print(label)

        X.append(img)
        y.append(label)

    print(f"Total {len(y)} images are loaded.")
    #print()

    X = np.array(X)
    y = np.array(y)
    #X = X.astype('float32')

    return X, y
```

[32]:
```
X, y = load_texture_dataset_xy(image_size = (128, 128),
                               dataset_name = "Multiband_Brodatz_Texture")

print()
print("num_of_samples: ", len(y))
print("shape: ", X.shape)

plt.imshow(np.uint8(X[0]))
plt.show()

del X, y
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (128, 128)
Total 154 images are loaded.

num_of_samples:  154
shape:  (154, 128, 128, 3)
```

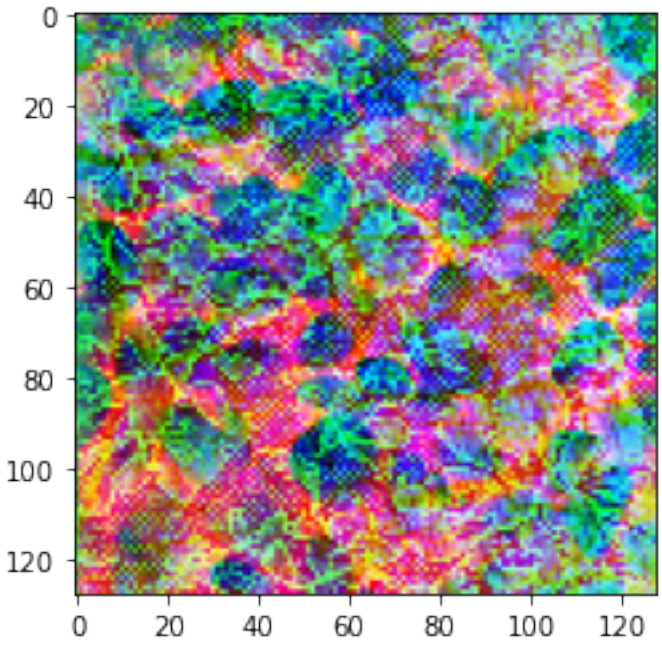


[25]:
```
def load_texture_dataset_as_dataframe(*, image_size = TEXTURE_DS_IMAGE_SIZE,␣
↪dataset_name):

    X, y = load_texture_dataset_xy(image_size = image_size, dataset_name =␣
↪dataset_name)

    data = {"X": list(X),
            "y": list(y)}

    df = pd.DataFrame(data)

    return df
```

[35]:
```
df = load_texture_dataset_as_dataframe(image_size = (128, 128),
                                       dataset_name = "Multiband_Brodatz_Texture")

print()
print("num_of_samples: ", len(df))

plt.imshow(np.uint8(df["X"][2]))
plt.show()

del df
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
```

```
image size:  (128, 128)
Total 154 images are loaded.

num_of_samples:  154
```



[31]:
```
def save_texture_dataset_as_numpy(*, image_size = TEXTURE_DS_IMAGE_SIZE,␣
↪dataset_name, save_prefix):

    X, y = load_texture_dataset_xy(image_size = image_size, dataset_name =␣
↪dataset_name)

    np.save(f"{save_prefix}_X.npy", X)
    np.save(f"{save_prefix}_y.npy", y)
```

7.1 Splitting the orignal dataset for training and testing regarding pixels

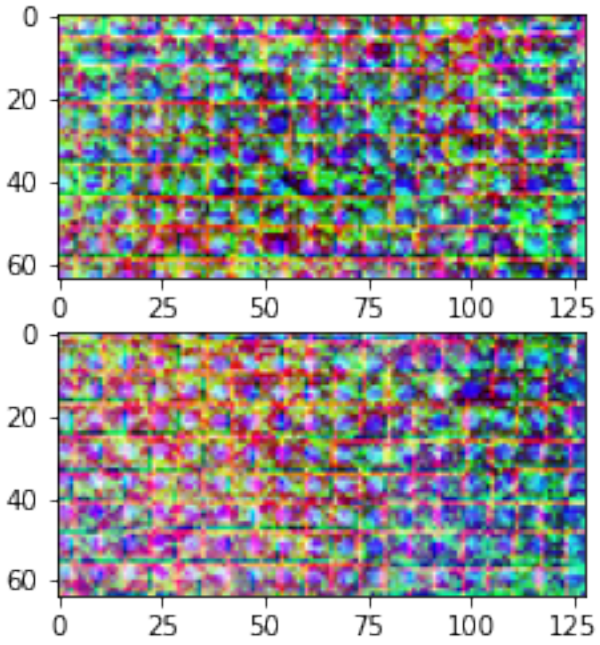
[6]:
```
import numpy as np
import pandas as pd
import os
import sys

#libpath = os.path.dirname(os.path.realpath(__file__)) + os.path.sep + ".." +␣
↪os.path.sep + "lib"
#libpath = os.path.dirname(os.path.realpath(__file__)) + os.path.sep + "."
#sys.path.append(libpath)
```

```
DS_DEFAULT_PIXEL_SPLIT_RATIO = 0.5

def split_dataset_by_pixel(X, y, split = DS_DEFAULT_PIXEL_SPLIT_RATIO):
    X_train = []
    y_train = []

    X_test = []
    y_test = []


    for Xi, yi in zip(X, y):
        Xi = np.array(Xi)
        #print(Xi.shape)
        #print(yi)

        height = Xi.shape[0]

        position = int(split * height)

        Xi_train = Xi[0:position, :, :]
        Xi_test = Xi[position:height, :, :]

        #print(Xi_train.shape)
        #print(Xi_test.shape)

        yi_train = yi
        yi_test = yi

        X_train.append(Xi_train)
        y_train.append(yi_train)

        X_test.append(Xi_test)
        y_test.append(yi_test)

    X_train = np.array(X_train)
    y_train = np.array(y_train)

    X_test = np.array(X_test)
    y_test = np.array(y_test)

    print()
    print("Splitting dataset into training and testing datasets ...")
    print(f"size of training dataset : {len(y_train)}")
    print(f"size of testing dataset : {len(y_test)}")
    print(f"training dataset shape: {X_train.shape}")
    print(f"testing dataset shape: {X_test.shape}")
```

```
    #print()

    return X_train, y_train, X_test, y_test
```

[43]:
```
X, y = load_texture_dataset_xy(image_size = (128, 128),
                               dataset_name = "Multiband_Brodatz_Texture")

X_train, y_train, X_test, y_test = split_dataset_by_pixel(X, y)

ax = plt.subplot(2, 1, 1)
plt.imshow(np.uint8(X_train[0]))

ax = plt.subplot(2, 1, 2)
plt.imshow(np.uint8(X_test[0]))

plt.show()

del X, y, X_train, y_train, X_test, y_test
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (128, 128)
Total 154 images are loaded.

Splitting dataset into training and testing datasets …
size of training dataset : 154
size of testing dataset : 154
training dataset shape: (154, 64, 128, 3)
testing dataset shape: (154, 64, 128, 3)
```



[44]:
```
def split_dataset_by_pixel_as_dataframe(X, y, split =␣
↪DS_DEFAULT_PIXEL_SPLIT_RATIO):

    X_train, y_train, X_test, y_test = split_dataset_by_pixel(X, y, split)

    data_train = {"X": list(X_train),
                  "y": list(y_train)}

    data_test = {"X": list(X_test),
                 "y": list(y_test)}

    df_train = pd.DataFrame(data_train)

    df_test = pd.DataFrame(data_test)

    #print("X_train.shape = ", np.array(X_train).shape)

    return df_train, df_test
```

[45]:
```
X, y = load_texture_dataset_xy(image_size = (128, 128),
                               dataset_name = "Multiband_Brodatz_Texture")

df_train, df_test = split_dataset_by_pixel_as_dataframe(X, y)

del X, y, df_train, df_test
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (128, 128)
Total 154 images are loaded.

Splitting dataset into training and testing datasets …
size of training dataset : 154
size of testing dataset : 154
training dataset shape: (154, 64, 128, 3)
testing dataset shape: (154, 64, 128, 3)
```

7.2 Boostrapping new dataset for training and testing

[46]:
```
import numpy as np
import pandas as pd
import os
import sys
import imageio

#libpath = os.path.dirname(os.path.realpath(__file__)) + os.path.sep + ".." +␣
 ↪os.path.sep + "lib"
#sys.path.append(libpath)


def create_dataset_from_xy( *,
                            X,
                            y,
                            dataset_path,
                            subdir,
                            imgaug,
                            n_images_per_class):

    print()
    print("dataset_path = ", dataset_path)
    print("subdir = ", subdir)
    print("n_images_per_class = ", n_images_per_class)

    for yi in y:
        #print(yi)
        yi_path = dataset_path + os.path.sep + subdir + os.path.sep + yi

        if not os.path.exists(yi_path):
            os.makedirs(yi_path)


    for i, (Xi, yi) in enumerate(zip(X, y)):
        yi_path = dataset_path + os.path.sep + subdir + os.path.sep + yi
```

```
        print(yi, end = ' ')
        Xi = np.expand_dims(Xi, axis = 0)
        for j in range(n_images_per_class):
            Xij = imgaug(Xi)
            Xij = Xij[0]
            Xij = np.array(Xij, dtype = np.uint8)
            Xij_name = yi_path + os.path.sep + f"{yi}_{j}.png"
            #print(Xij_name)
            imageio.imwrite(Xij_name, Xij)

    print()
```

[53]:
```
def create_dataset( *,
                   dataset_name = "Multiband_Brodatz_Texture",
                   dataset_root = "datasets_new",

                   output_size = (128, 128),

                   n_train_images_per_class = 200,
                   n_test_images_per_class = 50,
                   seed = 1921
                   ):

    dataset_path = dataset_root + os.path.sep +  dataset_name
    #output_shape = (*output_shape, n_channels)

    print("dataset_path = ", dataset_path)
    print("output_size = ", output_size)
    print("n_train_images_per_class = ", n_train_images_per_class)
    print("n_test_images_per_class = ", n_test_images_per_class)

    # loading size
    image_size = (512, 512)
    #n_image_channels = 3

    X, y = load_texture_dataset_xy(
                                    image_size = image_size,
                                    dataset_name = dataset_name
                                  )

    X_train, y_train, X_test, y_test = split_dataset_by_pixel(X, y)

    imgaug = CustomisedBootstrapImageAugmenter(
                                         target_size = output_size,
                                         seed = seed
                                         )
```

```
    if not os.path.exists(dataset_path):
        os.makedirs(dataset_path)

    if not os.path.exists(dataset_path + os.path.sep + "train"):
        os.makedirs(dataset_path + os.path.sep + "train")

    if not os.path.exists(dataset_path + os.path.sep + "test"):
        os.makedirs(dataset_path + os.path.sep + "test")

    create_dataset_from_xy( X = X_train,
                            y = y_train,
                            dataset_path = dataset_path,
                            subdir = "train",
                            imgaug = imgaug,
                            n_images_per_class = n_train_images_per_class)

    create_dataset_from_xy( X = X_test,
                            y = y_test,
                            dataset_path = dataset_path,
                            subdir = "test",
                            imgaug = imgaug,
                            n_images_per_class = n_test_images_per_class)


    print()
    print("Completed!")
    print()
```

[55]:
```
create_dataset(
                    dataset_name = "Multiband_Brodatz_Texture",
                    dataset_root = "datasets_new",
                    output_size = (128, 128),
                    n_train_images_per_class = 200,
                    n_test_images_per_class = 50,
                  )
```

```
dataset_path =  datasets_new_tmp/Multiband_Brodatz_Texture
output_size =  (128, 128)
n_train_images_per_class =  200
n_test_images_per_class =  50

Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (512, 512)
Total 154 images are loaded.

Splitting dataset into training and testing datasets …
size of training dataset : 154
size of testing dataset : 154
```

```
training dataset shape: (154, 256, 512, 3)
testing dataset shape: (154, 256, 512, 3)

dataset_path =  datasets_new_tmp/Multiband_Brodatz_Texture
subdir =  train
n_images_per_class =  200
Dz1 Dz10 Dz100 Dz101 Dz102 Dz103 Dz104 Dz105 Dz106 Dz107 Dz108 Dz109 Dz11 Dz110
Dz111 Dz112 Dz113 Dz114 Dz115 Dz116 Dz117 Dz118 Dz119 Dz12 Dz120 Dz121 Dz122
Dz123 Dz124 Dz125 Dz126 Dz127 Dz128 Dz129 Dz13 Dz130 Dz131 Dz132 Dz133 Dz134
Dz135 Dz136 Dz137 Dz138 Dz139 Dz14 Dz140 Dz141 Dz142 Dz143 Dz144 Dz145 Dz146
Dz147 Dz148 Dz149 Dz15 Dz150 Dz151 Dz152 Dz153 Dz154 Dz16 Dz17 Dz18 Dz19 Dz2
Dz20 Dz21 Dz22 Dz23 Dz24 Dz25 Dz26 Dz27 Dz28 Dz29 Dz3 Dz30 Dz31 Dz32 Dz33 Dz34
Dz35 Dz36 Dz37 Dz38 Dz39 Dz4 Dz40 Dz41 Dz42 Dz43 Dz44 Dz45 Dz46 Dz47 Dz48 Dz49
Dz5 Dz50 Dz51 Dz52 Dz53 Dz54 Dz55 Dz56 Dz57 Dz58 Dz59 Dz6 Dz60 Dz61 Dz62 Dz63
Dz64 Dz65 Dz66 Dz67 Dz68 Dz69 Dz7 Dz70 Dz71 Dz72 Dz73 Dz74 Dz75 Dz76 Dz77 Dz78
Dz79 Dz8 Dz80 Dz81 Dz82 Dz83 Dz84 Dz85 Dz86 Dz87 Dz88 Dz89 Dz9 Dz90 Dz91 Dz92
Dz93 Dz94 Dz95 Dz96 Dz97 Dz98 Dz99

dataset_path =  datasets_new_tmp/Multiband_Brodatz_Texture
subdir =  test
n_images_per_class =  50
Dz1 Dz10 Dz100 Dz101 Dz102 Dz103 Dz104 Dz105 Dz106 Dz107 Dz108 Dz109 Dz11 Dz110
Dz111 Dz112 Dz113 Dz114 Dz115 Dz116 Dz117 Dz118 Dz119 Dz12 Dz120 Dz121 Dz122
Dz123 Dz124 Dz125 Dz126 Dz127 Dz128 Dz129 Dz13 Dz130 Dz131 Dz132 Dz133 Dz134
Dz135 Dz136 Dz137 Dz138 Dz139 Dz14 Dz140 Dz141 Dz142 Dz143 Dz144 Dz145 Dz146
Dz147 Dz148 Dz149 Dz15 Dz150 Dz151 Dz152 Dz153 Dz154 Dz16 Dz17 Dz18 Dz19 Dz2
Dz20 Dz21 Dz22 Dz23 Dz24 Dz25 Dz26 Dz27 Dz28 Dz29 Dz3 Dz30 Dz31 Dz32 Dz33 Dz34
Dz35 Dz36 Dz37 Dz38 Dz39 Dz4 Dz40 Dz41 Dz42 Dz43 Dz44 Dz45 Dz46 Dz47 Dz48 Dz49
Dz5 Dz50 Dz51 Dz52 Dz53 Dz54 Dz55 Dz56 Dz57 Dz58 Dz59 Dz6 Dz60 Dz61 Dz62 Dz63
Dz64 Dz65 Dz66 Dz67 Dz68 Dz69 Dz7 Dz70 Dz71 Dz72 Dz73 Dz74 Dz75 Dz76 Dz77 Dz78
Dz79 Dz8 Dz80 Dz81 Dz82 Dz83 Dz84 Dz85 Dz86 Dz87 Dz88 Dz89 Dz9 Dz90 Dz91 Dz92
Dz93 Dz94 Dz95 Dz96 Dz97 Dz98 Dz99

Completed!
```

8 Optimising memory use

[346]:
```
import gc

gc.collect()
```

[346]: 64546

8.1 Visualising the bootstrapped datasets

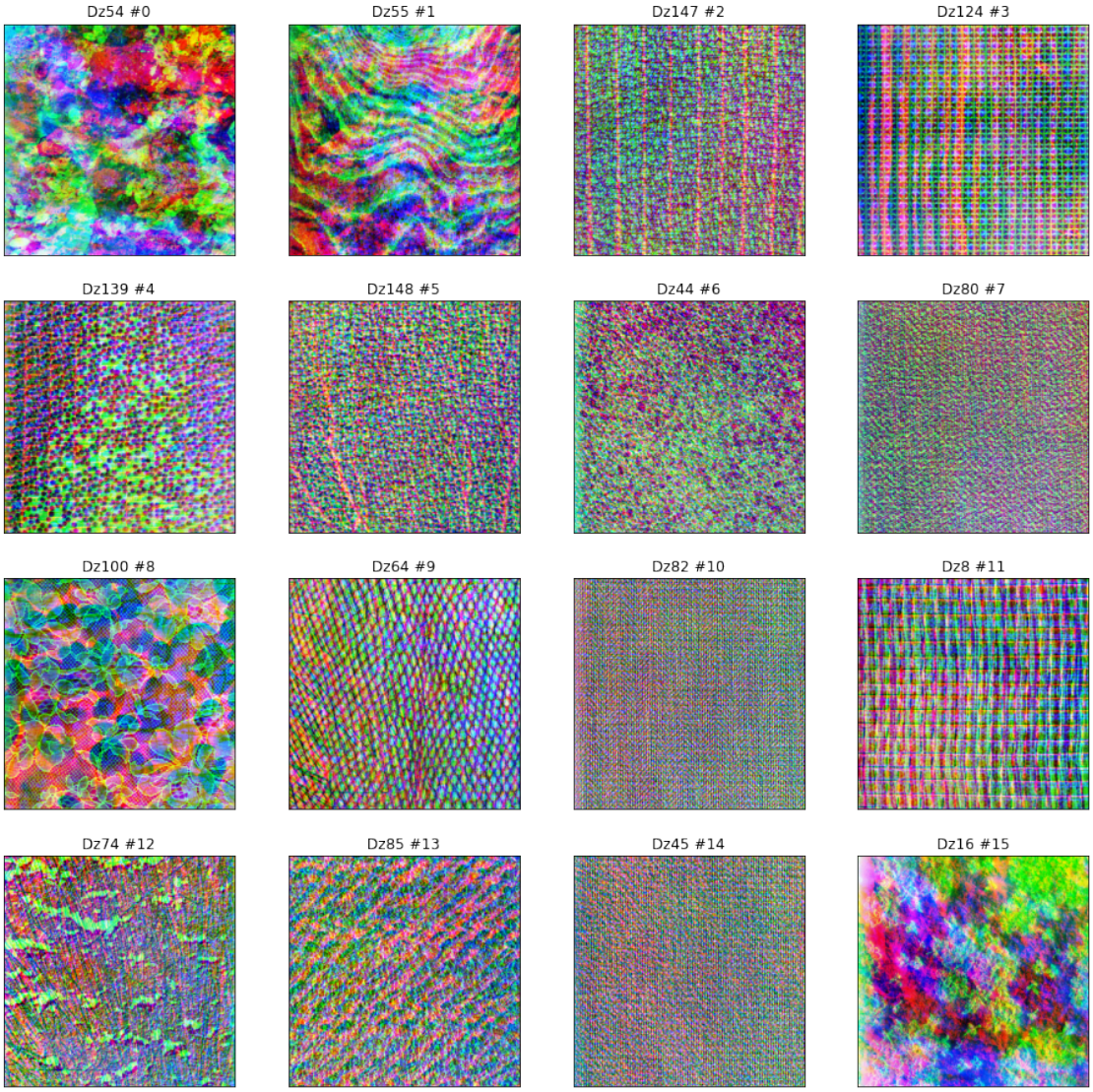
8.1.1 Plotting dataset samples

[74]:
```
import numpy as np
import matplotlib.pyplot as plt


""" We plot the sample images from the dataset.
"""

def plot_dataset_samples(*,
                         df,
                         nrows = 4,
                         ncols = 4,
                         subfig_height = 4,
                         subfig_width = 4,
                        ):


    """ Plotting the samples

    """

    figsize = (ncols * subfig_width, nrows * subfig_height)
    #figsize = (15, 15)



    """ Sampling

    """
    dfs = df.sample(n = nrows * ncols, replace = False)

    Xs = np.array(dfs["X"], dtype = object)
    ys = np.array(dfs["y"], dtype = object)


    fig, axes = plt.subplots(nrows = nrows,
                             ncols = ncols,
                             figsize = figsize)

    """ plt.subplots_adjust(left = 0.02,
                    right = 0.97,
                    bottom = 0.05,
                    hspace = 0.1,
                    wspace = 0.1,
                    top = 0.95)
    """
```

```
    axes_flat = axes.flat


    for row in range(nrows):
        for col in range(ncols):

            imgid = row * ncols + col

            img = Xs[imgid]
            #img = np.array(img, dtype = np.uint8) #print("img.shape", img.
 ↪shape)


            label = ys[imgid]

            ax = axes_flat[row * ncols + col]

            ax.set_xticks([])
            ax.set_yticks([])

            ax.imshow(img, vmin = 0, vmax = 1)
            #ax.imshow(img)
            ax.title.set_text(f"{label} #{imgid}")

    plt.show()
    plt.close()
```

[75]:
```
df = load_texture_dataset_as_dataframe(dataset_name =␣
 ↪"Multiband_Brodatz_Texture")

df["X"] /= 255

plot_dataset_samples(    df = df,
                         nrows = 4,
                         ncols = 4,
                         subfig_height = 4,
                         subfig_width = 4,
                        )

del df
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (512, 512)
Total 154 images are loaded.
```



8.1.2 Plotting augmented various samples

[355]:
```
import numpy as np
import matplotlib.pyplot as plt
import os

def plot_augmented_samples(*,
                           X,
                           y,
                           img_augmenter,
                           nrows = 2,
                           ncols = 4,
                           subfig_width = 4,
```

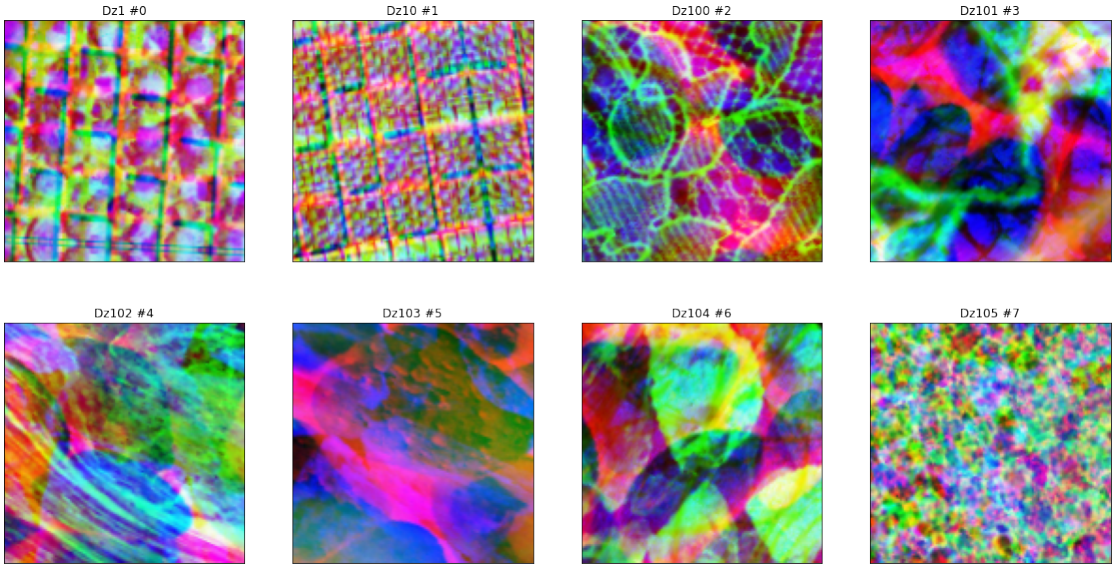
```
                    subfig_height = 4,
                    savename = None
                ):

#X, y = next(iter(dataset))

#X,y = load_mbt_dataset()

#X_train, y_train, X_test, y_test = split_mbt_dataset(X, y)

#img_augmenter = CustomisedUtilImageAugmenter()


figsize = (ncols * subfig_width, nrows * subfig_height)


fig, axes = plt.subplots(nrows = nrows,
                         ncols = ncols,
                         figsize = figsize)

plt.subplots_adjust(left = 0.02,
                    right = 0.98,
                    bottom = 0.02,
                    top = 0.98)

""" plt.subplots_adjust(left = 0.02,
                right = 0.97,
                bottom = 0.05,
                hspace = 0.1,
                wspace = 0.1,
                top = 0.95)
"""

axes_flat = axes.flat


for row in range(nrows):
    for col in range(ncols):

        imgid = row * ncols + col

        Xi = X[imgid, :, :, :]
        #Xi = X_train[3, :, :, :]
        Xi = Xi.copy()
        Xi = np.expand_dims(Xi, axis = 0)
        Xi = img_augmenter(Xi)
        #Xi = np.array(Xi, dtype = np.uint8)
```

```
            img = Xi[0, :, :, :]

            #img = X_train[imgid, :, :, :]
            #img = np.array(img, dtype = np.uint8) #print("img.shape", img.
↪shape)

            label = y[imgid]

            ax = axes_flat[row * ncols + col]

            ax.set_xticks([])
            ax.set_yticks([])

            ax.imshow(img, vmin = 0, vmax = 1.0)
            #ax.imshow(img)

            ax.title.set_text(f"{label} #{imgid}")


    if not os.path.exists("figures"):
        os.makedirs("figures")


    if savename:

        figpath = "figures" + os.path.sep + savename

        plt.savefig(figpath,
                    dpi=600,
                    format='pdf')

        print("saved to: ", figpath)


    plt.show()
    plt.close()
```

[356]:
```
img_augmenter = CustomisedBootstrapImageAugmenter(
                                        target_size = (128, 128),
                                        seed = 2113
                                    )

X, y = load_texture_dataset_xy(dataset_name = "Multiband_Brodatz_Texture")

plot_augmented_samples(
                    X = X / 255,
                    y = y,
```

```
                    img_augmenter = img_augmenter,
                    nrows = 2,
                    ncols = 4,
                    subfig_width = 4,
                    subfig_height = 4,
                    savename = "fig_augmented_samples.pdf"
                )

del img_augmenter, X, y
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (512, 512)
Total 154 images are loaded.
saved to:  figures/fig_augmented_samples.pdf
```



[357]:
```
def plot_augmented_samples_for_one_image(*,
                                         X,
                                         y,
                                         img_augmenter,
                                         nrows = 2,
                                         ncols = 4,
                                         subfig_width = 4,
                                         subfig_height = 4,
                                         savename = None,
                                        ):
```

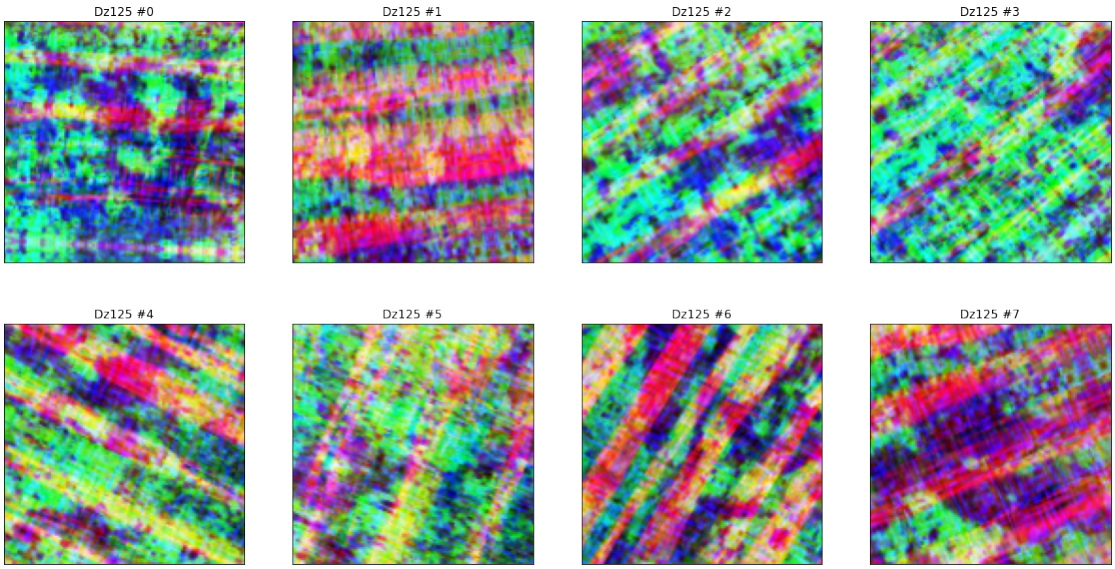
```
#X, y = next(iter(dataset))

#X,y = load_mbt_dataset()
#X_train, y_train, X_test, y_test = split_mbt_dataset(X, y)

#img_augmenter = CustomisedUtilImageAugmenter()


figsize = (ncols * subfig_width, nrows * subfig_height)

fig, axes = plt.subplots(nrows = nrows,
                         ncols = ncols,
                         figsize = figsize)

plt.subplots_adjust(left = 0.02,
                    right = 0.98,
                    bottom = 0.02,
                    top = 0.98)

""" plt.subplots_adjust(left = 0.02,
                 right = 0.97,
                 bottom = 0.05,
                 hspace = 0.1,
                 wspace = 0.1,
                 top = 0.95)
"""

axes_flat = axes.flat

indices = list(range(len(y)))
idx = np.random.choice(indices)
candidate_image = X[idx, :, :, :]



for row in range(nrows):
    for col in range(ncols):

        plotid = row * ncols + col

        Xi = candidate_image.copy()
        Xi = np.expand_dims(Xi, axis = 0)
        Xi = img_augmenter(Xi)
        #Xi = np.array(Xi * 255, dtype = np.uint8)
        img = Xi[0, :, :, :]
```

```
            #img = X_train[imgid, :, :, :]
            #img = np.array(img, dtype = np.uint8) #print("img.shape", img.
↪shape)

            label = y[idx]

            ax = axes_flat[row * ncols + col]

            ax.set_xticks([])
            ax.set_yticks([])

            ax.imshow(img, vmin = 0, vmax = 1.0)
            #ax.imshow(img)

            ax.title.set_text(f"{label} #{plotid}")


    if not os.path.exists("figures"):
        os.makedirs("figures")


    if savename:

        figpath = "figures" + os.path.sep + savename

        plt.savefig(figpath,
                    dpi=600,
                    format='pdf')

        print("saved to: ", figpath)

    plt.show()
    plt.close()
```

[368]:
```
img_augmenter = CustomisedBootstrapImageAugmenter(
                                        target_size = (128, 128),
                                        seed = 2113
                                    )

X, y = load_texture_dataset_xy(dataset_name = "Multiband_Brodatz_Texture")

plot_augmented_samples_for_one_image(
                                X = X / 255,
                                y = y,
                                img_augmenter = img_augmenter,
                                nrows = 2,
                                ncols = 4,
```

```
                                    subfig_width = 4,
                                    subfig_height = 4,
                                    savename = "fig_augmented_samples_for_one_image.
↪pdf"
                                )

del img_augmenter, X, y
```

```
Loading dataset from path: datasets_orig/Multiband_Brodatz_Texture …
image size:  (512, 512)
Total 154 images are loaded.
saved to:  figures/fig_augmented_samples_for_one_image.pdf
```



9 Loading the final training and testing datasets

9.1 Loading datasets

[3]:
```
train_dataset_ = tf.keras.preprocessing.image_dataset_from_directory(
                "datasets_new/Multiband_Brodatz_Texture/train",
                image_size = image_size,
                batch_size = batch_size,
                interpolation = "bilinear",
                color_mode = "rgb",
                shuffle = True,
                seed = 2113
                )
```

```
Found 30800 files belonging to 154 classes.
```

[4]:
```
test_dataset_ = tf.keras.preprocessing.image_dataset_from_directory(
                "datasets_new/Multiband_Brodatz_Texture/test",
                image_size = image_size,
                batch_size = batch_size,
                interpolation = "bilinear",
                color_mode = "rgb",
                shuffle = True,
                seed = 3371
                )
```

```
Found 7700 files belonging to 154 classes.
```

[5]:
```
n_classes = len(train_dataset_.class_names)
print("n_classes = ", n_classes)
```

```
n_classes =  154
```

[6]:
```
n_train_samples = len(train_dataset_) * batch_size
n_train_batches = len(train_dataset_)

print("n_train_samples = ", n_train_samples)
print("n_train_batches = ", n_train_batches)
```

```
n_train_samples =  30848
n_train_batches =  241
```

[7]:
```
n_test_samples = len(test_dataset_) * batch_size
n_test_batches = len(test_dataset_)

print("n_test_samples = ", n_test_samples)
print("n_test_batches = ", n_test_batches)
```

```
n_test_samples =  7808
n_test_batches =  61
```

[8]:
```
n_samples = n_train_samples + n_test_samples
n_batches = n_train_batches + n_test_batches

print("n_samples = ", n_samples)
print("n_batches = ", n_batches)
```

```
n_samples =  38656
n_batches =  302
```

9.2 Normalising datasets and setting data prefetching

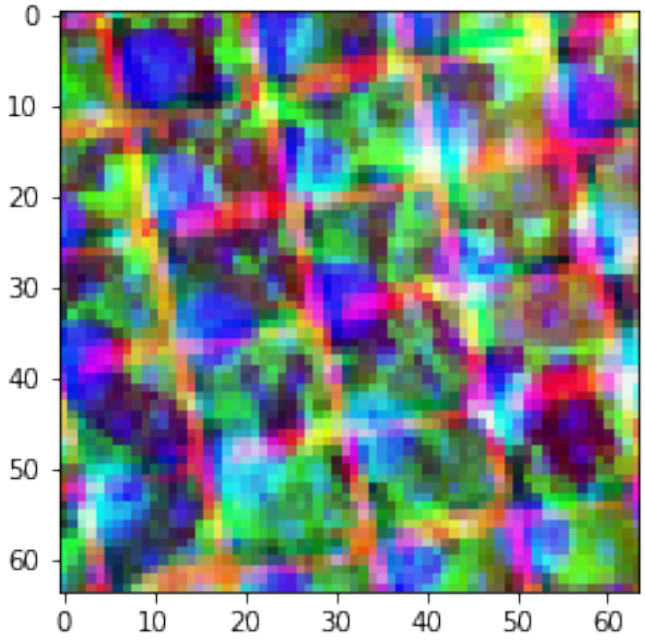
[9]:
```
train_dataset = train_dataset_.map(lambda x, y: (x / 255., y))
train_dataset = train_dataset.prefetch(buffer_size = tf.data.AUTOTUNE)

test_dataset = test_dataset_.map(lambda x, y: (x / 255., y))
test_dataset = test_dataset.prefetch(buffer_size = tf.data.AUTOTUNE)
```

9.3 Verifying loaded dataset

[92]:
```
x1 = next(iter(train_dataset))
x2 = x1[0]
x2.shape
```

[92]:
```
TensorShape([128, 64, 64, 3])
```

[93]:
```
import matplotlib.pyplot as plt

img = next(iter(train_dataset))[0][0]

plt.imshow(img, vmin=0, vmax=1)
plt.show()
```



10 Image augmentation model

10.1 Random color affine transformation layer

Random color affine transformation is crucial to avoid trivial solution of merely learning classification from color histogram information!

[10]:
```
 # We make it working with keras model save and load
# ref:
# https://keras.io/guides/serialization_and_saving/
# https://stackoverflow.com/questions/62280161/
 ↪saving-keras-models-with-custom-layers
# https://keras.io/examples/vision/semisupervised_simclr/

import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers.experimental import preprocessing as␣
 ↪keras_preprocessing_layers

class CustomisedRandomColorAffineLayer(keras.layers.Layer):

    def __init__(self,
                 brightness = 0,
                 jitter = 0,
                 name = 'color_affine',
                 **kwargs):

        self.brightness = brightness
        self.jitter = jitter

        super(CustomisedRandomColorAffineLayer, self).__init__(**kwargs)


    def get_config(self):

        config = super().get_config()

        config['brightness'] = self.brightness
        config['jitter'] = self.jitter

        #print("config = ", config)

        return config

    #@classmethod
    #def from_config(cls, config):
    #    return cls(**config)

    def call(self, images, training = True):
```

```
        if training:
            batch_size = tf.shape(images)[0]

            # For each pixels, we randomly adjust their brightnesses.
            brightness_scales = 1 + tf.random.uniform(
                            (batch_size, 1, 1, 1),
                            minval = -self.brightness,
                            maxval = self.brightness
                        )

            # Different for all colors
            jitter_matrices = tf.random.uniform(
                            (batch_size, 1, 3, 3),
                            minval = -self.jitter,
                            maxval = self.jitter
                        )

            color_transforms = (
                            tf.eye(3, batch_shape = [batch_size, 1]) *␣
 ↪brightness_scales
                                + jitter_matrices
                        )

            images = tf.clip_by_value(tf.matmul(images, color_transforms), 0, 1)

        return images
```

10.2 Image augmentation model for train

[11]:
```
import numpy as np
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.layers.experimental import preprocessing as␣
 ↪keras_preprocessing_layers


class CustomisedTrainImageAugmenter(keras.layers.Layer):
    def __init__(self,
                 min_area,
                 brightness,
                 jitter,
                 name = 'train_imgaug_layer',
                 **kwargs):

        #self.image_shape = image_shape
        self.min_area = min_area
        self.brightness = brightness
```

```
        self.jitter = jitter


        #self.zoom_factor = 1.0 - tf.sqrt(min_area)
        self.zoom_factor = 1.0 - np.sqrt(min_area)

        self.model = keras.Sequential(
           [
            #keras.layers.InputLayer(input_shape = image_shape),
            #keras_preprocessing_layers.Rescaling(1 / 255),
            keras_preprocessing_layers.RandomFlip("horizontal"),
            keras_preprocessing_layers.RandomTranslation(
                                        self.zoom_factor / 2,
                                        self.zoom_factor / 2
                                       ),
            keras_preprocessing_layers.RandomZoom(
                                        (-self.zoom_factor, 0.0),
                                        (-self.zoom_factor, 0.0)
                                    ),
            CustomisedRandomColorAffineLayer(
                                        brightness = brightness,
                                        jitter = jitter,
                                        name = "color_affine_for_train"
                                    ),
            ],
            name = "train_imgaug_model"
          )

        super(CustomisedTrainImageAugmenter, self).__init__(name = name,␣
↪**kwargs)

    def get_config(self):
        config = super().get_config()

        #config['image_shape'] = self.image_shape
        config['min_area'] = self.min_area
        config['brightness'] = self.brightness
        config['jitter'] = self.jitter
        config['zoom_factor'] = self.zoom_factor
        config['model'] = self.model

        #print(config)

        return config

    def call(self, images, training = True):
        if training:
```

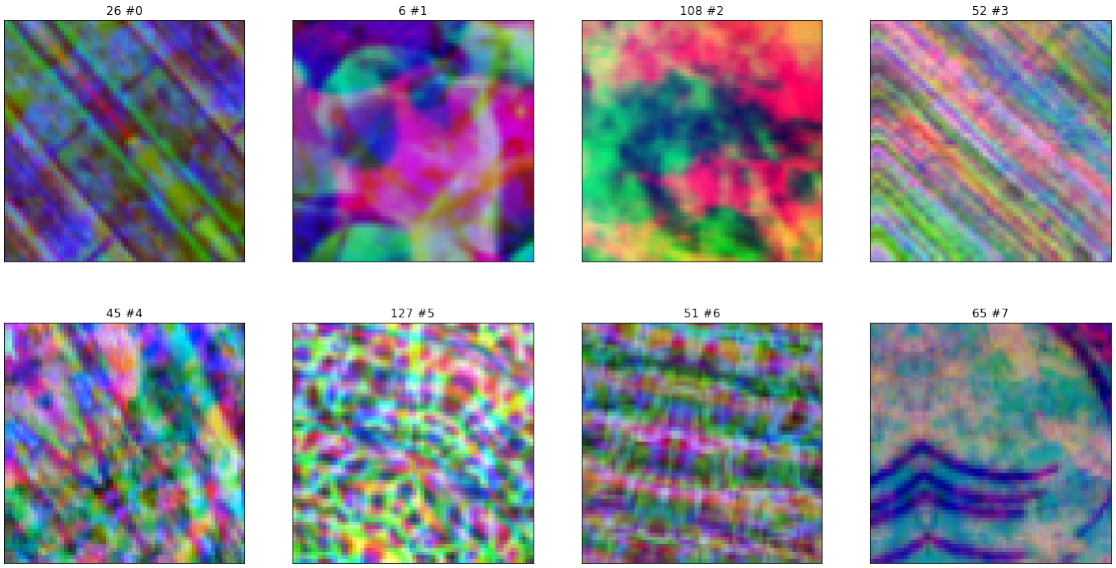
```
            outputs = self.model(images)
        else:
            outputs = images

        return outputs

    @classmethod
    def from_config(cls, config):
        return cls(**config)
```

11 Visualising image augmentation

11.1 Plotting augmented various samples

[371]:
```
img_augmenter = CustomisedTrainImageAugmenter(**imgaug_params)


X, y = next(iter(train_dataset))

X = X.numpy().astype("float32")

plot_augmented_samples(
                        X = X,
                        y = y,
                        img_augmenter = img_augmenter,
                        nrows = 2,
                        ncols = 4,
                        subfig_width = 4,
                        subfig_height = 4,
                        savename = "fig_augmented_samples_for_train.pdf"
                    )

del img_augmenter, X, y
```

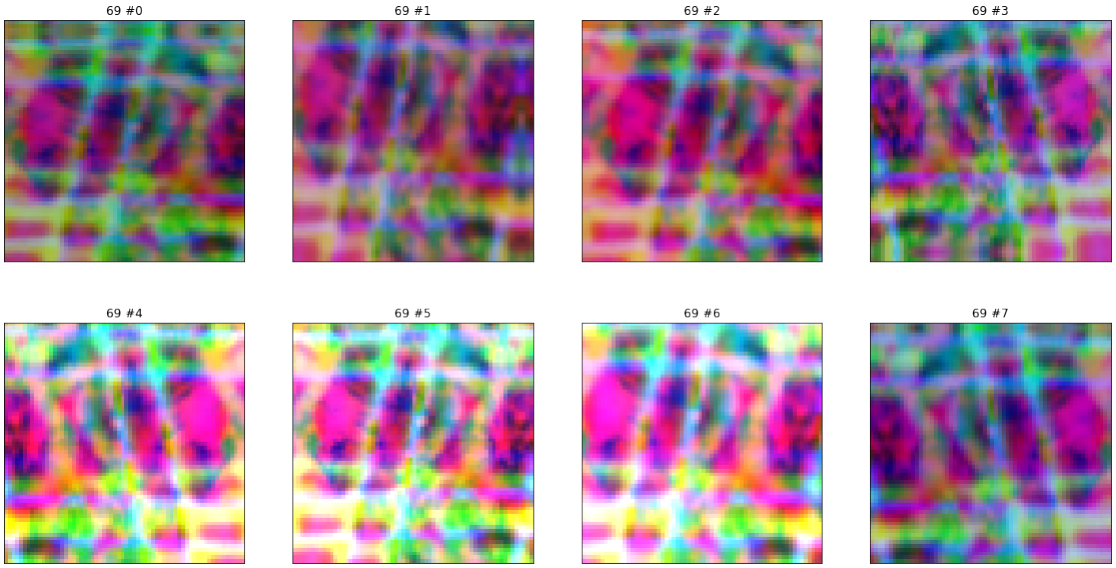
```
saved to:  figures/fig_augmented_samples_for_train.pdf
```



11.2 Plotting augmented samples for one image

[372]:
```
img_augmenter = CustomisedTrainImageAugmenter(**imgaug_params)

X, y = next(iter(train_dataset))

X = X.numpy().astype("float32")

plot_augmented_samples_for_one_image(
                                    X = X,
                                    y = y,
                                    img_augmenter = img_augmenter,
                                    nrows = 2,
                                    ncols = 4,
                                    subfig_width = 4,
                                    subfig_height = 4,
                                    savename =␣
 ↪"fig_augmented_samples_for_one_image_for_train.pdf"
                                )

del img_augmenter, X, y
```

```
saved to:  figures/fig_augmented_samples_for_one_image_for_train.pdf
```



12 Building supervised learning model with specified encoder

[277]:
```
def build_supervised_model( *,
                            learning_rate = 0.001,
                            image_shape,
                            n_classes,
                            encoder,
                            image_augmenter,
                            name
                           ):

    newhead = keras.Sequential(
                [
                    keras.layers.Dense(512, activation="relu", name =␣
↪"hidden_1"),
                    keras.layers.Dense(512, activation="relu", name =␣
↪"hidden_2"),
                    keras.layers.Dense(n_classes, name = "output"),
                ],
                name = "newhead"
            )


    model = keras.Sequential(
            [
                keras.layers.InputLayer(input_shape = image_shape),
```

```
                image_augmenter,␣
↪#CustomisedTrainImageAugmenter(**imgaug_params),
                encoder,
                newhead
            ],
            name = name,
        )

    model.compile(
            optimizer = keras.optimizers.Adam(learning_rate = learning_rate),
            loss = keras.losses.SparseCategoricalCrossentropy(from_logits =␣
↪True),
            metrics = [
                        keras.metrics.SparseCategoricalAccuracy(name =␣
↪"accuracy"),
                        keras.metrics.SparseTopKCategoricalAccuracy(5,␣
↪name="accuracy_top-5"),
                    ],
        )

    #print()
    #newhead.summary()

    #print()
    #encoder.summary()

    #print()
    #model.summary()

    return model
```

13 A framework of training, evaluating and saving

[294]:
```
import os
import pickle


def train_evaulate_and_save_models(*,
                   model,
                   encoder,
                   train_dataset,
                   test_dataset,
                   epochs,
                   savename,
                  ):
```

```
checkpoint_filepath = "checkpoints" + os.path.sep + savename

if not os.path.exists(checkpoint_filepath):
    os.makedirs(checkpoint_filepath)

checkpoint_callback = keras.callbacks.ModelCheckpoint(
    checkpoint_filepath,
    monitor="val_accuracy",
    save_best_only = False,
    save_weights_only = True,

)

print()
print("Training ...")
print()

history_train = model.fit(
                train_dataset,
                epochs = epochs,
                validation_data = test_dataset,
                verbose = 1,
                #callbacks = [checkpoint_callback],
               )

#loading the checkpoint
#model.load_weights(checkpoint_filepath)

savepath = "models" + os.path.sep + savename

if not os.path.exists(savepath):
    os.makedirs(savepath)


print()
print("Saving models ...")
print()

encoder.save(savepath + os.path.sep + "encoder.saved_model")


 #a tensorflow bug, must call the model first then
_ = model(next(iter(train_dataset))[0])
model.save(savepath + os.path.sep + "main.saved_model")
```

```
    print()
    print("Saving training history data ...")
    print()

    if not os.path.exists("results" + os.path.sep + savename):
        os.makedirs("results" + os.path.sep + savename)

    pickle.dump(history_train.history,
            open("results" + os.path.sep + savename + os.path.sep +␣
↪"history_train.pickle", "wb" ))

    print()
    print("Results:")
    print()
    history = history_train.history
    for k in history:

        if "loss" in k:
            continue

        max_v = float(max(history[k]))

        print(f"Maximal {k}: {max_v:.5f}")


    print()
    print("-- Completed --")
    print()
```

14 The facilities of plotting results

[46]:
```
import pickle
import matplotlib.pyplot as plt
from matplotlib import cm
from itertools import cycle

#from matplotlib.colors import ListedColormap, LinearSegmentedColormap

def plot_train_results(
                                resultfile,
                                title,
                                ylabel,
                                keys,
                                labels,
                                savename = None,
                                legend_location = "best",
```

```
                                normalise = False
                            ):

    if not os.path.exists(resultfile):
        return



    #fig_width = 10.
    #fig_height = fig_width*0.5
    #
    #fig = plt.figure(figsize=(fig_width, fig_height))
    #
    #
    #plt.subplots_adjust(left = 0.1,
    #                    right = 0.9,
    #                    bottom = 0.15,
    #                    top = 0.9)

    fig_width = 12.
    fig_height = fig_width*0.5

    fig = plt.figure(figsize=(fig_width, fig_height))


    plt.subplots_adjust(left = 0.05,
                        right = 0.95,
                        bottom = 0.1,
                        top = 0.95)


    history = pickle.load(open(resultfile, "rb"))

    n = len(keys)
    #colours = iter(cm.rainbow(np.linspace(0, 1, n)))
    colours = iter(cm.Set1(np.linspace(0, 1, n)))

    markers = cycle(["v", "^", "s", "<", ">", "D"])

    for k, label in zip(keys, labels):
        if k not in history:
            print(f"key {k} not found")
            continue

        v = history[k]

        if normalise:
```

```
            v = np.array(v) / max(v)

        c = next(colours)
        m = next(markers)

        #plt.plot(v, color = c, label = label, linewidth = 2)
        plt.plot(
                    v,
                    color = c,
                    label = label,
                    linewidth = 2.5,
                    #linestyle = ls,
                    marker = m,
                    markersize = 9
                )


    plt.xlabel("# of epochs", fontsize = 12)

    plt.ylabel(ylabel, fontsize = 12)

    k = list(keys)[0]
    v = history[k]
    plt.xlim(0, len(v) - 1)
    plt.ylim(0, 1.3)

    xticks = np.linspace(0,
                     len(v) - 1,
                     num = len(v),
                     endpoint = True,
                     dtype = int)
    xlabels = xticks

    plt.xticks(xticks, xlabels)
    plt.yticks([0, 0.25, 0.5, 0.75, 1], [0, 0.25, 0.5, 0.75, 1])

    plt.grid()

    plt.legend(
            loc = legend_location, #'upper center',
            fontsize = 12,
            ncol = 3,
            frameon = False)

    if not os.path.exists("figures"):
        os.makedirs("figures")
```

```
    if savename:
        figpath = "figures" + os.path.sep + savename
        plt.savefig(figpath,
                    dpi=600,
                    format='pdf')

        print("saved to: ", figpath)

    plt.title(title)

    plt.show()
```

15 Baseline: Supervised learning with simple encoder

15.1 Building simple encoder

[276]:
```
def build_simple_encoder(image_shape):
    return keras.Sequential(
        [
            keras.layers.InputLayer(input_shape=image_shape),

            keras.layers.Conv2D(32, kernel_size=3, strides=2,␣
↪activation="relu"),
            keras.layers.Conv2D(64, kernel_size=3, strides=2,␣
↪activation="relu"),
            keras.layers.BatchNormalization(),
            keras.layers.Dropout(0.3),

            keras.layers.Conv2D(128, kernel_size=3, strides=2,␣
↪activation="relu"),
            keras.layers.Conv2D(256, kernel_size=3, strides=2,␣
↪activation="relu"),
            keras.layers.BatchNormalization(),
            keras.layers.Dropout(0.3),

            keras.layers.Flatten(),

        ],

        name = "encoder_simple",
    )
```

15.2 Building model

[279]:
```
baseline_simple_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)
baseline_simple_encoder = build_simple_encoder(image_shape)

baseline_simple_model = build_supervised_model(
                            image_shape = image_shape,
                            n_classes = n_classes,
                            encoder = baseline_encoder_simple,
                            image_augmenter = baseline_simple_imgaug,
                            name = "baseline_simple_model",
                            learning_rate = 0.001)
```

15.3 Training from scratch

[280]:
```
train_evaulate_and_save_models(
                    model = baseline_simple_model,
                    encoder = baseline_simple_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "baseline_simple",
                   )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 53s 214ms/step - loss: 0.7938 -
accuracy: 0.8040 - accuracy_top-5: 0.9220 - val_loss: 1.1209 - val_accuracy:
0.7174 - val_accuracy_top-5: 0.9369
Epoch 2/20
241/241 [==============================] - 52s 214ms/step - loss: 0.1690 -
accuracy: 0.9431 - accuracy_top-5: 0.9982 - val_loss: 0.8526 - val_accuracy:
0.8052 - val_accuracy_top-5: 0.9577
Epoch 3/20
241/241 [==============================] - 58s 238ms/step - loss: 0.1324 -
accuracy: 0.9569 - accuracy_top-5: 0.9992 - val_loss: 1.2039 - val_accuracy:
0.7466 - val_accuracy_top-5: 0.9403
Epoch 4/20
241/241 [==============================] - 60s 247ms/step - loss: 0.1204 -
accuracy: 0.9615 - accuracy_top-5: 0.9996 - val_loss: 0.9634 - val_accuracy:
0.7766 - val_accuracy_top-5: 0.9629
Epoch 5/20
241/241 [==============================] - 51s 211ms/step - loss: 0.1088 -
accuracy: 0.9644 - accuracy_top-5: 0.9994 - val_loss: 2.3881 - val_accuracy:
0.6212 - val_accuracy_top-5: 0.8921
Epoch 6/20
```

```
241/241 [==============================] - 51s 211ms/step - loss: 0.1056 -
accuracy: 0.9658 - accuracy_top-5: 0.9998 - val_loss: 1.2140 - val_accuracy:
0.7464 - val_accuracy_top-5: 0.9505
Epoch 7/20
241/241 [==============================] - 51s 209ms/step - loss: 0.0921 -
accuracy: 0.9697 - accuracy_top-5: 0.9996 - val_loss: 0.9403 - val_accuracy:
0.8036 - val_accuracy_top-5: 0.9670
Epoch 8/20
241/241 [==============================] - 51s 210ms/step - loss: 0.0813 -
accuracy: 0.9739 - accuracy_top-5: 0.9998 - val_loss: 1.3903 - val_accuracy:
0.7338 - val_accuracy_top-5: 0.9395
Epoch 9/20
241/241 [==============================] - 51s 210ms/step - loss: 0.0798 -
accuracy: 0.9730 - accuracy_top-5: 0.9997 - val_loss: 1.0285 - val_accuracy:
0.7888 - val_accuracy_top-5: 0.9647
Epoch 10/20
241/241 [==============================] - 51s 211ms/step - loss: 0.0777 -
accuracy: 0.9748 - accuracy_top-5: 0.9997 - val_loss: 0.7458 - val_accuracy:
0.8543 - val_accuracy_top-5: 0.9660
Epoch 11/20
241/241 [==============================] - 51s 211ms/step - loss: 0.0753 -
accuracy: 0.9761 - accuracy_top-5: 0.9999 - val_loss: 0.9297 - val_accuracy:
0.8164 - val_accuracy_top-5: 0.9635
Epoch 12/20
241/241 [==============================] - 51s 211ms/step - loss: 0.0823 -
accuracy: 0.9734 - accuracy_top-5: 0.9998 - val_loss: 1.3488 - val_accuracy:
0.7304 - val_accuracy_top-5: 0.9534
Epoch 13/20
241/241 [==============================] - 51s 212ms/step - loss: 0.0672 -
accuracy: 0.9773 - accuracy_top-5: 0.9999 - val_loss: 1.7099 - val_accuracy:
0.7140 - val_accuracy_top-5: 0.9240
Epoch 14/20
241/241 [==============================] - 51s 211ms/step - loss: 0.0652 -
accuracy: 0.9793 - accuracy_top-5: 0.9998 - val_loss: 0.8247 - val_accuracy:
0.8240 - val_accuracy_top-5: 0.9701
Epoch 15/20
241/241 [==============================] - 52s 213ms/step - loss: 0.0661 -
accuracy: 0.9791 - accuracy_top-5: 0.9998 - val_loss: 1.0479 - val_accuracy:
0.7913 - val_accuracy_top-5: 0.9618
Epoch 16/20
241/241 [==============================] - 52s 213ms/step - loss: 0.0640 -
accuracy: 0.9786 - accuracy_top-5: 0.9998 - val_loss: 0.8423 - val_accuracy:
0.8369 - val_accuracy_top-5: 0.9668
Epoch 17/20
241/241 [==============================] - 51s 210ms/step - loss: 0.0557 -
accuracy: 0.9817 - accuracy_top-5: 0.9998 - val_loss: 1.1251 - val_accuracy:
0.7791 - val_accuracy_top-5: 0.9640
Epoch 18/20
```

```
241/241 [==============================] - 51s 211ms/step - loss: 0.0579 -
accuracy: 0.9815 - accuracy_top-5: 0.9998 - val_loss: 0.7612 - val_accuracy:
0.8425 - val_accuracy_top-5: 0.9742
Epoch 19/20
241/241 [==============================] - 51s 211ms/step - loss: 0.0656 -
accuracy: 0.9794 - accuracy_top-5: 0.9998 - val_loss: 0.9839 - val_accuracy:
0.8022 - val_accuracy_top-5: 0.9623
Epoch 20/20
241/241 [==============================] - 53s 217ms/step - loss: 0.0590 -
accuracy: 0.9810 - accuracy_top-5: 0.9999 - val_loss: 0.9123 - val_accuracy:
0.8231 - val_accuracy_top-5: 0.9705

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

INFO:tensorflow:Assets written to:
models/baseline_simple/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_simple/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_simple/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_simple/main.saved_model/assets


Saving training history data …


Results:

Maximal accuracy: 0.98172
Maximal accuracy_top-5: 0.99994
Maximal val_accuracy: 0.85429
Maximal val_accuracy_top-5: 0.97416

-- Completed --
```

15.4 Testing of loading models

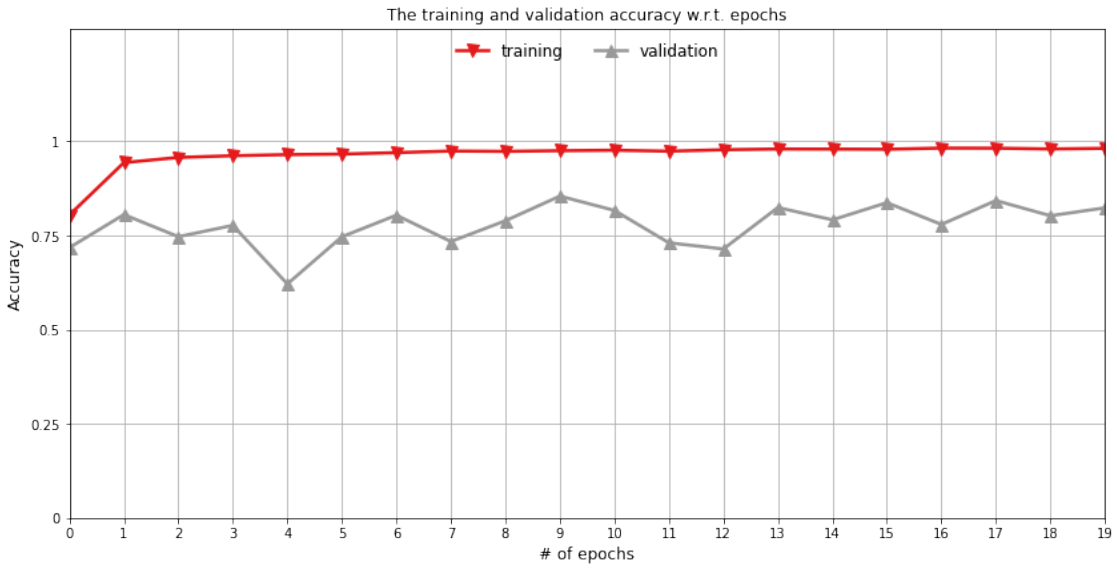
[ ]:
```
test_encoder = keras.models.load_model("models/baseline_simple/encoder.
↪saved_model")
test_model = keras.models.load_model("models/baseline_simple/main.saved_model")

del test_encoder
del test_model
```

[176]:
```
history = pickle.load(open(b"results/baseline_simple/history_train.pickle",␣
↪"rb"))
del history
```

15.5 Plotting results

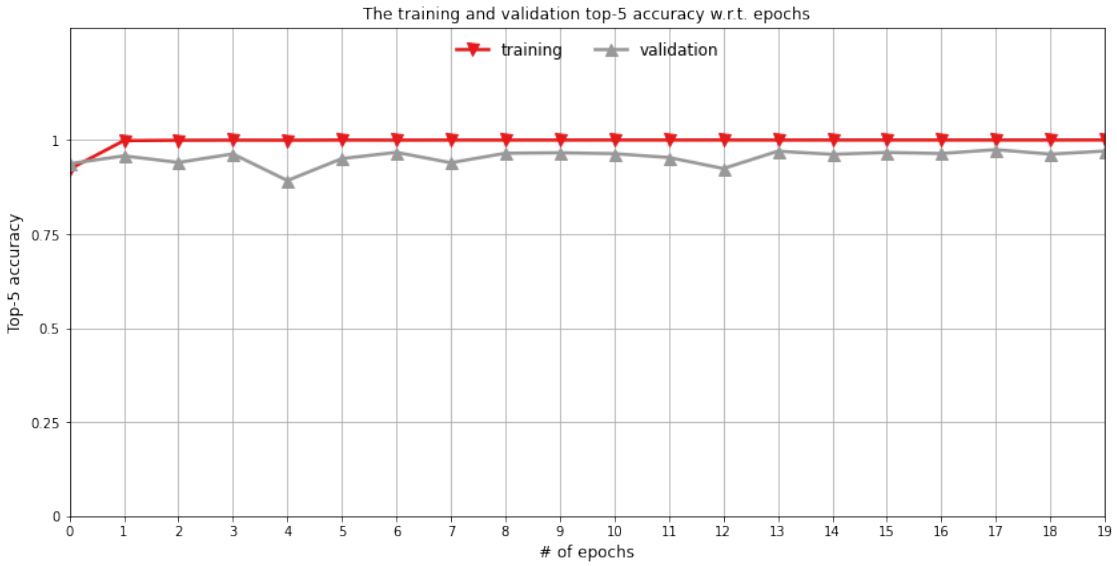
[47]:
```
plot_train_results(
                resultfile = "results/baseline_simple/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["accuracy", "val_accuracy"],
                labels = ["training", "validation"],
                savename = "fig_baseline_simple_accuracy.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_simple_accuracy.pdf
```



[48]:
```
plot_train_results(
                resultfile = "results/baseline_simple/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
 ↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["accuracy_top-5", "val_accuracy_top-5"],
                labels = ["training", "validation"],
                savename = "fig_baseline_simple_accuracy_top5.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_simple_accuracy_top5.pdf
```



16 Baseline: Supervised learning with VGG16

16.1 Building VGG16 encoder

[281]:
```
from tensorflow.keras.applications import VGG16
from tensorflow.keras.applications.vgg16 import preprocess_input as␣
 ↪vgg16_preprocess_input

def build_vgg16_encoder(image_shape):

    inputs = keras.Input(shape = image_shape, name = "inputs")


    #x = keras.layers.Lambda(vgg16_preprocess_input)(inputs)
```

```
    model_orig = VGG16(
            include_top = False,       # no pre-defined head
            input_tensor = inputs,     # input tensor
            input_shape = image_shape, # input shape
            weights = "imagenet",
            pooling = "max"            #max avg
            )

    outputs = model_orig.layers[-1].output
    #outputs = keras.layers.GlobalAveragePooling2D()(outputs)


    model_new = keras.Model(inputs = inputs, outputs = outputs, name =␣
↪"vgg16_encoder")

    return model_new
```

16.2 Building model

[282]:
```
baseline_vgg16_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)
baseline_vgg16_encoder = build_vgg16_encoder(image_shape)
baseline_vgg16_encoder.trainable = False

baseline_vgg16_model = build_supervised_model(
                           image_shape = image_shape,
                           n_classes = n_classes,
                           encoder = baseline_vgg16_encoder,
                           image_augmenter = baseline_vgg16_imgaug,
                           name = "baseline_vgg16_model",
                           learning_rate = 0.001)
```

16.3 Training

[283]:
```
train_evaulate_and_save_models(
                    model = baseline_vgg16_model,
                    encoder = baseline_vgg16_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "baseline_vgg16",
                   )
```

```
Training …

Epoch 1/20
```

```
241/241 [==============================] - 467s 2s/step - loss: 2.1863 -
accuracy: 0.4098 - accuracy_top-5: 0.7435 - val_loss: 1.7301 - val_accuracy:
0.4761 - val_accuracy_top-5: 0.8473
Epoch 2/20
241/241 [==============================] - 461s 2s/step - loss: 1.0717 -
accuracy: 0.6546 - accuracy_top-5: 0.9430 - val_loss: 1.7708 - val_accuracy:
0.4849 - val_accuracy_top-5: 0.8447
Epoch 3/20
241/241 [==============================] - 463s 2s/step - loss: 0.8569 -
accuracy: 0.7181 - accuracy_top-5: 0.9644 - val_loss: 1.6621 - val_accuracy:
0.5210 - val_accuracy_top-5: 0.8716
Epoch 4/20
241/241 [==============================] - 452s 2s/step - loss: 0.7524 -
accuracy: 0.7493 - accuracy_top-5: 0.9745 - val_loss: 1.6586 - val_accuracy:
0.5304 - val_accuracy_top-5: 0.8765
Epoch 5/20
241/241 [==============================] - 450s 2s/step - loss: 0.6838 -
accuracy: 0.7725 - accuracy_top-5: 0.9779 - val_loss: 1.5562 - val_accuracy:
0.5538 - val_accuracy_top-5: 0.8925
Epoch 6/20
241/241 [==============================] - 447s 2s/step - loss: 0.6366 -
accuracy: 0.7853 - accuracy_top-5: 0.9811 - val_loss: 1.6383 - val_accuracy:
0.5439 - val_accuracy_top-5: 0.8835
Epoch 7/20
241/241 [==============================] - 447s 2s/step - loss: 0.5936 -
accuracy: 0.8004 - accuracy_top-5: 0.9834 - val_loss: 1.4210 - val_accuracy:
0.6021 - val_accuracy_top-5: 0.9044
Epoch 8/20
241/241 [==============================] - 446s 2s/step - loss: 0.5733 -
accuracy: 0.8069 - accuracy_top-5: 0.9838 - val_loss: 1.8094 - val_accuracy:
0.5357 - val_accuracy_top-5: 0.8726
Epoch 9/20
241/241 [==============================] - 446s 2s/step - loss: 0.5563 -
accuracy: 0.8102 - accuracy_top-5: 0.9872 - val_loss: 1.5401 - val_accuracy:
0.5926 - val_accuracy_top-5: 0.8949
Epoch 10/20
241/241 [==============================] - 446s 2s/step - loss: 0.5342 -
accuracy: 0.8195 - accuracy_top-5: 0.9867 - val_loss: 1.6373 - val_accuracy:
0.5656 - val_accuracy_top-5: 0.8908
Epoch 11/20
241/241 [==============================] - 447s 2s/step - loss: 0.5080 -
accuracy: 0.8254 - accuracy_top-5: 0.9889 - val_loss: 1.7488 - val_accuracy:
0.5582 - val_accuracy_top-5: 0.8791
Epoch 12/20
241/241 [==============================] - 445s 2s/step - loss: 0.4891 -
accuracy: 0.8313 - accuracy_top-5: 0.9892 - val_loss: 1.5182 - val_accuracy:
0.6040 - val_accuracy_top-5: 0.9066
Epoch 13/20
```

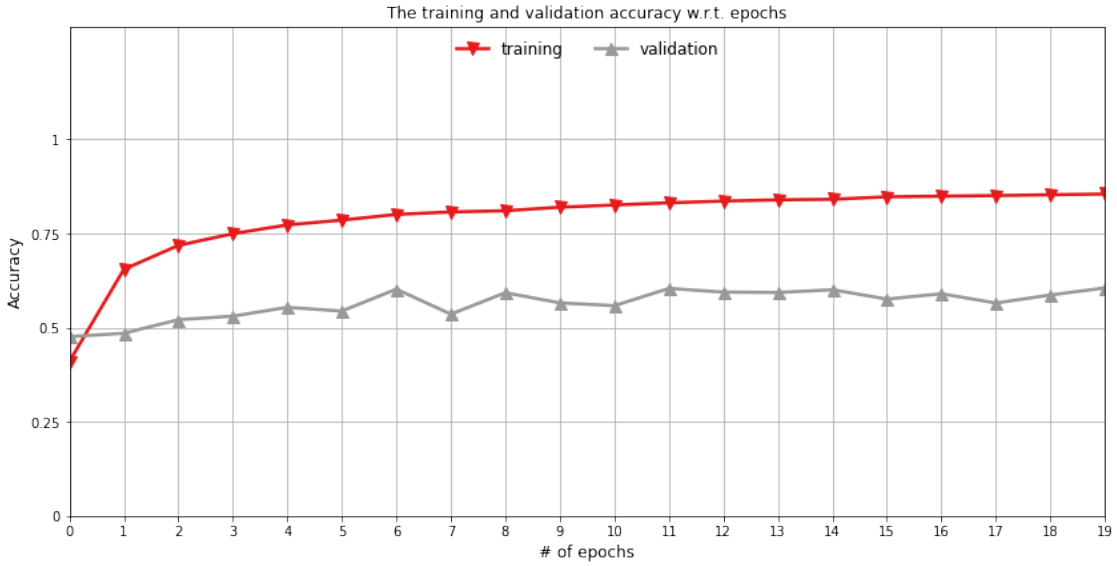
```
241/241 [==============================] - 446s 2s/step - loss: 0.4820 -
accuracy: 0.8357 - accuracy_top-5: 0.9895 - val_loss: 1.5841 - val_accuracy:
0.5943 - val_accuracy_top-5: 0.8953
Epoch 14/20
241/241 [==============================] - 466s 2s/step - loss: 0.4681 -
accuracy: 0.8390 - accuracy_top-5: 0.9892 - val_loss: 1.5904 - val_accuracy:
0.5931 - val_accuracy_top-5: 0.8921
Epoch 15/20
241/241 [==============================] - 530s 2s/step - loss: 0.4552 -
accuracy: 0.8405 - accuracy_top-5: 0.9916 - val_loss: 1.5642 - val_accuracy:
0.6005 - val_accuracy_top-5: 0.8990
Epoch 16/20
241/241 [==============================] - 505s 2s/step - loss: 0.4464 -
accuracy: 0.8471 - accuracy_top-5: 0.9912 - val_loss: 1.6770 - val_accuracy:
0.5757 - val_accuracy_top-5: 0.8961
Epoch 17/20
241/241 [==============================] - 496s 2s/step - loss: 0.4359 -
accuracy: 0.8488 - accuracy_top-5: 0.9919 - val_loss: 1.6840 - val_accuracy:
0.5899 - val_accuracy_top-5: 0.8887
Epoch 18/20
241/241 [==============================] - 506s 2s/step - loss: 0.4279 -
accuracy: 0.8504 - accuracy_top-5: 0.9921 - val_loss: 1.8029 - val_accuracy:
0.5652 - val_accuracy_top-5: 0.8913
Epoch 19/20
241/241 [==============================] - 503s 2s/step - loss: 0.4221 -
accuracy: 0.8526 - accuracy_top-5: 0.9918 - val_loss: 1.7181 - val_accuracy:
0.5866 - val_accuracy_top-5: 0.8913
Epoch 20/20
241/241 [==============================] - 514s 2s/step - loss: 0.4184 -
accuracy: 0.8545 - accuracy_top-5: 0.9924 - val_loss: 1.5603 - val_accuracy:
0.6053 - val_accuracy_top-5: 0.9035

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

INFO:tensorflow:Assets written to:
models/baseline_vgg16/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_vgg16/encoder.saved_model/assets

INFO:tensorflow:Assets written to: models/baseline_vgg16/main.saved_model/assets
```

```
INFO:tensorflow:Assets written to: models/baseline_vgg16/main.saved_model/assets

Saving training history data …


Results:

Maximal accuracy: 0.85448
Maximal accuracy_top-5: 0.99244
Maximal val_accuracy: 0.60532
Maximal val_accuracy_top-5: 0.90662

-- Completed --
```

16.4 Plotting results

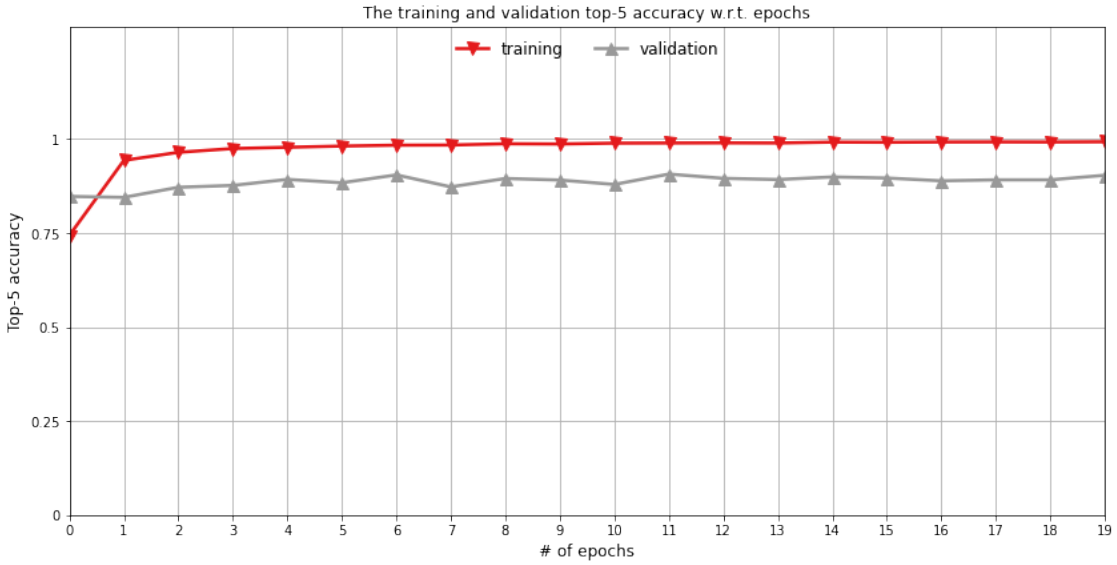
[49]:
```
plot_train_results(
                resultfile = "results/baseline_vgg16/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["accuracy", "val_accuracy"],
                labels = ["training", "validation"],
                savename = "fig_baseline_vgg16_accuracy.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_vgg16_accuracy.pdf
```



[50]:
```
plot_train_results(
                resultfile = "results/baseline_vgg16/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
 ↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["accuracy_top-5", "val_accuracy_top-5"],
                labels = ["training", "validation"],
                savename = "fig_baseline_vgg16_accuracy_top5.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_vgg16_accuracy_top5.pdf
```



17 Baseline: Supervised learning with ResNet50

17.1 Building ResNet50 encoder

[284]:
```
from tensorflow.keras.applications import ResNet50
from tensorflow.keras.applications.resnet50 import preprocess_input as␣
 ↪resnet50_preprocess_input

def build_resnet50_encoder(image_shape):

    inputs = keras.Input(shape = image_shape, name = "inputs")
```

```
    #x = tf.keras.layers.Lambda(resnet50_preprocess_input)(inputs)

    model_orig = ResNet50(
            include_top = False,       # no pre-defined head
            input_tensor = inputs,     # input tensor
            input_shape = image_shape, # input shape
            weights = "imagenet",
            pooling = "max"            #max avg
            )

    outputs = model_orig.layers[-1].output
    #outputs = keras.layers.GlobalAveragePooling2D()(outputs)




    model_new = keras.Model(inputs = inputs, outputs = outputs, name =␣
↪"resnet50_encoder")

    return model_new
```

17.2 Building model

[285]:
```
baseline_resnet_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)

baseline_resnet_encoder = build_resnet50_encoder(image_shape)
baseline_resnet_encoder.trainable = False


baseline_resnet_model = build_supervised_model(
                            image_shape = image_shape,
                            n_classes = n_classes,
                            encoder = baseline_resnet_encoder,
                            image_augmenter = baseline_resnet_imgaug,
                            name = "baseline_resnet_model",
                            learning_rate = 0.001)
```

17.3 Training

[286]:
```
train_evaulate_and_save_models(
                    model = baseline_resnet_model,
                    encoder = baseline_resnet_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "baseline_resnet",
                   )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 233s 948ms/step - loss: 4.5451 -
accuracy: 0.0314 - accuracy_top-5: 0.1317 - val_loss: 4.0374 - val_accuracy:
0.0523 - val_accuracy_top-5: 0.2010
Epoch 2/20
241/241 [==============================] - 241s 996ms/step - loss: 3.8605 -
accuracy: 0.0714 - accuracy_top-5: 0.2698 - val_loss: 4.0545 - val_accuracy:
0.0558 - val_accuracy_top-5: 0.2364
Epoch 3/20
241/241 [==============================] - 227s 939ms/step - loss: 3.6530 -
accuracy: 0.0949 - accuracy_top-5: 0.3277 - val_loss: 4.2026 - val_accuracy:
0.0596 - val_accuracy_top-5: 0.2452
Epoch 4/20
241/241 [==============================] - 232s 963ms/step - loss: 3.5193 -
accuracy: 0.1191 - accuracy_top-5: 0.3691 - val_loss: 4.7043 - val_accuracy:
0.0656 - val_accuracy_top-5: 0.2213
Epoch 5/20
241/241 [==============================] - 208s 864ms/step - loss: 3.4487 -
accuracy: 0.1279 - accuracy_top-5: 0.3946 - val_loss: 4.2191 - val_accuracy:
0.0732 - val_accuracy_top-5: 0.2803
Epoch 6/20
241/241 [==============================] - 204s 845ms/step - loss: 3.3893 -
accuracy: 0.1386 - accuracy_top-5: 0.4148 - val_loss: 4.2879 - val_accuracy:
0.0752 - val_accuracy_top-5: 0.2666
Epoch 7/20
241/241 [==============================] - 204s 844ms/step - loss: 3.3272 -
accuracy: 0.1454 - accuracy_top-5: 0.4293 - val_loss: 3.9732 - val_accuracy:
0.0991 - val_accuracy_top-5: 0.3201
Epoch 8/20
241/241 [==============================] - 203s 843ms/step - loss: 3.2706 -
accuracy: 0.1563 - accuracy_top-5: 0.4495 - val_loss: 4.1659 - val_accuracy:
0.1008 - val_accuracy_top-5: 0.3129
Epoch 9/20
241/241 [==============================] - 203s 841ms/step - loss: 3.2218 -
accuracy: 0.1636 - accuracy_top-5: 0.4645 - val_loss: 4.1969 - val_accuracy:
0.0882 - val_accuracy_top-5: 0.2995
Epoch 10/20
241/241 [==============================] - 203s 843ms/step - loss: 3.1888 -
accuracy: 0.1726 - accuracy_top-5: 0.4691 - val_loss: 4.2390 - val_accuracy:
0.0939 - val_accuracy_top-5: 0.3009
Epoch 11/20
241/241 [==============================] - 211s 875ms/step - loss: 3.1338 -
accuracy: 0.1761 - accuracy_top-5: 0.4905 - val_loss: 4.4350 - val_accuracy:
0.0887 - val_accuracy_top-5: 0.2860
Epoch 12/20
```

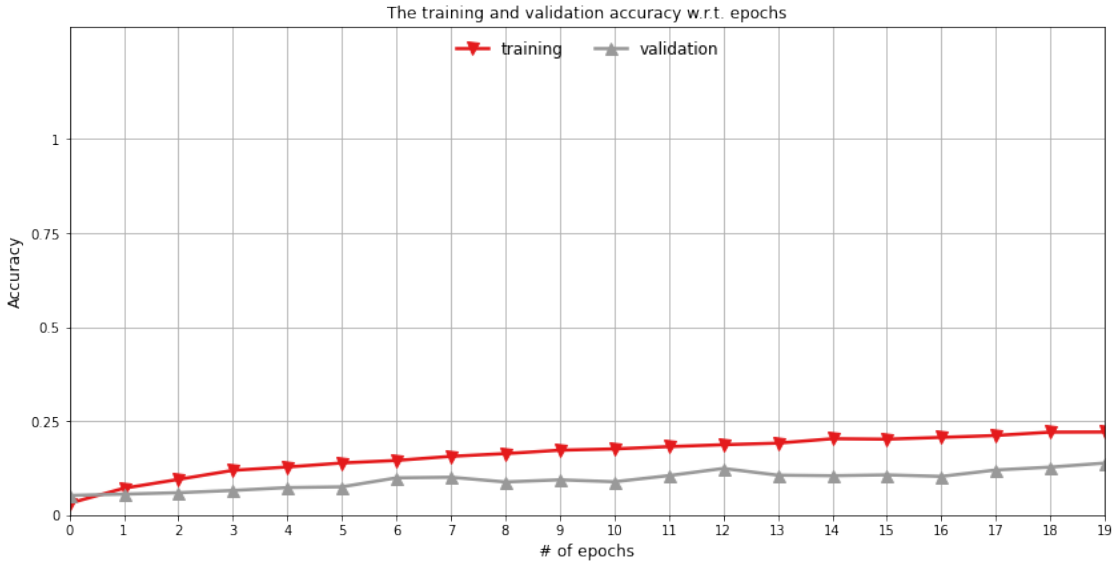
```
241/241 [==============================] - 207s 859ms/step - loss: 3.1264 -
accuracy: 0.1821 - accuracy_top-5: 0.4937 - val_loss: 4.1547 - val_accuracy:
0.1051 - val_accuracy_top-5: 0.3286
Epoch 13/20
241/241 [==============================] - 208s 861ms/step - loss: 3.0884 -
accuracy: 0.1872 - accuracy_top-5: 0.5026 - val_loss: 3.8290 - val_accuracy:
0.1242 - val_accuracy_top-5: 0.3662
Epoch 14/20
241/241 [==============================] - 208s 860ms/step - loss: 3.0680 -
accuracy: 0.1914 - accuracy_top-5: 0.5090 - val_loss: 4.2247 - val_accuracy:
0.1062 - val_accuracy_top-5: 0.3161
Epoch 15/20
241/241 [==============================] - 208s 862ms/step - loss: 3.0076 -
accuracy: 0.2031 - accuracy_top-5: 0.5265 - val_loss: 4.2707 - val_accuracy:
0.1048 - val_accuracy_top-5: 0.3274
Epoch 16/20
241/241 [==============================] - 208s 862ms/step - loss: 3.0037 -
accuracy: 0.2019 - accuracy_top-5: 0.5287 - val_loss: 4.2068 - val_accuracy:
0.1070 - val_accuracy_top-5: 0.3312
Epoch 17/20
241/241 [==============================] - 208s 862ms/step - loss: 2.9690 -
accuracy: 0.2067 - accuracy_top-5: 0.5383 - val_loss: 4.4619 - val_accuracy:
0.1030 - val_accuracy_top-5: 0.3079
Epoch 18/20
241/241 [==============================] - 208s 861ms/step - loss: 2.9677 -
accuracy: 0.2117 - accuracy_top-5: 0.5359 - val_loss: 4.1042 - val_accuracy:
0.1200 - val_accuracy_top-5: 0.3564
Epoch 19/20
241/241 [==============================] - 207s 857ms/step - loss: 2.9301 -
accuracy: 0.2207 - accuracy_top-5: 0.5469 - val_loss: 3.9254 - val_accuracy:
0.1277 - val_accuracy_top-5: 0.3735
Epoch 20/20
241/241 [==============================] - 208s 861ms/step - loss: 2.9103 -
accuracy: 0.2210 - accuracy_top-5: 0.5523 - val_loss: 3.7140 - val_accuracy:
0.1384 - val_accuracy_top-5: 0.3932

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
/usr/local/anaconda3/lib/python3.8/site-
packages/tensorflow/python/keras/utils/generic_utils.py:494: CustomMaskWarning:
Custom mask layers require a config and must override get_config. When loading,
```

```
the custom mask layer must be passed to the custom_objects argument.
  warnings.warn('Custom mask layers require a config and must override '

INFO:tensorflow:Assets written to:
models/baseline_resnet/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_resnet/encoder.saved_model/assets
/usr/local/anaconda3/lib/python3.8/site-
packages/tensorflow/python/keras/utils/generic_utils.py:494: CustomMaskWarning:
Custom mask layers require a config and must override get_config. When loading,
the custom mask layer must be passed to the custom_objects argument.
  warnings.warn('Custom mask layers require a config and must override '

INFO:tensorflow:Assets written to:
models/baseline_resnet/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_resnet/main.saved_model/assets


Saving training history data …


Results:

Maximal accuracy: 0.22104
Maximal accuracy_top-5: 0.55231
Maximal val_accuracy: 0.13844
Maximal val_accuracy_top-5: 0.39325

-- Completed --
```

17.4 Plotting results

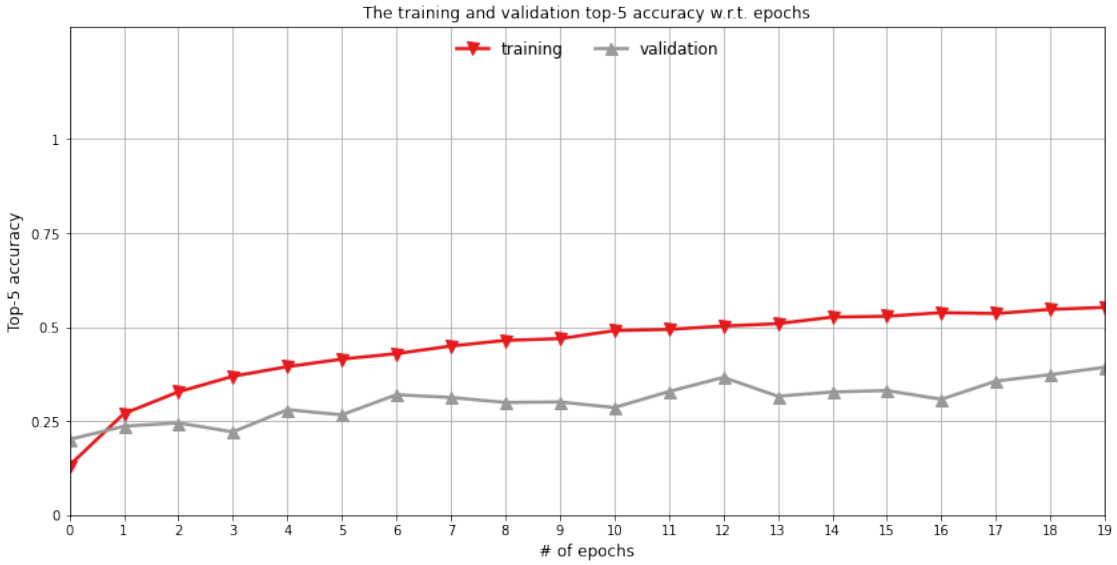
[51]:
```
plot_train_results(
                resultfile = "results/baseline_resnet/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["accuracy", "val_accuracy"],
                labels = ["training", "validation"],
                savename = "fig_baseline_resnet_accuracy.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_resnet_accuracy.pdf
```



[52]:
```
plot_train_results(
                resultfile = "results/baseline_resnet/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["accuracy_top-5", "val_accuracy_top-5"],
                labels = ["training", "validation"],
                savename = "fig_baseline_resnet_accuracy_top5.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_resnet_accuracy_top5.pdf
```



18 Baseline: Supervised learning with MobileNet

18.1 Building MobileNet encoder

[287]:
```
from tensorflow.keras.applications import MobileNet
from tensorflow.keras.applications.mobilenet import preprocess_input as␣
 ↪mobilenet_preprocess_input

def build_mobilenet_encoder(image_shape):

    inputs = keras.Input(shape = image_shape, name = "inputs")

    #x = tf.keras.layers.Lambda(resnet50_preprocess_input)(inputs)

    model_orig = MobileNet(
            include_top = False,       # no pre-defined head
            input_tensor = inputs,     # input tensor
            input_shape = image_shape, # input shape
            weights = "imagenet",
            pooling = "max"            #max avg
            )

    outputs = model_orig.layers[-1].output
    #outputs = keras.layers.GlobalAveragePooling2D()(outputs)
```

```
    model_new = keras.Model(inputs = inputs, outputs = outputs, name =␣
↪"mobilenet_encoder")

    return model_new
```

18.2 Building model

[288]:
```
baseline_mobilenet_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)

baseline_mobilenet_encoder = build_mobilenet_encoder(image_shape)
baseline_mobilenet_encoder.trainable = False


baseline_mobilenet_model = build_supervised_model(
                           image_shape = image_shape,
                           n_classes = n_classes,
                           encoder = baseline_mobilenet_encoder,
                           image_augmenter = baseline_mobilenet_imgaug,
                           name = "baseline_mobilenet_model",
                           learning_rate = 0.001)
```

```
WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not in
[128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the
default.

WARNING:tensorflow:`input_shape` is undefined or non-square, or `rows` is not in
[128, 160, 192, 224]. Weights for input shape (224, 224) will be loaded as the
default.
```

18.3 Training

[289]:
```
train_evaulate_and_save_models(
                    model = baseline_mobilenet_model,
                    encoder = baseline_mobilenet_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "baseline_mobilenet",
                   )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 64s 260ms/step - loss: 2.4931 -
accuracy: 0.3477 - accuracy_top-5: 0.6658 - val_loss: 2.2340 - val_accuracy:
0.3710 - val_accuracy_top-5: 0.7335
```

```
Epoch 2/20
241/241 [==============================] - 67s 279ms/step - loss: 1.7051 -
accuracy: 0.4984 - accuracy_top-5: 0.8263 - val_loss: 2.1422 - val_accuracy:
0.4055 - val_accuracy_top-5: 0.7561
Epoch 3/20
241/241 [==============================] - 66s 272ms/step - loss: 1.5596 -
accuracy: 0.5334 - accuracy_top-5: 0.8530 - val_loss: 2.1210 - val_accuracy:
0.4112 - val_accuracy_top-5: 0.7708
Epoch 4/20
241/241 [==============================] - 66s 272ms/step - loss: 1.4793 -
accuracy: 0.5541 - accuracy_top-5: 0.8654 - val_loss: 2.0638 - val_accuracy:
0.4256 - val_accuracy_top-5: 0.7782
Epoch 5/20
241/241 [==============================] - 66s 273ms/step - loss: 1.4380 -
accuracy: 0.5682 - accuracy_top-5: 0.8699 - val_loss: 2.0302 - val_accuracy:
0.4339 - val_accuracy_top-5: 0.7845
Epoch 6/20
241/241 [==============================] - 66s 274ms/step - loss: 1.3908 -
accuracy: 0.5783 - accuracy_top-5: 0.8769 - val_loss: 2.0262 - val_accuracy:
0.4456 - val_accuracy_top-5: 0.7845
Epoch 7/20
241/241 [==============================] - 66s 273ms/step - loss: 1.3625 -
accuracy: 0.5875 - accuracy_top-5: 0.8826 - val_loss: 2.0048 - val_accuracy:
0.4435 - val_accuracy_top-5: 0.7906
Epoch 8/20
241/241 [==============================] - 66s 274ms/step - loss: 1.3366 -
accuracy: 0.5960 - accuracy_top-5: 0.8870 - val_loss: 2.0435 - val_accuracy:
0.4421 - val_accuracy_top-5: 0.7814
Epoch 9/20
241/241 [==============================] - 66s 275ms/step - loss: 1.3171 -
accuracy: 0.6019 - accuracy_top-5: 0.8903 - val_loss: 2.0178 - val_accuracy:
0.4549 - val_accuracy_top-5: 0.7857
Epoch 10/20
241/241 [==============================] - 66s 274ms/step - loss: 1.3008 -
accuracy: 0.6036 - accuracy_top-5: 0.8916 - val_loss: 2.0072 - val_accuracy:
0.4512 - val_accuracy_top-5: 0.7903
Epoch 11/20
241/241 [==============================] - 68s 281ms/step - loss: 1.2757 -
accuracy: 0.6127 - accuracy_top-5: 0.8944 - val_loss: 2.0162 - val_accuracy:
0.4497 - val_accuracy_top-5: 0.7887
Epoch 12/20
241/241 [==============================] - 66s 274ms/step - loss: 1.2496 -
accuracy: 0.6158 - accuracy_top-5: 0.8979 - val_loss: 2.0461 - val_accuracy:
0.4540 - val_accuracy_top-5: 0.7899
Epoch 13/20
241/241 [==============================] - 66s 275ms/step - loss: 1.2539 -
accuracy: 0.6178 - accuracy_top-5: 0.8978 - val_loss: 1.9397 - val_accuracy:
0.4652 - val_accuracy_top-5: 0.8047
```

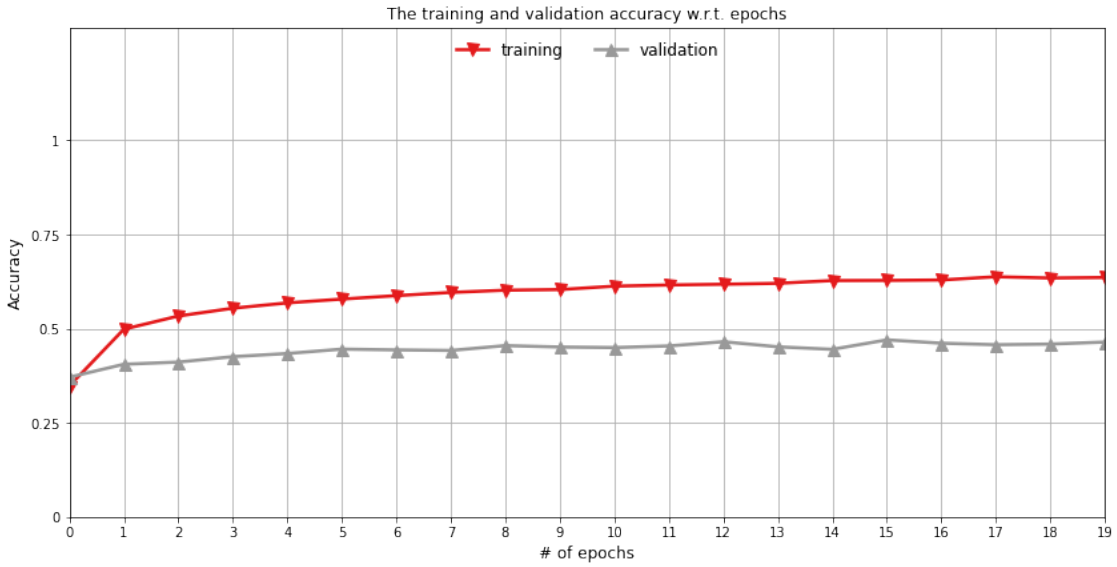
```
Epoch 14/20
241/241 [==============================] - 66s 273ms/step - loss: 1.2385 -
accuracy: 0.6202 - accuracy_top-5: 0.8990 - val_loss: 2.0581 - val_accuracy:
0.4517 - val_accuracy_top-5: 0.7908
Epoch 15/20
241/241 [==============================] - 67s 275ms/step - loss: 1.2247 -
accuracy: 0.6275 - accuracy_top-5: 0.9018 - val_loss: 2.0957 - val_accuracy:
0.4451 - val_accuracy_top-5: 0.7912
Epoch 16/20
241/241 [==============================] - 66s 273ms/step - loss: 1.2138 -
accuracy: 0.6279 - accuracy_top-5: 0.9015 - val_loss: 1.9720 - val_accuracy:
0.4701 - val_accuracy_top-5: 0.7994
Epoch 17/20
241/241 [==============================] - 66s 274ms/step - loss: 1.2114 -
accuracy: 0.6291 - accuracy_top-5: 0.9032 - val_loss: 1.9953 - val_accuracy:
0.4613 - val_accuracy_top-5: 0.7975
Epoch 18/20
241/241 [==============================] - 67s 276ms/step - loss: 1.1877 -
accuracy: 0.6376 - accuracy_top-5: 0.9061 - val_loss: 2.0240 - val_accuracy:
0.4573 - val_accuracy_top-5: 0.7988
Epoch 19/20
241/241 [==============================] - 66s 274ms/step - loss: 1.1915 -
accuracy: 0.6343 - accuracy_top-5: 0.9065 - val_loss: 2.0109 - val_accuracy:
0.4590 - val_accuracy_top-5: 0.8014
Epoch 20/20
241/241 [==============================] - 67s 276ms/step - loss: 1.1861 -
accuracy: 0.6356 - accuracy_top-5: 0.9040 - val_loss: 2.0127 - val_accuracy:
0.4643 - val_accuracy_top-5: 0.7986

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

INFO:tensorflow:Assets written to:
models/baseline_mobilenet/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_mobilenet/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_mobilenet/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/baseline_mobilenet/main.saved_model/assets
```

```
Saving training history data …


Results:

Maximal accuracy: 0.63760
Maximal accuracy_top-5: 0.90649
Maximal val_accuracy: 0.47013
Maximal val_accuracy_top-5: 0.80468

-- Completed --
```

18.4 Plotting results

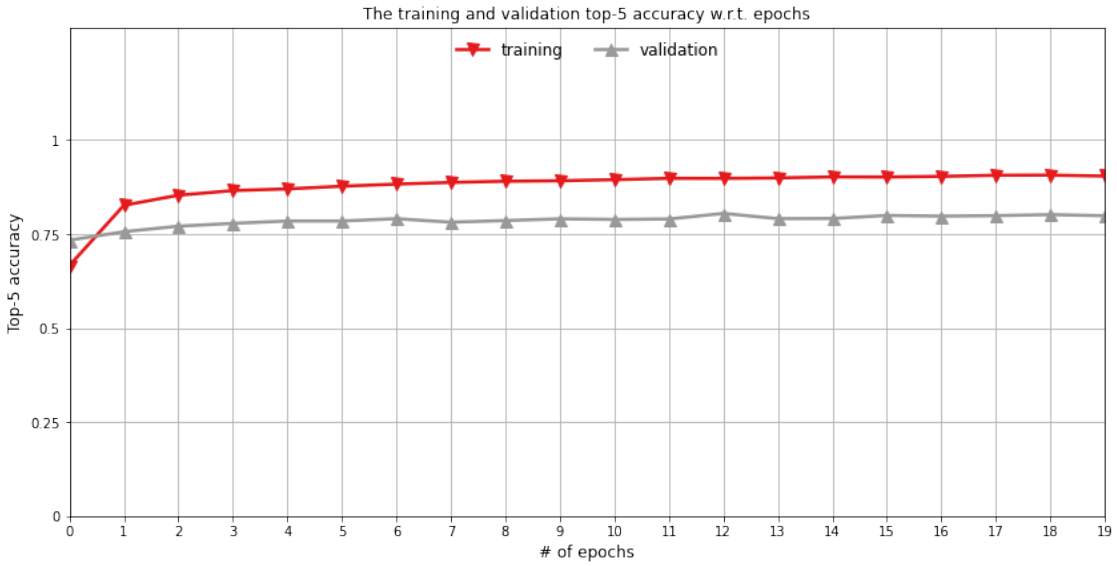
[53]:
```
plot_train_results(
                resultfile = "results/baseline_mobilenet/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["accuracy", "val_accuracy"],
                labels = ["training", "validation"],
                savename = "fig_baseline_mobilenet_accuracy.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_mobilenet_accuracy.pdf
```



[54]:
```
plot_train_results(
                resultfile = "results/baseline_mobilenet/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
 ↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["accuracy_top-5", "val_accuracy_top-5"],
                labels = ["training", "validation"],
                savename = "fig_baseline_mobilenet_accuracy_top5.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_baseline_mobilenet_accuracy_top5.pdf
```



19 Contrastive learning model

[334]:
```
#We refer the framework from https://keras.io/examples/vision/
 ↪semisupervised_simclr/


import numpy as np

import tensorflow as tf
from tensorflow import keras


class ContrastiveModel(keras.Model):
```

```
    def __init__(self,
                 *,
                 temperature = 0.5,

                 contrastive_loss_func = None, #use default loss

                 encoder = None,

                 projhead_hidden_dims = (512, 512,), #one hidden layer by␣
↪default
                 projhead_hidden_activation = "swish",
                 projhead_output_dim = 512,      #one linear output layer

                 image_augmenter,

                 n_classes,  #number of classes, used for linear-regression␣
↪metric


                 **kwargs
                 ):


        #contrastive_loss_name_to_func_dict = {
        #                    "infonce": self.infonce_contrastive_loss_func,     ␣
↪
        #                    #"npairs": self.npairs_contrastive_loss_func
        #            }

        #assert (contrastive_loss_func in contrastive_loss_name_to_func_dict),
        #                "invalid contrastive_loss_func"

        super(ContrastiveModel, self).__init__(**kwargs)

        self.temperature = temperature

        self.image_augmenter = image_augmenter

        self.encoder = encoder

        self.n_classes = n_classes

        self.projhead_input_shape = self.encoder.layers[-1].output.shape[1]
        self.projhead_hidden_dims = projhead_hidden_dims
        self.projhead_hidden_activation = projhead_hidden_activation
        self.projhead_output_dim = projhead_output_dim
```

```
        #print("projhead_input_shape = ", self.projhead_input_shape)
        #print("projhead_hidden_dims = ", self.projhead_hidden_dims)
        #print("projhead_hidden_activation = ", self.projhead_hidden_activation)
        #print("projhead_output_dim = ", self.projhead_output_dim)


        # build projection head
        self.projhead_model = self.build_projhead_model(
                                input_shape = self.projhead_input_shape,
                                hidden_dims = self.projhead_hidden_dims,
                                output_dim = self.projhead_output_dim
                              )


        # Single dense layer for linear probing
        self.probe_model = self.build_probe_model(
                                n_classes = self.n_classes,
                                input_shape = self.projhead_output_dim
                              )

        #self.encoder.summary()
        #self.projhead_model.summary()
        #self.probe_model.summary()


        if not contrastive_loss_func:
            self.contrastive_loss_func = self.infonce_contrastive_loss_func
        else:
            self.contrastive_loss_func = contrastive_loss_func




    def build_probe_model(self, *, n_classes, input_shape):
        return keras.Sequential(
                [
                 keras.layers.InputLayer(input_shape = input_shape),
                 keras.layers.Dense(n_classes), #pure linear
                ],
                 name="linear_probe"
                )

    def build_projhead_model(self, *, input_shape, hidden_dims, output_dim):

        inputs = keras.layers.Input(shape = input_shape, name =␣
↪"projhead_input")
```

```
        x = keras.layers.Flatten(name = "projhead_flatten")(inputs)

        if not self.projhead_hidden_activation:
            self.projhead_hidden_activation = "swish"

        for idx, dim in enumerate(hidden_dims):
            x = keras.layers.Dense(dim,
                                   activation = self.projhead_hidden_activation,
                                   name = f"projhead_hidden_{idx+1}")(x)

        outputs = keras.layers.Dense(output_dim)(x)

        model = keras.Model(inputs = inputs, outputs = outputs, name =␣
↪"projhead_output")

        return model

    def compile(self, contrastive_optimizer, probe_optimizer, **kwargs):

        super().compile(**kwargs)

        self.contrastive_optimizer = contrastive_optimizer
        self.probe_optimizer = probe_optimizer

        self.probe_loss = keras.losses.
↪SparseCategoricalCrossentropy(from_logits=True)

        self.contrastive_loss_tracker = keras.metrics.Mean(
                                                    name="contrastive_loss"
                                                )
        self.contrastive_accuracy = keras.metrics.SparseCategoricalAccuracy(
                                                    name="contrastive_accuracy"
                                                )
        self.contrastive_accuracy_top5 = keras.metrics.
↪SparseTopKCategoricalAccuracy(
                                                    5,
                                                   ␣
↪name="contrastive_accuracy_top-5"
                                                )


        self.probe_loss_tracker = keras.metrics.Mean(
                                                    name="probe_loss"
                                                )
        self.probe_accuracy = keras.metrics.SparseCategoricalAccuracy(
                                                    name="probe_accuracy"
                                                )
```

```
        self.probe_accuracy_top5 = keras.metrics.SparseTopKCategoricalAccuracy(
                                                    5,
                                                    name="probe_accuracy_top-5"
                                                )

    @property
    def metrics(self):
        return [
            self.contrastive_loss_tracker, #contrastive loss

            self.contrastive_accuracy, #contrastive accuracy
            self.contrastive_accuracy_top5,

            self.probe_loss_tracker, #linear prober loss

            self.probe_accuracy, #linear prober accuracy
            self.probe_accuracy_top5,
        ]


    def infonce_contrastive_loss_func(self, projections_1, projections_2):

        # We first normalise the projections for the two batches.
        projections_1 = tf.math.l2_normalize(projections_1, axis=1)
        projections_2 = tf.math.l2_normalize(projections_2, axis=1)

        # Computing A * B^T, all similarities will be computed at this point.
        similarities = (
            tf.matmul(projections_1, projections_2, transpose_b=True) / self.
↪temperature
        )

        batch_size = tf.shape(projections_1)[0]

        fake_labels = tf.range(batch_size)

        # Update the projection head accuracy
        self.contrastive_accuracy.update_state(fake_labels, similarities)
        self.contrastive_accuracy.update_state(fake_labels, tf.
↪transpose(similarities))

        self.contrastive_accuracy_top5.update_state(fake_labels, similarities)
        self.contrastive_accuracy_top5.update_state(fake_labels, tf.
↪transpose(similarities))
```

```
        # Compute the loss
        loss_1_2 = keras.losses.sparse_categorical_crossentropy(
            fake_labels, similarities, from_logits=True
        )

        loss_2_1 = keras.losses.sparse_categorical_crossentropy(
            fake_labels, tf.transpose(similarities), from_logits=True
        )

        return (loss_1_2 + loss_2_1) / 2

    def train_step(self, data):

        #unpacking the training images and labels (fake) in the batch
        images,labels = data


        """ The contrastive learning episode

        """

        # We randomly sample two transformation functions
        # and use them to augment the input batch (N images).
        augmented_images_1 = self.image_augmenter(images)
        augmented_images_2 = self.image_augmenter(images)


        # We now have 2*N augmented images


        # tf.GradientTape is a basic facility in tensorflow, which implemented
        # of recording operations for automatic differentiation..
        #
        # ref: https://www.tensorflow.org/api_docs/python/tf/GradientTape
        # ref:

        # Create a GradientTape instance to record the forward process
        with tf.GradientTape() as tape:
            # Feeding augmented images (2*N) into the base encoder
            # to extract their features (2*N)
            features_1 = self.encoder(augmented_images_1)
            features_2 = self.encoder(augmented_images_2)

            # Feeding the features (2*N) into the projection head, which is
            # a MLP, the final layer is a pure linear layer.
            projections_1 = self.projhead_model(features_1)
```

```
            projections_2 = self.projhead_model(features_2)

            # We now have 2*N projections from the projection head
            # and compute the contrastive loss (info-NCE)
            contrastive_loss = self.contrastive_loss_func(projections_1,␣
↪projections_2)

        # Computing the gradients w.r.t. every trainable variables by␣
↪back-propogating the errors
        # the *gradients* has the results with the form dL / dW
        gradients = tape.gradient(
                contrastive_loss,
                self.encoder.trainable_weights + self.projhead_model.
↪trainable_weights,
            )

        # Optimising the weights by the computed gradients.
        self.contrastive_optimizer.apply_gradients(
                zip(
                    gradients,
                    self.encoder.trainable_weights + self.projhead_model.
↪trainable_weights,
                )
            )


        # Updating the loss history.
        self.contrastive_loss_tracker.update_state(contrastive_loss)


        """ Updating the weights of the linear prediction model

        """

        augmented_images_3 = self.image_augmenter(images)

        # Forward
        with tf.GradientTape() as tape:

            features = self.encoder(augmented_images_3)

            features_2 = self.projhead_model(features)

            class_logits = self.probe_model(features_2)

            probe_loss = self.probe_loss(labels, class_logits)
```

```
        # backwards, computing the gradients w.r.t. the linear prober
        gradients = tape.gradient(probe_loss, self.probe_model.
↪trainable_weights)

        # updating the weights.
        self.probe_optimizer.apply_gradients(
            zip(gradients, self.probe_model.trainable_weights)
        )

        # updating history.
        self.probe_loss_tracker.update_state(probe_loss)

        self.probe_accuracy.update_state(labels, class_logits)
        self.probe_accuracy_top5.update_state(labels, class_logits)


        return {m.name: m.result() for m in self.metrics}

    # for validation
    def test_step(self, data):

        images, labels = data

        # Update probe
        augmented_images = self.image_augmenter(images, training=False)

        features = self.encoder(augmented_images, training=False)
        features_2 = self.projhead_model(features, training=False)

        class_logits = self.probe_model(features_2, training=False)
        probe_loss = self.probe_loss(labels, class_logits)

        self.probe_loss_tracker.update_state(probe_loss)

        self.probe_accuracy.update_state(labels, class_logits)
        self.probe_accuracy_top5.update_state(labels, class_logits)

        # Update contrastive
        augmented_images_1 = self.image_augmenter(images)
        augmented_images_2 = self.image_augmenter(images)

        features_1 = self.encoder(augmented_images_1)
        features_2 = self.encoder(augmented_images_2)

        projections_1 = self.projhead_model(features_1)
        projections_2 = self.projhead_model(features_2)
```

```
        #accuracy will be computed here
        _ = self.contrastive_loss_func(projections_1, projections_2)

        return {m.name: m.result() for m in self.metrics[2:]}

    #@tf.function
    def call(self, inputs, training = False, mask = None):

        #augmented_images = self.image_augmenter(inputs)
        #features = self.encoder(augmented_images)

        features = self.encoder(inputs)
        outputs = self.projhead_model(features)

        return outputs
```

20 Contrastive learning with simple encoder

20.1 Building model

[337]:
```
contrastive_simple_encoder = build_simple_encoder(image_shape)
contrastive_simple_encoder.trainable = True

contrastive_simple_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)

contrastive_simple_model = ContrastiveModel(
                                temperature = temperature,

                                encoder = contrastive_simple_encoder,

                                projhead_hidden_dims = (512, 512,),
                                projhead_hidden_activation = "swish",
                                projhead_output_dim = 512,

                                image_augmenter = contrastive_simple_imgaug,
                                n_classes = n_classes
                            )

contrastive_simple_model.compile(
            contrastive_optimizer = keras.optimizers.Adam(learning_rate = 0.
 ↪001),
            probe_optimizer = keras.optimizers.Adam(),
        )
```

20.2 Training

[338]:
```
train_evaulate_and_save_models(
                    model = contrastive_simple_model,
                    encoder = contrastive_simple_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "contrastive_simple",
                   )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 87s 344ms/step - contrastive_loss:
2.2404 - contrastive_accuracy: 0.7355 - contrastive_accuracy_top-5: 0.8958 -
probe_loss: 4.5939 - probe_accuracy: 0.0335 - probe_accuracy_top-5: 0.1385 -
val_contrastive_accuracy_top-5: 0.9623 - val_probe_loss: 4.4781 -
val_probe_accuracy: 0.0339 - val_probe_accuracy_top-5: 0.1449
Epoch 2/20
241/241 [==============================] - 77s 319ms/step - contrastive_loss:
1.6832 - contrastive_accuracy: 0.8894 - contrastive_accuracy_top-5: 0.9808 -
probe_loss: 3.9923 - probe_accuracy: 0.0760 - probe_accuracy_top-5: 0.2721 -
val_contrastive_accuracy_top-5: 0.9908 - val_probe_loss: 4.2383 -
val_probe_accuracy: 0.0439 - val_probe_accuracy_top-5: 0.2005
Epoch 3/20
241/241 [==============================] - 78s 322ms/step - contrastive_loss:
1.4508 - contrastive_accuracy: 0.9327 - contrastive_accuracy_top-5: 0.9946 -
probe_loss: 3.6740 - probe_accuracy: 0.1038 - probe_accuracy_top-5: 0.3514 -
val_contrastive_accuracy_top-5: 0.9954 - val_probe_loss: 4.0537 -
val_probe_accuracy: 0.0582 - val_probe_accuracy_top-5: 0.2443
Epoch 4/20
241/241 [==============================] - 79s 325ms/step - contrastive_loss:
1.3428 - contrastive_accuracy: 0.9618 - contrastive_accuracy_top-5: 0.9978 -
probe_loss: 3.3929 - probe_accuracy: 0.1372 - probe_accuracy_top-5: 0.4265 -
val_contrastive_accuracy_top-5: 0.9988 - val_probe_loss: 4.0570 -
val_probe_accuracy: 0.0699 - val_probe_accuracy_top-5: 0.2627
Epoch 5/20
241/241 [==============================] - 78s 324ms/step - contrastive_loss:
1.2696 - contrastive_accuracy: 0.9735 - contrastive_accuracy_top-5: 0.9991 -
probe_loss: 3.1508 - probe_accuracy: 0.1753 - probe_accuracy_top-5: 0.4956 -
val_contrastive_accuracy_top-5: 0.9988 - val_probe_loss: 3.7342 -
val_probe_accuracy: 0.1086 - val_probe_accuracy_top-5: 0.3519
Epoch 6/20
241/241 [==============================] - 79s 325ms/step - contrastive_loss:
1.2192 - contrastive_accuracy: 0.9804 - contrastive_accuracy_top-5: 0.9993 -
probe_loss: 2.9469 - probe_accuracy: 0.2098 - probe_accuracy_top-5: 0.5539 -
```

```
val_contrastive_accuracy_top-5: 0.9994 - val_probe_loss: 4.6687 -
val_probe_accuracy: 0.0861 - val_probe_accuracy_top-5: 0.2721
Epoch 7/20
241/241 [==============================] - 79s 327ms/step - contrastive_loss:
1.1874 - contrastive_accuracy: 0.9838 - contrastive_accuracy_top-5: 0.9998 -
probe_loss: 2.8156 - probe_accuracy: 0.2294 - probe_accuracy_top-5: 0.5909 -
val_contrastive_accuracy_top-5: 0.9995 - val_probe_loss: 3.6150 -
val_probe_accuracy: 0.1495 - val_probe_accuracy_top-5: 0.4217
Epoch 8/20
241/241 [==============================] - 79s 327ms/step - contrastive_loss:
1.1598 - contrastive_accuracy: 0.9875 - contrastive_accuracy_top-5: 0.9997 -
probe_loss: 2.7121 - probe_accuracy: 0.2464 - probe_accuracy_top-5: 0.6199 -
val_contrastive_accuracy_top-5: 0.9998 - val_probe_loss: 3.4005 -
val_probe_accuracy: 0.1591 - val_probe_accuracy_top-5: 0.4770
Epoch 9/20
241/241 [==============================] - 79s 327ms/step - contrastive_loss:
1.1434 - contrastive_accuracy: 0.9880 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.6453 - probe_accuracy: 0.2586 - probe_accuracy_top-5: 0.6387 -
val_contrastive_accuracy_top-5: 0.9998 - val_probe_loss: 3.6535 -
val_probe_accuracy: 0.1469 - val_probe_accuracy_top-5: 0.4395
Epoch 10/20
241/241 [==============================] - 79s 329ms/step - contrastive_loss:
1.1223 - contrastive_accuracy: 0.9879 - contrastive_accuracy_top-5: 0.9998 -
probe_loss: 2.5299 - probe_accuracy: 0.2781 - probe_accuracy_top-5: 0.6661 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 3.5019 -
val_probe_accuracy: 0.1631 - val_probe_accuracy_top-5: 0.4729
Epoch 11/20
241/241 [==============================] - 81s 336ms/step - contrastive_loss:
1.1199 - contrastive_accuracy: 0.9891 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.5478 - probe_accuracy: 0.2755 - probe_accuracy_top-5: 0.6650 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 3.5174 -
val_probe_accuracy: 0.1629 - val_probe_accuracy_top-5: 0.4736
Epoch 12/20
241/241 [==============================] - 80s 330ms/step - contrastive_loss:
1.1056 - contrastive_accuracy: 0.9905 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.5096 - probe_accuracy: 0.2819 - probe_accuracy_top-5: 0.6751 -
val_contrastive_accuracy_top-5: 0.9998 - val_probe_loss: 3.4485 -
val_probe_accuracy: 0.1690 - val_probe_accuracy_top-5: 0.4899
Epoch 13/20
241/241 [==============================] - 80s 331ms/step - contrastive_loss:
1.0958 - contrastive_accuracy: 0.9906 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.4322 - probe_accuracy: 0.2989 - probe_accuracy_top-5: 0.6976 -
val_contrastive_accuracy_top-5: 0.9995 - val_probe_loss: 3.5370 -
val_probe_accuracy: 0.1735 - val_probe_accuracy_top-5: 0.4803
Epoch 14/20
241/241 [==============================] - 80s 330ms/step - contrastive_loss:
1.0829 - contrastive_accuracy: 0.9918 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.4299 - probe_accuracy: 0.2979 - probe_accuracy_top-5: 0.6951 -
```

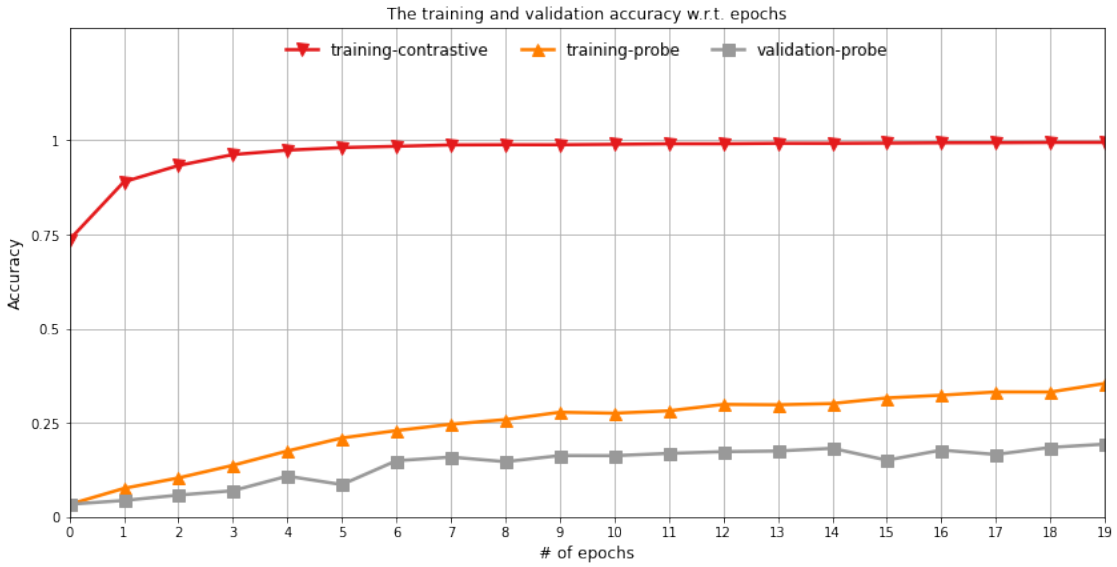
```
val_contrastive_accuracy_top-5: 1.0000 - val_probe_loss: 3.4338 -
val_probe_accuracy: 0.1752 - val_probe_accuracy_top-5: 0.5074
Epoch 15/20
241/241 [==============================] - 80s 330ms/step - contrastive_loss:
1.0838 - contrastive_accuracy: 0.9917 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.4151 - probe_accuracy: 0.3012 - probe_accuracy_top-5: 0.7006 -
val_contrastive_accuracy_top-5: 1.0000 - val_probe_loss: 3.4068 -
val_probe_accuracy: 0.1823 - val_probe_accuracy_top-5: 0.5039
Epoch 16/20
241/241 [==============================] - 82s 339ms/step - contrastive_loss:
1.0737 - contrastive_accuracy: 0.9924 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.3480 - probe_accuracy: 0.3161 - probe_accuracy_top-5: 0.7148 -
val_contrastive_accuracy_top-5: 0.9999 - val_probe_loss: 4.1869 -
val_probe_accuracy: 0.1508 - val_probe_accuracy_top-5: 0.4313
Epoch 17/20
241/241 [==============================] - 83s 341ms/step - contrastive_loss:
1.0660 - contrastive_accuracy: 0.9931 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.3215 - probe_accuracy: 0.3233 - probe_accuracy_top-5: 0.7244 -
val_contrastive_accuracy_top-5: 1.0000 - val_probe_loss: 3.4944 -
val_probe_accuracy: 0.1777 - val_probe_accuracy_top-5: 0.5058
Epoch 18/20
241/241 [==============================] - 82s 337ms/step - contrastive_loss:
1.0578 - contrastive_accuracy: 0.9933 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 2.2736 - probe_accuracy: 0.3320 - probe_accuracy_top-5: 0.7344 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 3.7932 -
val_probe_accuracy: 0.1661 - val_probe_accuracy_top-5: 0.4842
Epoch 19/20
241/241 [==============================] - 86s 356ms/step - contrastive_loss:
1.0518 - contrastive_accuracy: 0.9940 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 2.2730 - probe_accuracy: 0.3318 - probe_accuracy_top-5: 0.7407 -
val_contrastive_accuracy_top-5: 0.9998 - val_probe_loss: 3.3576 -
val_probe_accuracy: 0.1848 - val_probe_accuracy_top-5: 0.5235
Epoch 20/20
241/241 [==============================] - 89s 366ms/step - contrastive_loss:
1.0388 - contrastive_accuracy: 0.9941 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 2.1412 - probe_accuracy: 0.3546 - probe_accuracy_top-5: 0.7669 -
val_contrastive_accuracy_top-5: 1.0000 - val_probe_loss: 3.4939 -
val_probe_accuracy: 0.1935 - val_probe_accuracy_top-5: 0.5277

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
```

```
INFO:tensorflow:Assets written to:
models/contrastive_simple/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/contrastive_simple/encoder.saved_model/assets
WARNING:absl:Found untraced functions such as train_imgaug_layer_layer_call_fn,
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_fn,
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_and_return_conditional_losses while saving
(showing 5 of 5). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to:
models/contrastive_simple/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/contrastive_simple/main.saved_model/assets


Saving training history data …


Results:

Maximal contrastive_accuracy: 0.99414
Maximal contrastive_accuracy_top-5: 0.99997
Maximal probe_accuracy: 0.35458
Maximal probe_accuracy_top-5: 0.76692
Maximal val_contrastive_accuracy_top-5: 1.00000
Maximal val_probe_accuracy: 0.19351
Maximal val_probe_accuracy_top-5: 0.52766

-- Completed --
```

20.3 Plotting results

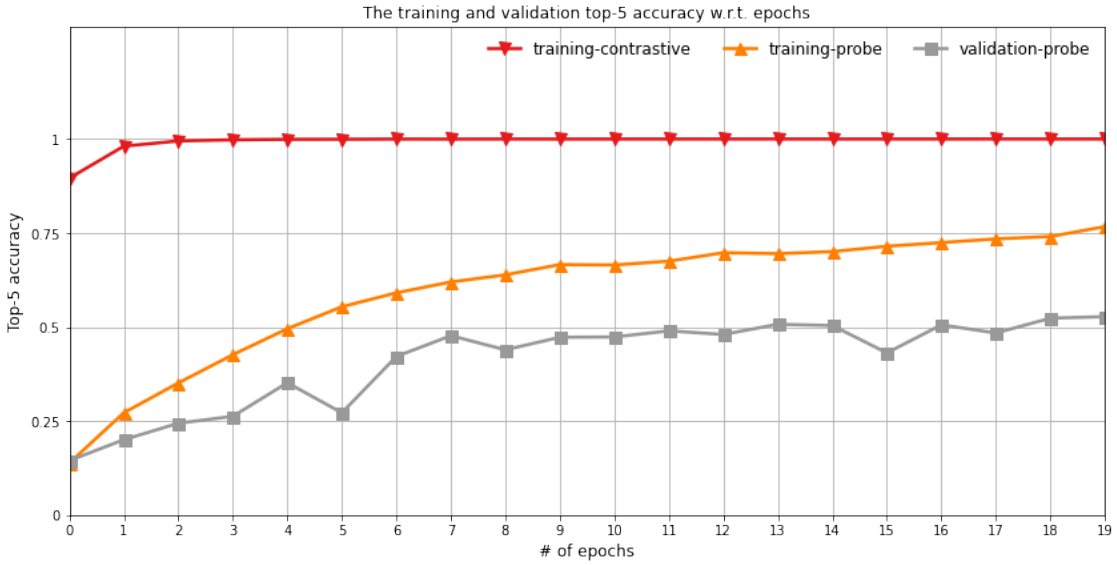
[55]:
```
plot_train_results(
                resultfile = "results/contrastive_simple/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["contrastive_accuracy",
                       "probe_accuracy", "val_probe_accuracy"],
                labels = ["training-contrastive",
                         "training-probe", "validation-probe"],
                savename = "fig_contrastive_simple_accuracy.pdf",
                legend_location = "upper center",
                normalise = False
            )
```

```
saved to:  figures/fig_contrastive_simple_accuracy.pdf
```



[56]:
```
plot_train_results(
                resultfile = "results/contrastive_simple/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
 ↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["contrastive_accuracy_top-5",
                        "probe_accuracy_top-5", "val_probe_accuracy_top-5"],
                labels = ["training-contrastive",
                          "training-probe", "validation-probe"],
                savename = "fig_contrastive_simple_accuracy_top5.pdf",
                legend_location = "best",
                normalise = False
            )
```

```
saved to:  figures/fig_contrastive_simple_accuracy_top5.pdf
```



21 Contrastive learning with VGG16 without fine-tuning

[339]:
```
contrastive_vgg16_encoder = build_vgg16_encoder(image_shape)
contrastive_vgg16_encoder.trainable = False

contrastive_vgg16_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)

contrastive_vgg16_model = ContrastiveModel(
                                temperature = temperature,

                                encoder = contrastive_vgg16_encoder,

                                projhead_hidden_dims = (512, 512,),
                                projhead_hidden_activation = "swish",
                                projhead_output_dim = 512,

                                image_augmenter = contrastive_vgg16_imgaug,
                                n_classes = n_classes
                            )

contrastive_vgg16_model.compile(
            contrastive_optimizer = keras.optimizers.Adam(learning_rate = 0.
↪001),
            probe_optimizer = keras.optimizers.Adam(),
        )
```

21.1 Training

[340]:
```
train_evaulate_and_save_models(
                    model = contrastive_vgg16_model,
                    encoder = contrastive_vgg16_encoder,
                    train_dataset = train_dataset,
                    test_dataset = test_dataset,
                    epochs = n_epochs,
                    savename = "contrastive_vgg16",
                   )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 1194s 5s/step - contrastive_loss:
1.7681 - contrastive_accuracy: 0.8889 - contrastive_accuracy_top-5: 0.9875 -
probe_loss: 3.3692 - probe_accuracy: 0.4048 - probe_accuracy_top-5: 0.7501 -
val_contrastive_accuracy_top-5: 0.9950 - val_probe_loss: 2.3002 -
val_probe_accuracy: 0.4545 - val_probe_accuracy_top-5: 0.8314
Epoch 2/20
241/241 [==============================] - 1204s 5s/step - contrastive_loss:
1.5591 - contrastive_accuracy: 0.9196 - contrastive_accuracy_top-5: 0.9958 -
probe_loss: 1.5817 - probe_accuracy: 0.6359 - probe_accuracy_top-5: 0.9307 -
val_contrastive_accuracy_top-5: 0.9951 - val_probe_loss: 1.6658 -
val_probe_accuracy: 0.5336 - val_probe_accuracy_top-5: 0.8696
Epoch 3/20
241/241 [==============================] - 1199s 5s/step - contrastive_loss:
1.4746 - contrastive_accuracy: 0.9192 - contrastive_accuracy_top-5: 0.9962 -
probe_loss: 1.1043 - probe_accuracy: 0.6843 - probe_accuracy_top-5: 0.9516 -
val_contrastive_accuracy_top-5: 0.9969 - val_probe_loss: 1.5470 -
val_probe_accuracy: 0.5479 - val_probe_accuracy_top-5: 0.8803
Epoch 4/20
241/241 [==============================] - 1262s 5s/step - contrastive_loss:
1.4211 - contrastive_accuracy: 0.9216 - contrastive_accuracy_top-5: 0.9968 -
probe_loss: 0.9430 - probe_accuracy: 0.7088 - probe_accuracy_top-5: 0.9582 -
val_contrastive_accuracy_top-5: 0.9972 - val_probe_loss: 1.6620 -
val_probe_accuracy: 0.5308 - val_probe_accuracy_top-5: 0.8732
Epoch 5/20
241/241 [==============================] - 1501s 6s/step - contrastive_loss:
1.3889 - contrastive_accuracy: 0.9225 - contrastive_accuracy_top-5: 0.9969 -
probe_loss: 0.8625 - probe_accuracy: 0.7242 - probe_accuracy_top-5: 0.9646 -
val_contrastive_accuracy_top-5: 0.9969 - val_probe_loss: 1.5644 -
val_probe_accuracy: 0.5743 - val_probe_accuracy_top-5: 0.8913
Epoch 6/20
241/241 [==============================] - 1559s 6s/step - contrastive_loss:
1.3654 - contrastive_accuracy: 0.9225 - contrastive_accuracy_top-5: 0.9973 -
probe_loss: 0.8213 - probe_accuracy: 0.7371 - probe_accuracy_top-5: 0.9692 -
```

```
val_contrastive_accuracy_top-5: 0.9973 - val_probe_loss: 1.6253 -
val_probe_accuracy: 0.5647 - val_probe_accuracy_top-5: 0.8873
Epoch 7/20
241/241 [==============================] - 1458s 6s/step - contrastive_loss:
1.3493 - contrastive_accuracy: 0.9210 - contrastive_accuracy_top-5: 0.9970 -
probe_loss: 0.8042 - probe_accuracy: 0.7412 - probe_accuracy_top-5: 0.9715 -
val_contrastive_accuracy_top-5: 0.9979 - val_probe_loss: 1.7103 -
val_probe_accuracy: 0.5701 - val_probe_accuracy_top-5: 0.8894
Epoch 8/20
241/241 [==============================] - 1490s 6s/step - contrastive_loss:
1.3325 - contrastive_accuracy: 0.9228 - contrastive_accuracy_top-5: 0.9977 -
probe_loss: 0.7767 - probe_accuracy: 0.7504 - probe_accuracy_top-5: 0.9733 -
val_contrastive_accuracy_top-5: 0.9975 - val_probe_loss: 1.7753 -
val_probe_accuracy: 0.5584 - val_probe_accuracy_top-5: 0.8886
Epoch 9/20
241/241 [==============================] - 1521s 6s/step - contrastive_loss:
1.3150 - contrastive_accuracy: 0.9231 - contrastive_accuracy_top-5: 0.9976 -
probe_loss: 0.7717 - probe_accuracy: 0.7547 - probe_accuracy_top-5: 0.9738 -
val_contrastive_accuracy_top-5: 0.9971 - val_probe_loss: 1.8085 -
val_probe_accuracy: 0.5701 - val_probe_accuracy_top-5: 0.8930
Epoch 10/20
241/241 [==============================] - 1447s 6s/step - contrastive_loss:
1.3038 - contrastive_accuracy: 0.9233 - contrastive_accuracy_top-5: 0.9976 -
probe_loss: 0.7564 - probe_accuracy: 0.7571 - probe_accuracy_top-5: 0.9759 -
val_contrastive_accuracy_top-5: 0.9966 - val_probe_loss: 1.7845 -
val_probe_accuracy: 0.5729 - val_probe_accuracy_top-5: 0.8943
Epoch 11/20
241/241 [==============================] - 1407s 6s/step - contrastive_loss:
1.2898 - contrastive_accuracy: 0.9251 - contrastive_accuracy_top-5: 0.9979 -
probe_loss: 0.7583 - probe_accuracy: 0.7574 - probe_accuracy_top-5: 0.9762 -
val_contrastive_accuracy_top-5: 0.9958 - val_probe_loss: 1.7824 -
val_probe_accuracy: 0.5823 - val_probe_accuracy_top-5: 0.8931
Epoch 12/20
241/241 [==============================] - 1424s 6s/step - contrastive_loss:
1.2785 - contrastive_accuracy: 0.9245 - contrastive_accuracy_top-5: 0.9981 -
probe_loss: 0.7580 - probe_accuracy: 0.7596 - probe_accuracy_top-5: 0.9762 -
val_contrastive_accuracy_top-5: 0.9977 - val_probe_loss: 1.8548 -
val_probe_accuracy: 0.5662 - val_probe_accuracy_top-5: 0.8875
Epoch 13/20
241/241 [==============================] - 1383s 6s/step - contrastive_loss:
1.2749 - contrastive_accuracy: 0.9225 - contrastive_accuracy_top-5: 0.9981 -
probe_loss: 0.7529 - probe_accuracy: 0.7588 - probe_accuracy_top-5: 0.9761 -
val_contrastive_accuracy_top-5: 0.9968 - val_probe_loss: 1.8414 -
val_probe_accuracy: 0.5722 - val_probe_accuracy_top-5: 0.8940
Epoch 14/20
241/241 [==============================] - 1325s 6s/step - contrastive_loss:
1.2587 - contrastive_accuracy: 0.9278 - contrastive_accuracy_top-5: 0.9982 -
probe_loss: 0.7193 - probe_accuracy: 0.7681 - probe_accuracy_top-5: 0.9780 -
```

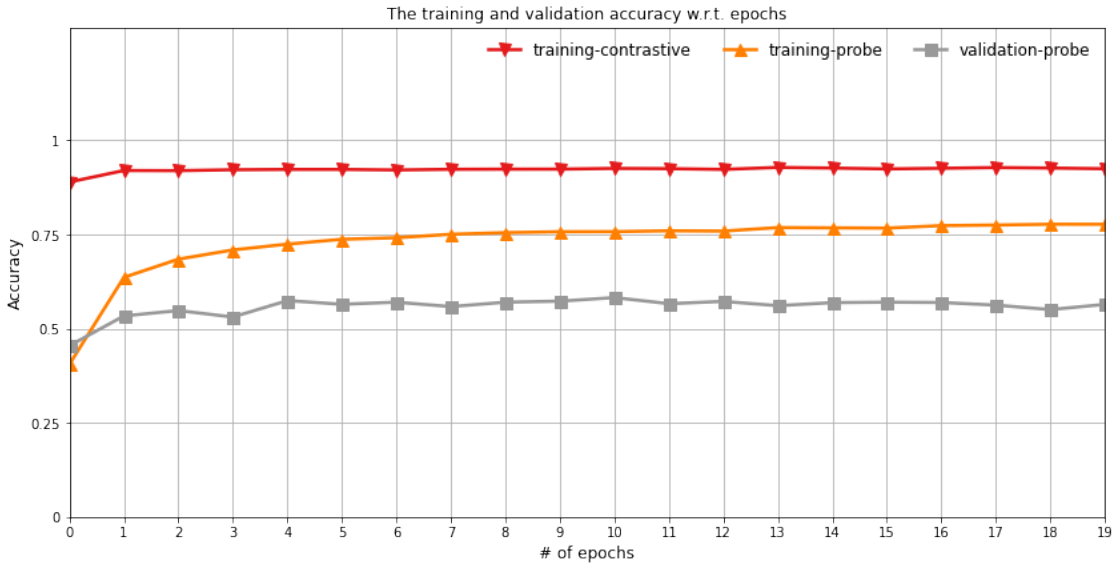
```
val_contrastive_accuracy_top-5: 0.9966 - val_probe_loss: 1.9528 -
val_probe_accuracy: 0.5609 - val_probe_accuracy_top-5: 0.8912
Epoch 15/20
241/241 [==============================] - 1340s 6s/step - contrastive_loss:
1.2500 - contrastive_accuracy: 0.9261 - contrastive_accuracy_top-5: 0.9979 -
probe_loss: 0.7274 - probe_accuracy: 0.7674 - probe_accuracy_top-5: 0.9780 -
val_contrastive_accuracy_top-5: 0.9955 - val_probe_loss: 1.9163 -
val_probe_accuracy: 0.5690 - val_probe_accuracy_top-5: 0.8874
Epoch 16/20
241/241 [==============================] - 1332s 6s/step - contrastive_loss:
1.2479 - contrastive_accuracy: 0.9238 - contrastive_accuracy_top-5: 0.9981 -
probe_loss: 0.7316 - probe_accuracy: 0.7668 - probe_accuracy_top-5: 0.9775 -
val_contrastive_accuracy_top-5: 0.9969 - val_probe_loss: 1.9087 -
val_probe_accuracy: 0.5701 - val_probe_accuracy_top-5: 0.8870
Epoch 17/20
241/241 [==============================] - 1253s 5s/step - contrastive_loss:
1.2400 - contrastive_accuracy: 0.9255 - contrastive_accuracy_top-5: 0.9980 -
probe_loss: 0.7140 - probe_accuracy: 0.7733 - probe_accuracy_top-5: 0.9799 -
val_contrastive_accuracy_top-5: 0.9972 - val_probe_loss: 1.9538 -
val_probe_accuracy: 0.5694 - val_probe_accuracy_top-5: 0.8856
Epoch 18/20
241/241 [==============================] - 1240s 5s/step - contrastive_loss:
1.2298 - contrastive_accuracy: 0.9275 - contrastive_accuracy_top-5: 0.9984 -
probe_loss: 0.7101 - probe_accuracy: 0.7749 - probe_accuracy_top-5: 0.9788 -
val_contrastive_accuracy_top-5: 0.9965 - val_probe_loss: 2.1624 -
val_probe_accuracy: 0.5623 - val_probe_accuracy_top-5: 0.8790
Epoch 19/20
241/241 [==============================] - 1232s 5s/step - contrastive_loss:
1.2245 - contrastive_accuracy: 0.9262 - contrastive_accuracy_top-5: 0.9984 -
probe_loss: 0.7002 - probe_accuracy: 0.7770 - probe_accuracy_top-5: 0.9803 -
val_contrastive_accuracy_top-5: 0.9955 - val_probe_loss: 2.1414 -
val_probe_accuracy: 0.5505 - val_probe_accuracy_top-5: 0.8749
Epoch 20/20
241/241 [==============================] - 1279s 5s/step - contrastive_loss:
1.2212 - contrastive_accuracy: 0.9243 - contrastive_accuracy_top-5: 0.9982 -
probe_loss: 0.7031 - probe_accuracy: 0.7769 - probe_accuracy_top-5: 0.9802 -
val_contrastive_accuracy_top-5: 0.9960 - val_probe_loss: 2.0835 -
val_probe_accuracy: 0.5643 - val_probe_accuracy_top-5: 0.8799

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
```

```
INFO:tensorflow:Assets written to:
models/contrastive_vgg16/encoder.saved_model/assets

INFO:tensorflow:Assets written to:
models/contrastive_vgg16/encoder.saved_model/assets
WARNING:absl:Found untraced functions such as train_imgaug_layer_layer_call_fn,
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_fn,
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_and_return_conditional_losses while saving
(showing 5 of 5). These functions will not be directly callable after loading.

INFO:tensorflow:Assets written to:
models/contrastive_vgg16/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/contrastive_vgg16/main.saved_model/assets


Saving training history data …


Results:

Maximal contrastive_accuracy: 0.92782
Maximal contrastive_accuracy_top-5: 0.99838
Maximal probe_accuracy: 0.77701
Maximal probe_accuracy_top-5: 0.98029
Maximal val_contrastive_accuracy_top-5: 0.99792
Maximal val_probe_accuracy: 0.58234
Maximal val_probe_accuracy_top-5: 0.89429

-- Completed --
```

21.2 Plotting results

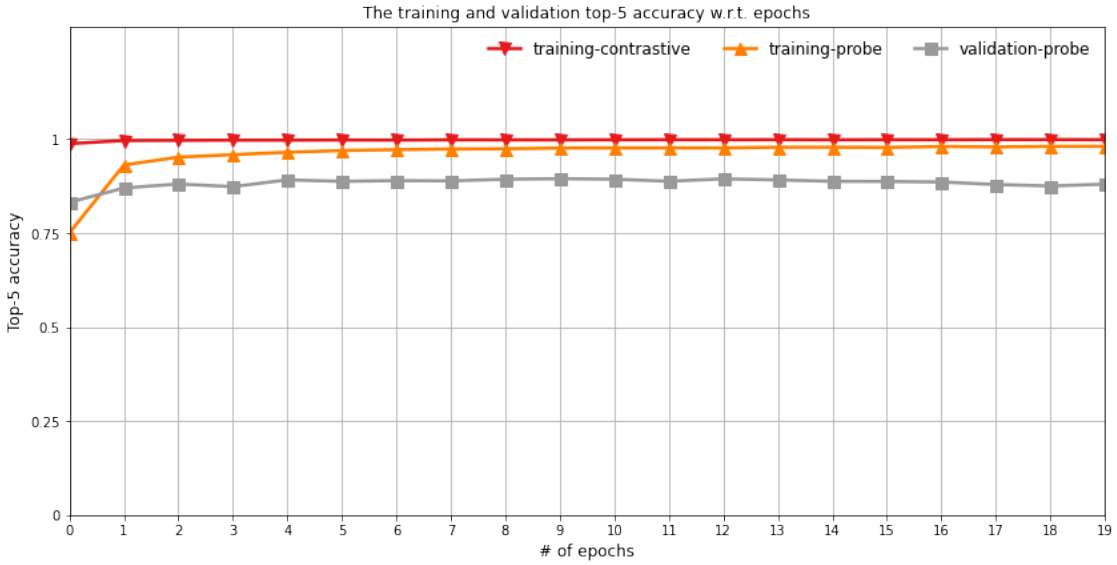
[57]:
```
plot_train_results(
                resultfile = "results/contrastive_vgg16/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["contrastive_accuracy",
                        "probe_accuracy", "val_probe_accuracy"],
                labels = ["training-contrastive",
                          "training-probe", "validation-probe"],
                savename = "fig_contrastive_vgg16_accuracy.pdf",
                legend_location = "best",
                normalise = False
            )
```

```
saved to:  figures/fig_contrastive_vgg16_accuracy.pdf
```



[58]:
```
plot_train_results(
                resultfile = "results/contrastive_vgg16/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
 ↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["contrastive_accuracy_top-5",
                        "probe_accuracy_top-5", "val_probe_accuracy_top-5"],
                labels = ["training-contrastive",
                          "training-probe", "validation-probe"],
                savename = "fig_contrastive_vgg16_accuracy_top5.pdf",
                legend_location = "best",
                normalise = False
            )
```

```
saved to:  figures/fig_contrastive_vgg16_accuracy_top5.pdf
```



22 Contrastive learning with vision transformer (ViT) encoder

22.1 Vision transformer (ViT) encoder

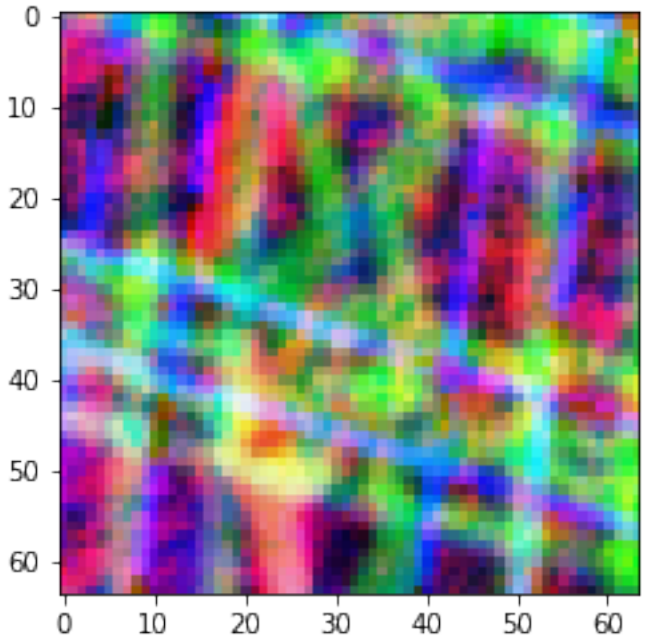
[ ]:
```
# ref: https://keras.io/examples/vision/
 ↪image_classification_with_vision_transformer/
import tensorflow_addons as tfa

patch_size = 6
n_patches = (image_size[0] // patch_size) ** 2

patch_projection_dim = 64

#attention heads
n_heads = 4
```

22.2 Creating patches

[ ]:
```
class Patches(keras.layers.Layer):
    def __init__(self, patch_size):
        super(Patches, self).__init__()
        self.patch_size = patch_size

    def call(self, images):
        batch_size = tf.shape(images)[0]
        patches = tf.image.extract_patches(
            images=images,
```

```
            sizes=[1, self.patch_size, self.patch_size, 1],
            strides=[1, self.patch_size, self.patch_size, 1],
            rates=[1, 1, 1, 1],
            padding="VALID",
        )
        patch_dims = patches.shape[-1]
        patches = tf.reshape(patches, [batch_size, -1, patch_dims])
        return patches
```

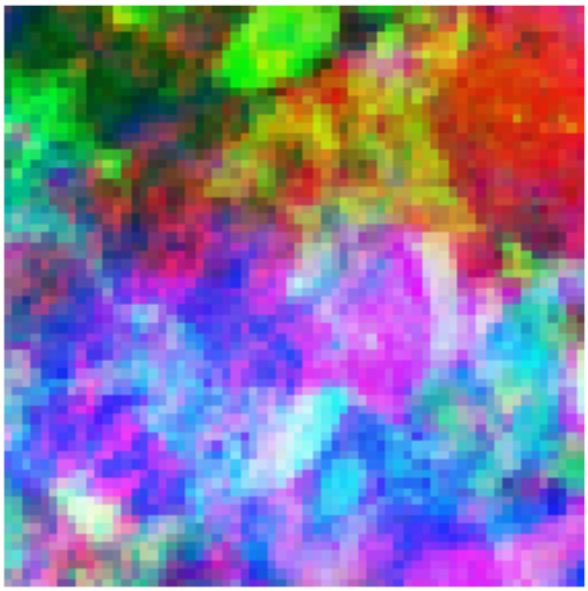
[263]:
```
x_batch = next(iter(train_dataset))[0]
x_batch = x_batch.numpy()
x_batch.shape

plt.imshow(x_batch[0])
plt.show()
```

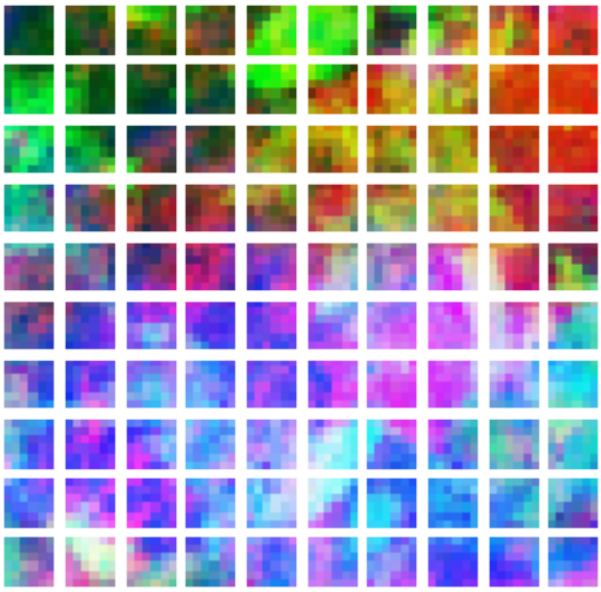


[251]:
```
import matplotlib.pyplot as plt

plt.figure(figsize=(4, 4))

x_batch = next(iter(train_dataset))[0]
x_batch = x_batch.numpy()

image = x_batch[np.random.choice(range(x_batch.shape[0]))]
#plt.imshow(image.astype("uint8"))
```

```
plt.imshow(image)
plt.axis("off")

resized_image = tf.image.resize(
        tf.convert_to_tensor([image]), size=image_size
    )

patches = Patches(patch_size)(resized_image)
print(f"Image size: {image_size}")
print(f"Patch size: {patch_size} X {patch_size}")
print(f"Patches per image: {patches.shape[1]}")
print(f"Elements per patch: {patches.shape[-1]}")

n = int(np.sqrt(patches.shape[1]))
plt.figure(figsize=(4, 4))
for i, patch in enumerate(patches[0]):
    ax = plt.subplot(n, n, i + 1)
    patch_img = tf.reshape(patch, (patch_size, patch_size, 3))
    #plt.imshow(patch_img.numpy().astype("uint8"))
    plt.imshow(patch_img.numpy())
    plt.axis("off")
```

```
Image size: (64, 64)
Patch size: 6 X 6
Patches per image: 100
Elements per patch: 108
```





22.3 Patch encoder

[ ]:
```
class PatchEncoder(keras.layers.Layer):
    def __init__(self, n_patches, patch_projection_dim):
        super(PatchEncoder, self).__init__()
        self.n_patches = n_patches

        self.projection = keras.layers.Dense(units = patch_projection_dim)

        self.position_embedding = keras.layers.Embedding(
            input_dim = n_patches, output_dim=patch_projection_dim
        )

    def call(self, patch):
        positions = tf.range(start=0, limit=self.n_patches, delta=1)
        encoded = self.projection(patch) + self.position_embedding(positions)
        return encoded
```

22.4 ViT MLP

[ ]:
```
def vit_mlp(x):

    #x = keras.layers.Dense(patch_projection_dim, activation=tf.nn.gelu)(x)
    #x = keras.layers.Dense(patch_projection_dim, activation=tf.nn.gelu)(x)

    x = keras.layers.Dense(patch_projection_dim, activation="swish")(x)
    x = keras.layers.Dense(patch_projection_dim, activation="swish")(x)
```

```
    x = keras.layers.Dropout(0.1)(x)


    return x
```

22.5 ViT encoder

[ ]:
```
def build_vit_encoder(#*,
                      image_shape,
                      #patch_size,
                      #n_patches,
                      #projection_dim
                     ):

    inputs = keras.layers.Input(shape=image_shape)
    patches = Patches(patch_size)(inputs)
    encoded_patches = PatchEncoder(n_patches, patch_projection_dim)(patches)


    for _ in range(3):
        # Layer normalization 1.
        x1 = keras.layers.LayerNormalization(epsilon = 1e-6)(encoded_patches)

        # Create a multi-head attention layer.
        attention_output = keras.layers.MultiHeadAttention(
            num_heads = n_heads, key_dim = patch_projection_dim, dropout=0.1
        )(x1, x1)

        # Skip connection 1.
        x2 = keras.layers.Add()([attention_output, encoded_patches])

        # Layer normalization 2.
        x3 = keras.layers.LayerNormalization(epsilon=1e-6)(x2)

        # MLP.
        #x3 = vit_mlp(x3, hidden_units=transformer_units, dropout_rate=0.1)
        x3 = vit_mlp(x3)

        # Skip connection 2.
        encoded_patches = keras.layers.Add()([x3, x2])

    # Create a [batch_size, projection_dim] tensor.
    representation = keras.layers.
↪LayerNormalization(epsilon=1e-6)(encoded_patches)
    representation = keras.layers.Flatten()(representation)
    representation = keras.layers.Dropout(0.5)(representation)
```

```
    model = keras.Model(inputs=inputs, outputs=representation)

    return model
```

22.6 Building model

[341]:
```
contrastive_vit_encoder = build_vit_encoder(image_shape)
contrastive_vit_encoder.trainable = True

contrastive_vit_imgaug = CustomisedTrainImageAugmenter(**imgaug_params)

contrastive_vit_model = ContrastiveModel(
                                temperature = temperature,

                                encoder = contrastive_vit_encoder,

                                projhead_hidden_dims = (512, 512,),
                                projhead_hidden_activation = "swish",
                                projhead_output_dim = 512,

                                image_augmenter = contrastive_vit_imgaug,
                                n_classes = n_classes
                            )

contrastive_vit_model.compile(
            contrastive_optimizer = keras.optimizers.Adam(learning_rate = 0.
↪001),
            probe_optimizer = keras.optimizers.Adam(),
       )
```

22.7 Training

[342]:
```
train_evaulate_and_save_models(
                   model = contrastive_vit_model,
                   encoder = contrastive_vit_encoder,
                   train_dataset = train_dataset,
                   test_dataset = test_dataset,
                   epochs = n_epochs,
                   savename = "contrastive_vit",
                  )
```

```
Training …

Epoch 1/20
241/241 [==============================] - 425s 2s/step - contrastive_loss:
```

```
2.2592 - contrastive_accuracy: 0.6784 - contrastive_accuracy_top-5: 0.8165 -
probe_loss: 6.0214 - probe_accuracy: 0.0683 - probe_accuracy_top-5: 0.2238 -
val_contrastive_accuracy_top-5: 0.9962 - val_probe_loss: 4.3649 -
val_probe_accuracy: 0.1217 - val_probe_accuracy_top-5: 0.3758
Epoch 2/20
241/241 [==============================] - 447s 2s/step - contrastive_loss:
1.2982 - contrastive_accuracy: 0.9596 - contrastive_accuracy_top-5: 0.9981 -
probe_loss: 3.2758 - probe_accuracy: 0.2435 - probe_accuracy_top-5: 0.6194 -
val_contrastive_accuracy_top-5: 0.9975 - val_probe_loss: 4.4618 -
val_probe_accuracy: 0.1648 - val_probe_accuracy_top-5: 0.4796
Epoch 3/20
241/241 [==============================] - 459s 2s/step - contrastive_loss:
1.2178 - contrastive_accuracy: 0.9711 - contrastive_accuracy_top-5: 0.9990 -
probe_loss: 2.9967 - probe_accuracy: 0.3239 - probe_accuracy_top-5: 0.7285 -
val_contrastive_accuracy_top-5: 0.9988 - val_probe_loss: 4.8128 -
val_probe_accuracy: 0.2039 - val_probe_accuracy_top-5: 0.5483
Epoch 4/20
241/241 [==============================] - 436s 2s/step - contrastive_loss:
1.1821 - contrastive_accuracy: 0.9770 - contrastive_accuracy_top-5: 0.9994 -
probe_loss: 3.1125 - probe_accuracy: 0.3584 - probe_accuracy_top-5: 0.7618 -
val_contrastive_accuracy_top-5: 0.9990 - val_probe_loss: 5.1279 -
val_probe_accuracy: 0.2638 - val_probe_accuracy_top-5: 0.6221
Epoch 5/20
241/241 [==============================] - 478s 2s/step - contrastive_loss:
1.1509 - contrastive_accuracy: 0.9784 - contrastive_accuracy_top-5: 0.9996 -
probe_loss: 3.2500 - probe_accuracy: 0.3891 - probe_accuracy_top-5: 0.7905 -
val_contrastive_accuracy_top-5: 0.9992 - val_probe_loss: 5.7315 -
val_probe_accuracy: 0.2294 - val_probe_accuracy_top-5: 0.5852
Epoch 6/20
241/241 [==============================] - 416s 2s/step - contrastive_loss:
1.1209 - contrastive_accuracy: 0.9826 - contrastive_accuracy_top-5: 0.9998 -
probe_loss: 3.2871 - probe_accuracy: 0.4217 - probe_accuracy_top-5: 0.8121 -
val_contrastive_accuracy_top-5: 0.9992 - val_probe_loss: 6.6449 -
val_probe_accuracy: 0.2743 - val_probe_accuracy_top-5: 0.6377
Epoch 7/20
241/241 [==============================] - 417s 2s/step - contrastive_loss:
1.0928 - contrastive_accuracy: 0.9865 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 3.4034 - probe_accuracy: 0.4414 - probe_accuracy_top-5: 0.8326 -
val_contrastive_accuracy_top-5: 0.9996 - val_probe_loss: 7.6489 -
val_probe_accuracy: 0.1931 - val_probe_accuracy_top-5: 0.5257
Epoch 8/20
241/241 [==============================] - 428s 2s/step - contrastive_loss:
1.0716 - contrastive_accuracy: 0.9884 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 3.3560 - probe_accuracy: 0.4787 - probe_accuracy_top-5: 0.8576 -
val_contrastive_accuracy_top-5: 0.9996 - val_probe_loss: 6.6716 -
val_probe_accuracy: 0.3184 - val_probe_accuracy_top-5: 0.6782
Epoch 9/20
241/241 [==============================] - 429s 2s/step - contrastive_loss:
```

```
1.0534 - contrastive_accuracy: 0.9891 - contrastive_accuracy_top-5: 0.9998 -
probe_loss: 3.5097 - probe_accuracy: 0.4984 - probe_accuracy_top-5: 0.8720 -
val_contrastive_accuracy_top-5: 0.9996 - val_probe_loss: 7.1888 -
val_probe_accuracy: 0.3377 - val_probe_accuracy_top-5: 0.6883
Epoch 10/20
241/241 [==============================] - 429s 2s/step - contrastive_loss:
1.0419 - contrastive_accuracy: 0.9895 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.7257 - probe_accuracy: 0.5110 - probe_accuracy_top-5: 0.8792 -
val_contrastive_accuracy_top-5: 0.9995 - val_probe_loss: 7.2412 -
val_probe_accuracy: 0.3578 - val_probe_accuracy_top-5: 0.7127
Epoch 11/20
241/241 [==============================] - 427s 2s/step - contrastive_loss:
1.0272 - contrastive_accuracy: 0.9900 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 3.7500 - probe_accuracy: 0.5379 - probe_accuracy_top-5: 0.8956 -
val_contrastive_accuracy_top-5: 0.9998 - val_probe_loss: 8.5597 -
val_probe_accuracy: 0.3270 - val_probe_accuracy_top-5: 0.6936
Epoch 12/20
241/241 [==============================] - 440s 2s/step - contrastive_loss:
1.0165 - contrastive_accuracy: 0.9914 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.9947 - probe_accuracy: 0.5454 - probe_accuracy_top-5: 0.9026 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 8.7870 -
val_probe_accuracy: 0.3682 - val_probe_accuracy_top-5: 0.7234
Epoch 13/20
241/241 [==============================] - 455s 2s/step - contrastive_loss:
1.0045 - contrastive_accuracy: 0.9912 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.9589 - probe_accuracy: 0.5810 - probe_accuracy_top-5: 0.9191 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 8.3446 -
val_probe_accuracy: 0.4019 - val_probe_accuracy_top-5: 0.7510
Epoch 14/20
241/241 [==============================] - 431s 2s/step - contrastive_loss:
0.9933 - contrastive_accuracy: 0.9916 - contrastive_accuracy_top-5: 0.9999 -
probe_loss: 3.9768 - probe_accuracy: 0.6004 - probe_accuracy_top-5: 0.9300 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 10.0748 -
val_probe_accuracy: 0.3573 - val_probe_accuracy_top-5: 0.7247
Epoch 15/20
241/241 [==============================] - 463s 2s/step - contrastive_loss:
0.9830 - contrastive_accuracy: 0.9921 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 4.0690 - probe_accuracy: 0.6257 - probe_accuracy_top-5: 0.9364 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 9.9598 -
val_probe_accuracy: 0.4068 - val_probe_accuracy_top-5: 0.7429
Epoch 16/20
241/241 [==============================] - 477s 2s/step - contrastive_loss:
0.9726 - contrastive_accuracy: 0.9926 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.8421 - probe_accuracy: 0.6582 - probe_accuracy_top-5: 0.9507 -
val_contrastive_accuracy_top-5: 0.9999 - val_probe_loss: 10.3157 -
val_probe_accuracy: 0.4177 - val_probe_accuracy_top-5: 0.7719
Epoch 17/20
241/241 [==============================] - 434s 2s/step - contrastive_loss:
```

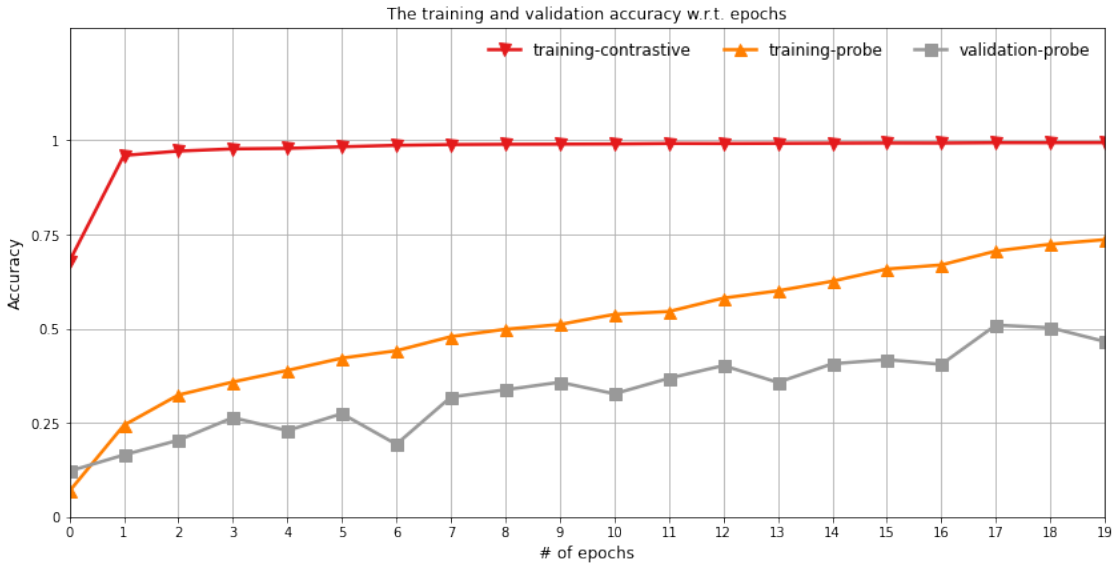
```
0.9692 - contrastive_accuracy: 0.9925 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 4.1109 - probe_accuracy: 0.6690 - probe_accuracy_top-5: 0.9537 -
val_contrastive_accuracy_top-5: 0.9995 - val_probe_loss: 11.4945 -
val_probe_accuracy: 0.4052 - val_probe_accuracy_top-5: 0.7318
Epoch 18/20
241/241 [==============================] - 454s 2s/step - contrastive_loss:
0.9505 - contrastive_accuracy: 0.9934 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.7773 - probe_accuracy: 0.7059 - probe_accuracy_top-5: 0.9632 -
val_contrastive_accuracy_top-5: 0.9999 - val_probe_loss: 10.2274 -
val_probe_accuracy: 0.5094 - val_probe_accuracy_top-5: 0.8197
Epoch 19/20
241/241 [==============================] - 450s 2s/step - contrastive_loss:
0.9465 - contrastive_accuracy: 0.9934 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.8877 - probe_accuracy: 0.7240 - probe_accuracy_top-5: 0.9686 -
val_contrastive_accuracy_top-5: 0.9999 - val_probe_loss: 11.3634 -
val_probe_accuracy: 0.5025 - val_probe_accuracy_top-5: 0.8178
Epoch 20/20
241/241 [==============================] - 438s 2s/step - contrastive_loss:
0.9375 - contrastive_accuracy: 0.9936 - contrastive_accuracy_top-5: 1.0000 -
probe_loss: 3.9642 - probe_accuracy: 0.7361 - probe_accuracy_top-5: 0.9721 -
val_contrastive_accuracy_top-5: 0.9997 - val_probe_loss: 12.5799 -
val_probe_accuracy: 0.4657 - val_probe_accuracy_top-5: 0.7788

Saving models …

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.

WARNING:tensorflow:Compiled the loaded model, but the compiled metrics have yet
to be built. `model.compile_metrics` will be empty until you train or evaluate
the model.
WARNING:absl:Found untraced functions such as dense_63_layer_call_fn,
dense_63_layer_call_and_return_conditional_losses, embedding_1_layer_call_fn,
embedding_1_layer_call_and_return_conditional_losses, query_layer_call_fn while
saving (showing 5 of 100). These functions will not be directly callable after
loading.

INFO:tensorflow:Assets written to:
models/contrastive_vit/encoder.saved_model/assets

/usr/local/anaconda3/lib/python3.8/site-
packages/tensorflow/python/keras/utils/generic_utils.py:494: CustomMaskWarning:
Custom mask layers require a config and must override get_config. When loading,
the custom mask layer must be passed to the custom_objects argument.
  warnings.warn('Custom mask layers require a config and must override '
INFO:tensorflow:Assets written to:
models/contrastive_vit/encoder.saved_model/assets
WARNING:absl:Found untraced functions such as train_imgaug_layer_layer_call_fn,
```

```
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_fn,
train_imgaug_layer_layer_call_and_return_conditional_losses,
train_imgaug_layer_layer_call_and_return_conditional_losses while saving
(showing 5 of 105). These functions will not be directly callable after loading.
/usr/local/anaconda3/lib/python3.8/site-
packages/tensorflow/python/keras/utils/generic_utils.py:494: CustomMaskWarning:
Custom mask layers require a config and must override get_config. When loading,
the custom mask layer must be passed to the custom_objects argument.
  warnings.warn('Custom mask layers require a config and must override '

INFO:tensorflow:Assets written to:
models/contrastive_vit/main.saved_model/assets

INFO:tensorflow:Assets written to:
models/contrastive_vit/main.saved_model/assets


Saving training history data …


Results:

Maximal contrastive_accuracy: 0.99360
Maximal contrastive_accuracy_top-5: 1.00000
Maximal probe_accuracy: 0.73614
Maximal probe_accuracy_top-5: 0.97208
Maximal val_contrastive_accuracy_top-5: 0.99994
Maximal val_probe_accuracy: 0.50935
Maximal val_probe_accuracy_top-5: 0.81974

-- Completed --
```

22.8 Plotting results

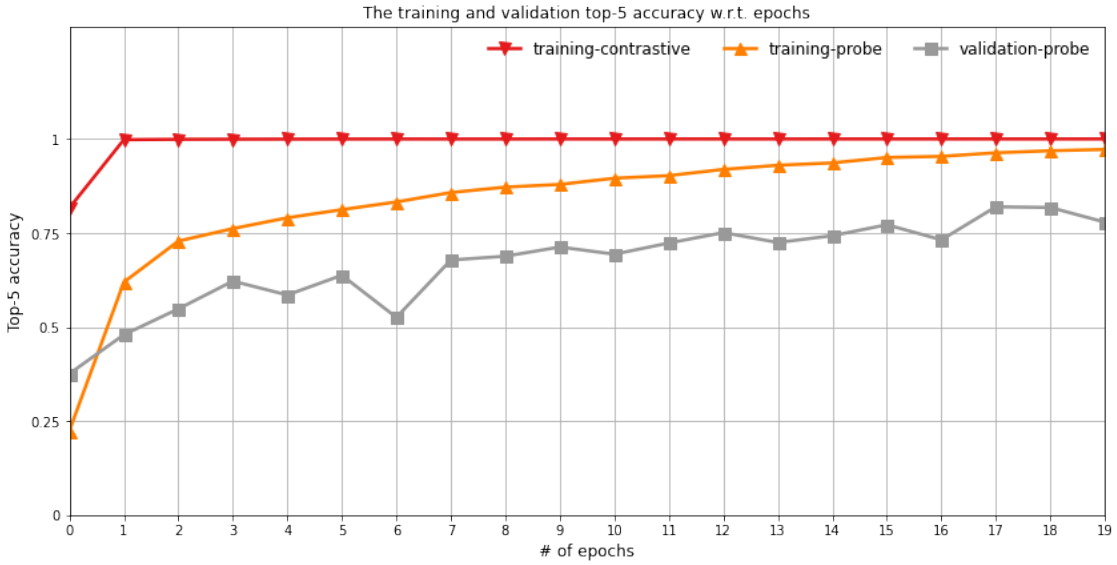
[59]:
```
plot_train_results(
                resultfile = "results/contrastive_vit/history_train.pickle",
                title = "The training and validation accuracy w.r.t. epochs",
                ylabel = "Accuracy",
                keys = ["contrastive_accuracy",
                       "probe_accuracy", "val_probe_accuracy"],
                labels = ["training-contrastive",
                         "training-probe", "validation-probe"],
                savename = "fig_contrastive_vit_accuracy.pdf",
                legend_location = "best",
                normalise = False
            )
```

saved to: figures/fig_contrastive_vit_accuracy.pdf



[60]:
```
plot_train_results(
                resultfile = "results/contrastive_vit/history_train.pickle",
                title = "The training and validation top-5 accuracy w.r.t.␣
↪epochs",
                ylabel = "Top-5 accuracy",
                keys = ["contrastive_accuracy_top-5",
                        "probe_accuracy_top-5", "val_probe_accuracy_top-5"],
                labels = ["training-contrastive",
                          "training-probe", "validation-probe"],
                savename = "fig_contrastive_vit_accuracy_top5.pdf",
                legend_location = "best",
                normalise = False
            )
```

saved to: figures/fig_contrastive_vit_accuracy_top5.pdf



23 The facilities of plotting comparisons

[482]:
```
import pickle

import matplotlib.pyplot as plt
from matplotlib import cm

from itertools import cycle

def plot_comparing_results(
                                resultfiles, #a list of files
                                keys,
                                labels,

                                title,
                                ylabel,

                                legend_location = "best",

                                savename = None,
                                normalise_data = False
                           ):




    fig_width = 12.
```

```
    fig_height = fig_width*0.5

    fig = plt.figure(figsize=(fig_width, fig_height))


    plt.subplots_adjust(left = 0.05,
                        right = 0.95,
                        bottom = 0.1,
                        top = 0.95)



    n = len(keys)

    colours = iter(cm.tab10(np.linspace(0, 1, n)))

    linestyles = cycle(["-", "--", "-.", ":"])

    markers = cycle(["v", "^", "s", "<", ">", "D"])

    for f, k, label in zip(resultfiles, keys, labels):

        print(f"loading {f} with key: {k} and label: {label} ...")

        if not os.path.exists(f):
            continue

        history = pickle.load(open(f, "rb"))

        if k not in history:
            print(f"key {k} not found")
            continue

        v = history[k]

        if normalise_data:
            v = np.array(v) / max(v)

        c = next(colours)
        ls = next(linestyles)
        m = next(markers)

        plt.plot(
                    v,
                    color = c,
                    label = label,
                    linewidth = 2.5,
```

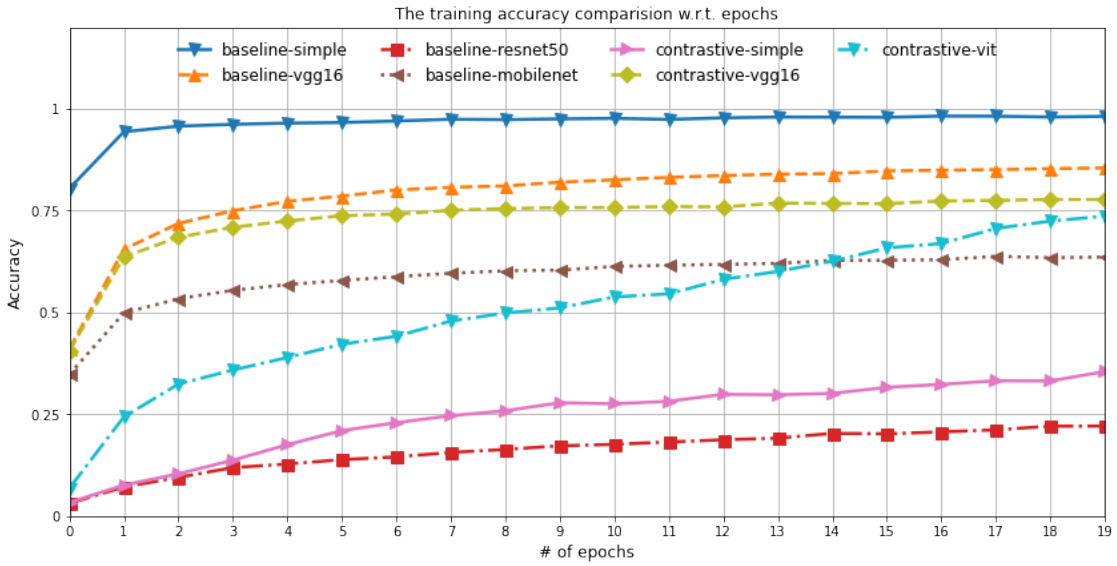
```
                linestyle = ls,
                marker = m,
                markersize = 9
            )

    plt.xlabel("# of epochs", fontsize = 12)

    plt.ylabel(ylabel, fontsize = 12)

    #k = keys[0]
    #v = history[k]
    plt.xlim(0, len(v) - 1)
    plt.ylim(0, 1.2)

    xticks = np.linspace(0,
                    len(v) - 1,
                    num = len(v),
                    endpoint = True,
                    dtype = int)
    xlabels = xticks

    plt.xticks(xticks, xlabels)
    plt.yticks([0, 0.25, 0.5, 0.75, 1], [0, 0.25, 0.5, 0.75, 1])

    plt.grid()

    plt.legend(
            loc = legend_location, #'upper center',
            fontsize = 12,
            ncol = 4,
            frameon = False)

    if not os.path.exists("figures"):
        os.makedirs("figures")

    if savename:
        figpath = "figures" + os.path.sep + savename
        plt.savefig(figpath,
                    dpi=600,
                    format='pdf')

        print("saved to: ", figpath)

    plt.title(title)

    plt.show()
```

24 Comparing training probe accuracy

[483]:
```
keys = [
        "accuracy",
        "accuracy",
        "accuracy",
        "accuracy",

        "probe_accuracy",
        "probe_accuracy",
        "probe_accuracy",
    ]

resultfiles = [
        "results/baseline_simple/history_train.pickle",
        "results/baseline_vgg16/history_train.pickle",
        "results/baseline_resnet/history_train.pickle",
        "results/baseline_mobilenet/history_train.pickle",

        "results/contrastive_simple/history_train.pickle",
        "results/contrastive_vgg16/history_train.pickle",
        "results/contrastive_vit/history_train.pickle",
    ]

labels = [
        "baseline-simple",
        "baseline-vgg16",
        "baseline-resnet50",
        "baseline-mobilenet",

        "contrastive-simple",
        "contrastive-vgg16",
        "contrastive-vit",
    ]

plot_comparing_results(
                                resultfiles = resultfiles,
                                keys = keys,
                                labels = labels,

                                title = "The training accuracy comparision w.r.
 ↪t. epochs",
                                ylabel = "Accuracy",

                                legend_location = "upper center",
```

```
                                savename = "fig_training_accuracy_comparison.
↪pdf",

                                normalise_data = False
                            )
```

```
loading results/baseline_simple/history_train.pickle with key: accuracy and
label: baseline-simple …
loading results/baseline_vgg16/history_train.pickle with key: accuracy and
label: baseline-vgg16 …
loading results/baseline_resnet/history_train.pickle with key: accuracy and
label: baseline-resnet50 …
loading results/baseline_mobilenet/history_train.pickle with key: accuracy and
label: baseline-mobilenet …
loading results/contrastive_simple/history_train.pickle with key: probe_accuracy
and label: contrastive-simple …
loading results/contrastive_vgg16/history_train.pickle with key: probe_accuracy
and label: contrastive-vgg16 …
loading results/contrastive_vit/history_train.pickle with key: probe_accuracy
and label: contrastive-vit …
saved to:  figures/fig_training_accuracy_comparison.pdf
```

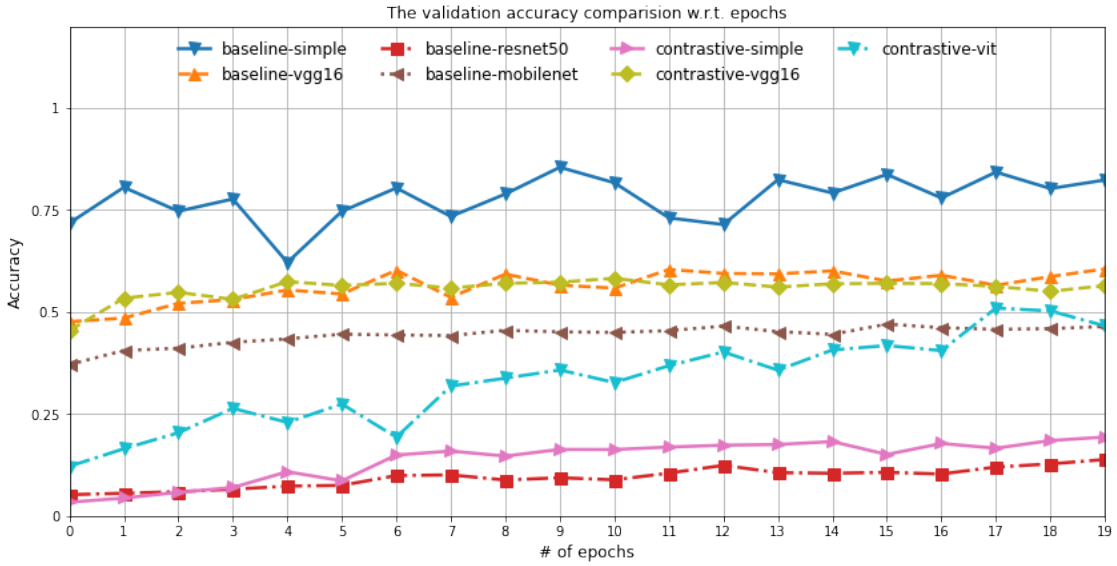


25 Comparing validation accuracy

[484]:
```
keys = [
        "val_accuracy",
        "val_accuracy",
```

```
        "val_accuracy",
        "val_accuracy",

        "val_probe_accuracy",
        "val_probe_accuracy",
        "val_probe_accuracy",
    ]

resultfiles = [
        "results/baseline_simple/history_train.pickle",
        "results/baseline_vgg16/history_train.pickle",
        "results/baseline_resnet/history_train.pickle",
        "results/baseline_mobilenet/history_train.pickle",

        "results/contrastive_simple/history_train.pickle",
        "results/contrastive_vgg16/history_train.pickle",
        "results/contrastive_vit/history_train.pickle",
    ]

labels = [
        "baseline-simple",
        "baseline-vgg16",
        "baseline-resnet50",
        "baseline-mobilenet",

        "contrastive-simple",
        "contrastive-vgg16",
        "contrastive-vit",
    ]

plot_comparing_results(
                                resultfiles = resultfiles,
                                keys = keys,
                                labels = labels,

                                title = "The validation accuracy comparision w.
 ↪r.t. epochs",
                                ylabel = "Accuracy",

                                legend_location = "upper center",

                                savename = "fig_validation_accuracy_comparison.
 ↪pdf",

                                normalise_data = False
                            )
```

```
loading results/baseline_simple/history_train.pickle with key: val_accuracy and
label: baseline-simple …
loading results/baseline_vgg16/history_train.pickle with key: val_accuracy and
label: baseline-vgg16 …
loading results/baseline_resnet/history_train.pickle with key: val_accuracy and
label: baseline-resnet50 …
loading results/baseline_mobilenet/history_train.pickle with key: val_accuracy
and label: baseline-mobilenet …
loading results/contrastive_simple/history_train.pickle with key:
val_probe_accuracy and label: contrastive-simple …
loading results/contrastive_vgg16/history_train.pickle with key:
val_probe_accuracy and label: contrastive-vgg16 …
loading results/contrastive_vit/history_train.pickle with key:
val_probe_accuracy and label: contrastive-vit …
saved to:  figures/fig_validation_accuracy_comparison.pdf
```



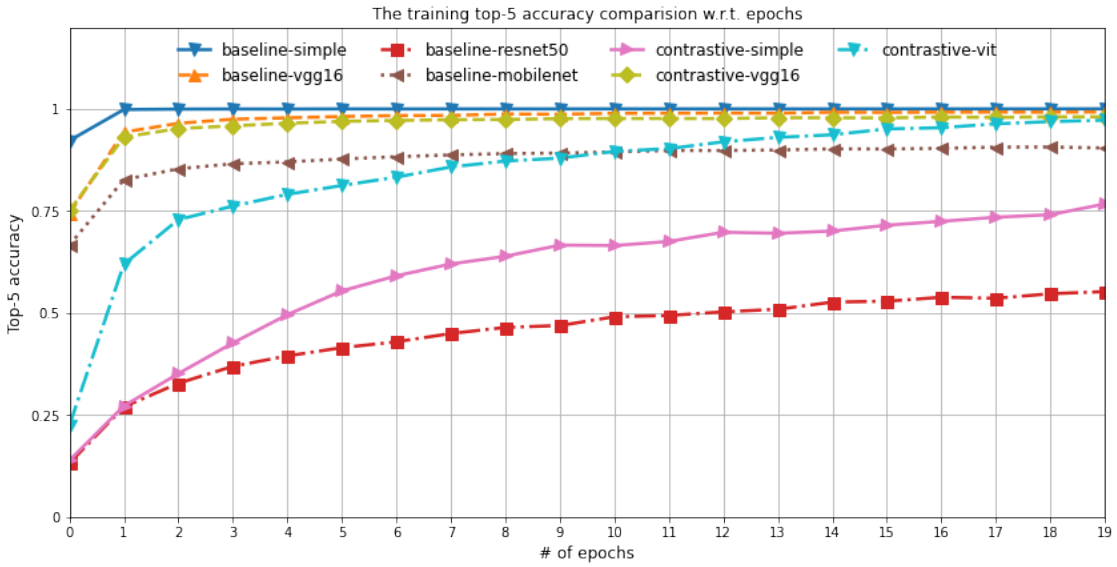
26 Comparing top-5 training accuracy

[485]:
```
keys = [
        "accuracy_top-5",
        "accuracy_top-5",
        "accuracy_top-5",
        "accuracy_top-5",

        "probe_accuracy_top-5",
        "probe_accuracy_top-5",
        "probe_accuracy_top-5",
```

```
    ]

resultfiles = [
        "results/baseline_simple/history_train.pickle",
        "results/baseline_vgg16/history_train.pickle",
        "results/baseline_resnet/history_train.pickle",
        "results/baseline_mobilenet/history_train.pickle",

        "results/contrastive_simple/history_train.pickle",
        "results/contrastive_vgg16/history_train.pickle",
        "results/contrastive_vit/history_train.pickle",
    ]

labels = [
        "baseline-simple",
        "baseline-vgg16",
        "baseline-resnet50",
        "baseline-mobilenet",

        "contrastive-simple",
        "contrastive-vgg16",
        "contrastive-vit",
    ]

plot_comparing_results(
                                resultfiles = resultfiles,
                                keys = keys,
                                labels = labels,

                                title = "The training top-5 accuracy␣
 ↪comparision w.r.t. epochs",
                                ylabel = "Top-5 accuracy",

                                legend_location = "upper center",

                                savename =␣
 ↪"fig_training_accuracy_comparison_top5.pdf",

                                normalise_data = False
                            )
```

```
loading results/baseline_simple/history_train.pickle with key: accuracy_top-5
and label: baseline-simple …
loading results/baseline_vgg16/history_train.pickle with key: accuracy_top-5 and
label: baseline-vgg16 …
loading results/baseline_resnet/history_train.pickle with key: accuracy_top-5
and label: baseline-resnet50 …
```

```
loading results/baseline_mobilenet/history_train.pickle with key: accuracy_top-5
and label: baseline-mobilenet …
loading results/contrastive_simple/history_train.pickle with key:
probe_accuracy_top-5 and label: contrastive-simple …
loading results/contrastive_vgg16/history_train.pickle with key:
probe_accuracy_top-5 and label: contrastive-vgg16 …
loading results/contrastive_vit/history_train.pickle with key:
probe_accuracy_top-5 and label: contrastive-vit …
saved to:  figures/fig_training_accuracy_comparison_top5.pdf
```



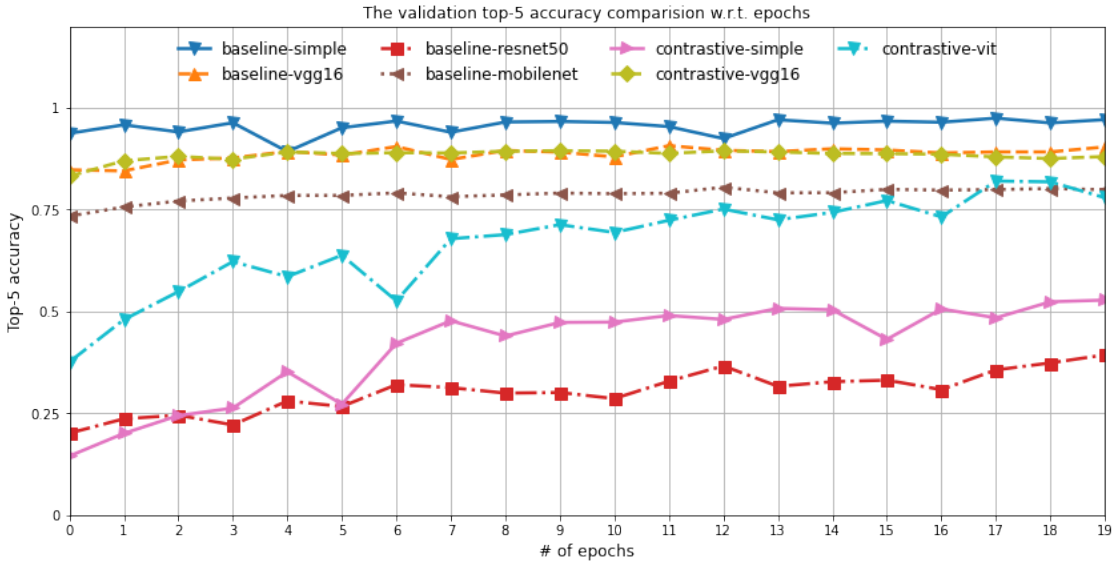
27 Comparing top-5 validation accuracy

[486]:
```
keys = [
        "val_accuracy_top-5",
        "val_accuracy_top-5",
        "val_accuracy_top-5",
        "val_accuracy_top-5",

        "val_probe_accuracy_top-5",
        "val_probe_accuracy_top-5",
        "val_probe_accuracy_top-5",
    ]

resultfiles = [
        "results/baseline_simple/history_train.pickle",
        "results/baseline_vgg16/history_train.pickle",
        "results/baseline_resnet/history_train.pickle",
```

```
        "results/baseline_mobilenet/history_train.pickle",

        "results/contrastive_simple/history_train.pickle",
        "results/contrastive_vgg16/history_train.pickle",
        "results/contrastive_vit/history_train.pickle",
    ]

labels = [
        "baseline-simple",
        "baseline-vgg16",
        "baseline-resnet50",
        "baseline-mobilenet",

        "contrastive-simple",
        "contrastive-vgg16",
        "contrastive-vit",
    ]

plot_comparing_results(
                                resultfiles = resultfiles,
                                keys = keys,
                                labels = labels,

                                title = "The validation top-5 accuracy␣
 ↪comparision w.r.t. epochs",
                                ylabel = "Top-5 accuracy",

                                legend_location = "upper center",

                                savename =␣
 ↪"fig_validation_accuracy_comparison_top5.pdf",

                                normalise_data = False
                            )
```

```
loading results/baseline_simple/history_train.pickle with key:
val_accuracy_top-5 and label: baseline-simple …
loading results/baseline_vgg16/history_train.pickle with key: val_accuracy_top-5
and label: baseline-vgg16 …
loading results/baseline_resnet/history_train.pickle with key:
val_accuracy_top-5 and label: baseline-resnet50 …
loading results/baseline_mobilenet/history_train.pickle with key:
val_accuracy_top-5 and label: baseline-mobilenet …
loading results/contrastive_simple/history_train.pickle with key:
val_probe_accuracy_top-5 and label: contrastive-simple …
loading results/contrastive_vgg16/history_train.pickle with key:
val_probe_accuracy_top-5 and label: contrastive-vgg16 …
```

```
loading results/contrastive_vit/history_train.pickle with key:
val_probe_accuracy_top-5 and label: contrastive-vit …
saved to:  figures/fig_validation_accuracy_comparison_top5.pdf
```



28 The facilities of plotting 2D projections regarding cosine similarity

[33]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
from matplotlib import cm

import os
import sys

import random

from sklearn.manifold import TSNE
#from sklearn.metrics import pairwise_distances
import umap

def plot_projections(
                    features,
                    labels,

                    title,
```

```
                legend_location = "best",

                savename = None
            ):


fig_width = 7
fig_height = 7

fig = plt.figure(figsize=(fig_width, fig_height))


plt.subplots_adjust(left = 0.05,
                    right = 0.95,
                    bottom = 0.05,
                    top = 0.95)

#building colours
colours_dict = {}
colours = iter(cm.rainbow(np.linspace(0, 1, len(set(labels)))))
#colours = ["red", "yellow", "blue", "green", "pink", "teal"]

for label in set(labels):
    colours_dict[label] = next(colours)


n_classes = len(set(labels))

class_labels = list(set(labels))

reducer = TSNE( metric = "cosine",
                square_distances = True,
                n_iter = 15000,
                n_jobs = -1,
                random_state = 1133)

#reducer = umap.UMAP(
#                    #metric = "cosine"
#                )

projections = reducer.fit_transform(features)

print("projections.shape = ", projections.shape)


s = np.std(projections, axis = 0)
```

```
    m = np.mean(projections, axis = 0)

    #print("s=", s)
    #print("m=", m)

    #projections = (projections - m) / s




    for idx, (xi, label) in enumerate(zip(projections, labels)):
        plt.scatter(xi[0],
                    xi[1],
                    s = 70,
                    alpha = 0.5,
                    edgecolors = None,
                    linewidths = 0,
                    color = colours_dict[label],
                    label = f"class-{label}")


    #plt.tight_layout()
    #plt.axis('off')
    #plt.xticks([])
    #plt.yticks([])

    if not os.path.exists("figures"):
        os.makedirs("figures")

    if savename:
        figpath = "figures" + os.path.sep + savename

        plt.savefig(figpath,
                    dpi = 600,
                    format = 'pdf')

        print("saved to: ", figpath)


    plt.show()


    plt.close()
```

29 Sampling images for projection visualisation

[13]:
```
def sample_projection_images(
                        dataset,
                        n_classes = 6,
                        n_images_per_class = 20,
                    ):

    # convert tensorflow dataset to numpy
    X = []
    y = []

    for xi, yi in dataset.as_numpy_iterator():
        X = X + list(xi)
        y = y + list(yi)

    X = np.array(X, dtype = object)
    y = np.array(y, dtype = object)


    print("X.shape = ", X.shape)
    print("y.shape = ", y.shape)


    # randomly choose classes
    chosen_classes = np.random.choice(list(set(y)),
                                      size = n_classes,
                                      replace = False)
    print("chosen_classes = ", chosen_classes)


    images = []
    labels = []

    for label in chosen_classes:

        indices = np.where(y == label)
        indices = indices[0]

        if len(indices) < n_images_per_class:
            size = len(indices)
        else:
            size = n_images_per_class

        #print(size)

        chosen_indices = np.random.choice(list(indices),
```

```
                                    size = size,
                                    replace = False)

        images = images + list(X[chosen_indices])
        labels = labels + list(y[chosen_indices])

    images = np.array(images, dtype = object)
    labels = np.array(labels, dtype = object)

    print("images.shape = ", images.shape)
    print("labels.shape = ", labels.shape)

    return images, labels
```

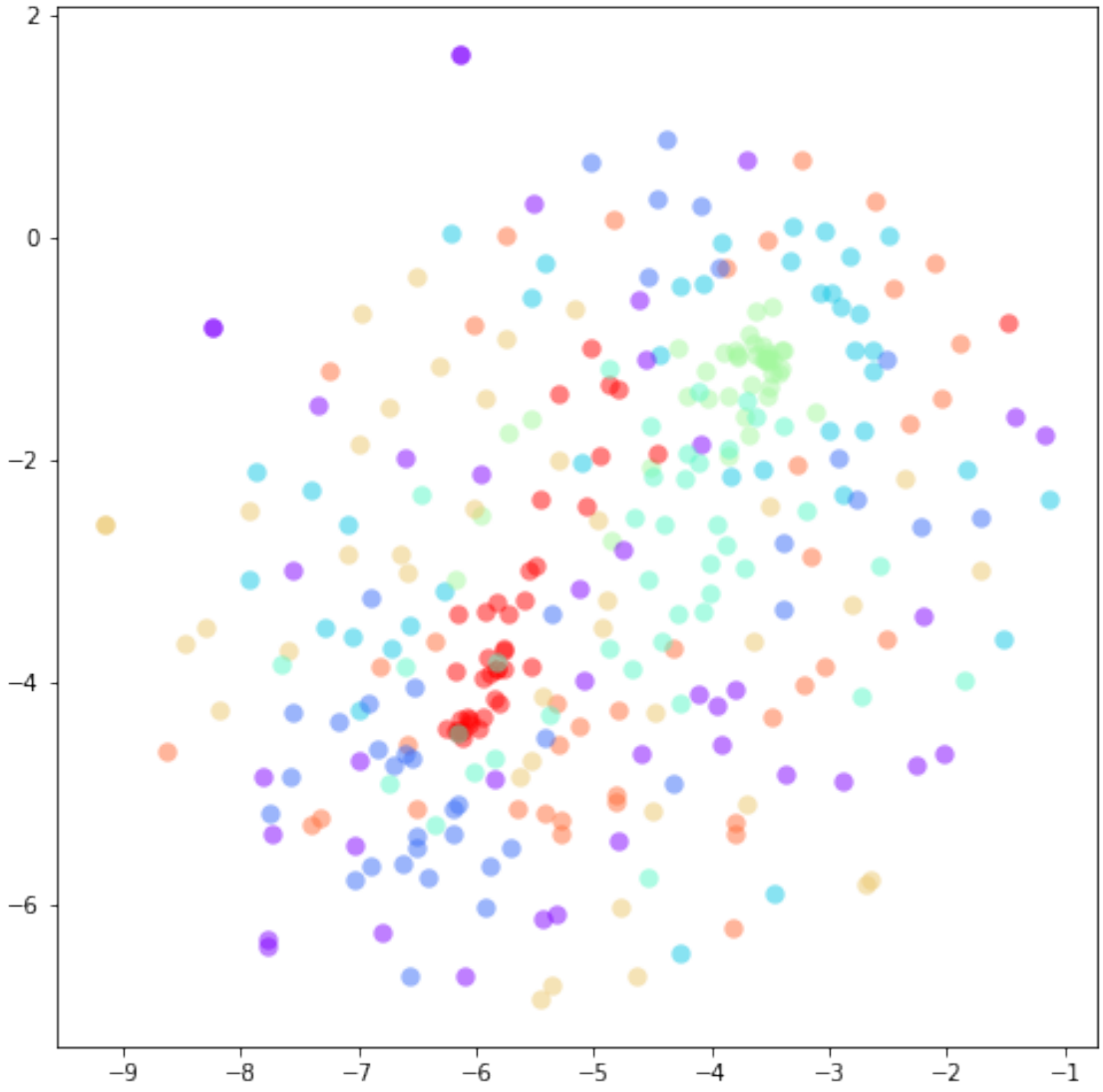
[14]:
```
images, labels = sample_projection_images(
                        dataset = test_dataset,
                        n_classes = 8,
                        n_images_per_class = 40
                    )
```

```
X.shape =  (7700, 64, 64, 3)
y.shape =  (7700,)
chosen_classes =  [ 77  16  55 109 150  91   6 143]
images.shape =  (320, 64, 64, 3)
labels.shape =  (320,)
```

30 Projecting raw images

[35]:
```
n_feature_dims = np.prod(images[0].shape)

features = images.reshape(-1, n_feature_dims)
print("features.shape = ", features.shape)

plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of raw images",

                    legend_location = "best",

                    savename = "fig_2d_proj_raw.pdf"
                )
```

```
features.shape =  (320, 12288)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_raw.pdf
```



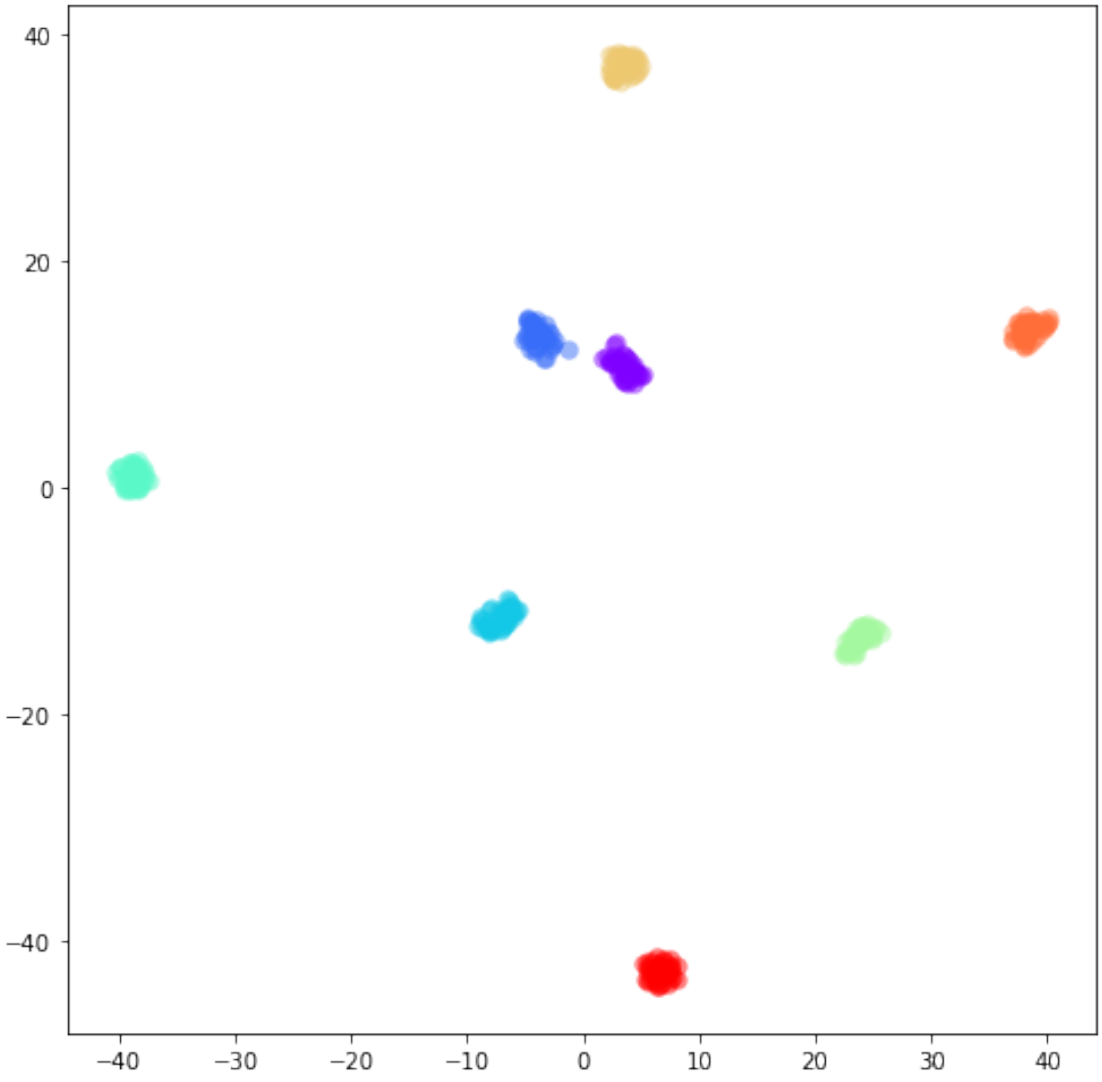
31 Projecting with baseline simple model

[61]:
```
model = keras.models.load_model("models/baseline_simple/main.saved_model")

images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()

print("features.shape = ", features.shape)
```

```
plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of baseline simple model",

                    legend_location = "best",

                    savename = "fig_2d_proj_baseline_simple.pdf"
                )

del model
```

```
WARNING:absl:Importing a function
(__inference_conv2d_1_layer_call_and_return_conditional_losses_28219846) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_baseline_simple_model_layer_call_
and_return_conditional_losses_28221690) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_encoder_simple_layer_call_and_return_conditional_losses_28222766)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_2_layer_call_and_return_conditional_losses_28223436) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference__wrapped_model_28218849) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_baseline_simple_model_layer_call_
and_return_conditional_losses_28222148) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_3_layer_call_and_return_conditional_losses_28223461) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_2_layer_call_and_return_conditional_losses_28219902) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_layer_call_and_return_conditional_losses_28223235) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_1_layer_call_and_return_conditional_losses_28223260) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_conv2d_layer_call_and_return_conditional_losses_28219824) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_encoder_simple_layer_call_and_return_conditional_losses_28222668)
with ops with custom gradients. Will likely fail if a gradient is requested.
```

```
WARNING:absl:Importing a function
(__inference_conv2d_3_layer_call_and_return_conditional_losses_28219924) with
ops with custom gradients. Will likely fail if a gradient is requested.

features.shape =  (320, 154)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_baseline_simple.pdf
```

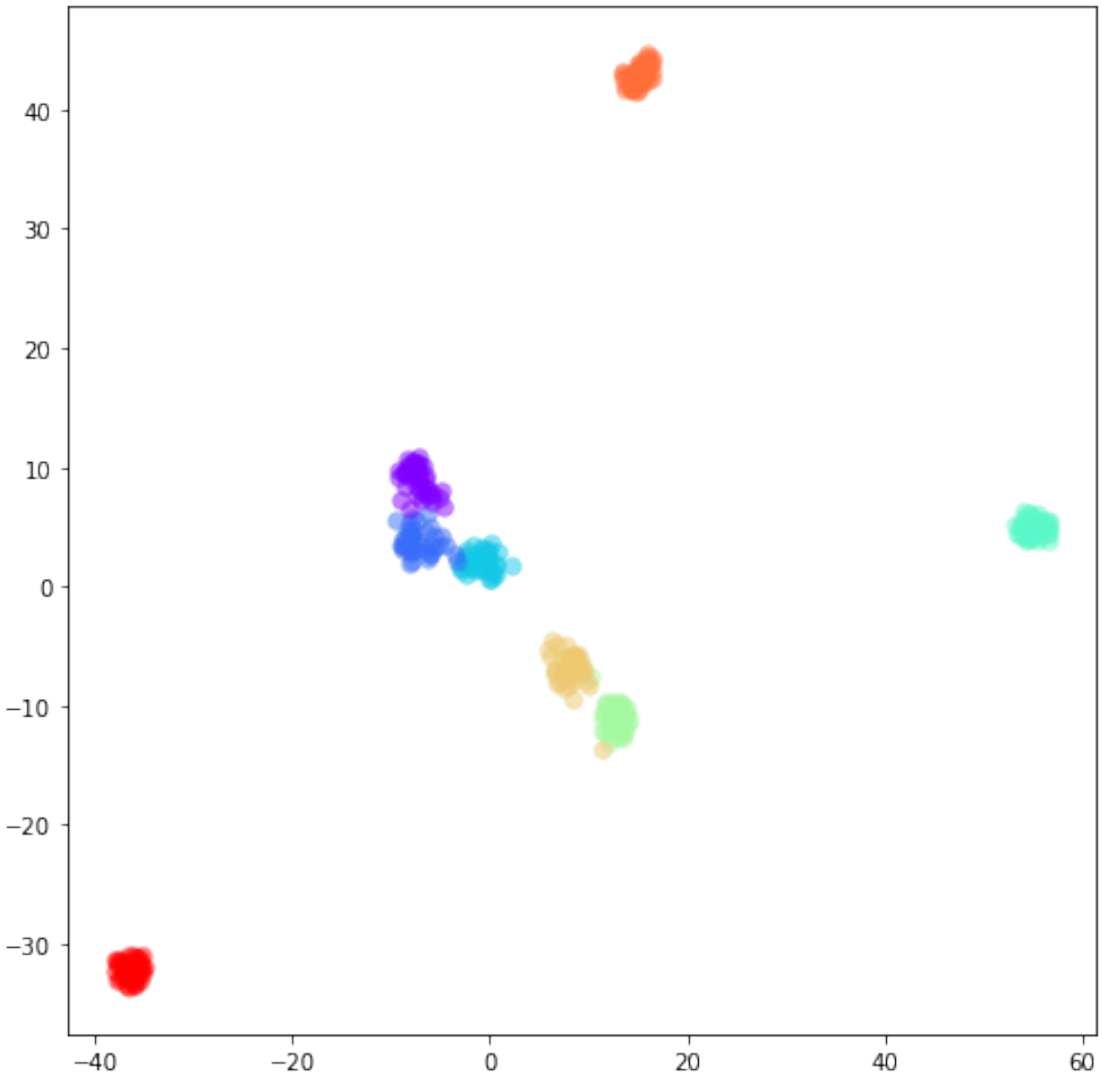


32 Projecting with baseline VGG16

[37]:
```
model = keras.models.load_model("models/baseline_vgg16/main.saved_model")

images_ = images.astype("float32")
```

```
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()

print("features.shape = ", features.shape)

plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of baseline VGG16 model",

                    legend_location = "best",

                    savename = "fig_2d_proj_baseline_vgg16.pdf"
                )

del model
```

```
features.shape =  (320, 154)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_baseline_vgg16.pdf
```

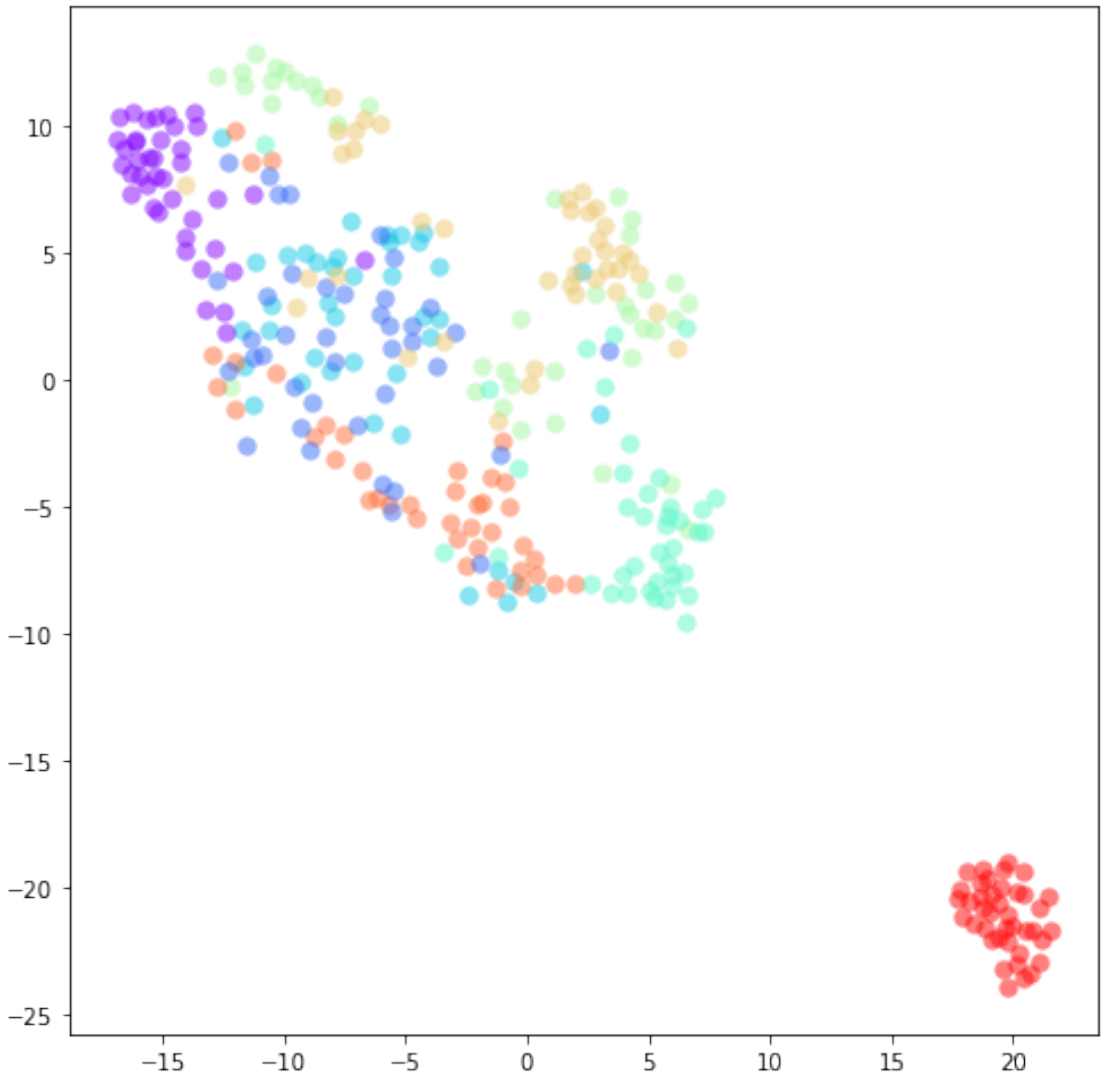


33 Projecting with baseline ResNet50

[38]:
```
model = keras.models.load_model("models/baseline_resnet/main.saved_model")


images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()

print("features.shape = ", features.shape)
```

```
plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of baseline ResNet50 model",

                    legend_location = "best",

                    savename = "fig_2d_proj_baseline_resnet.pdf"
                )

del model
```

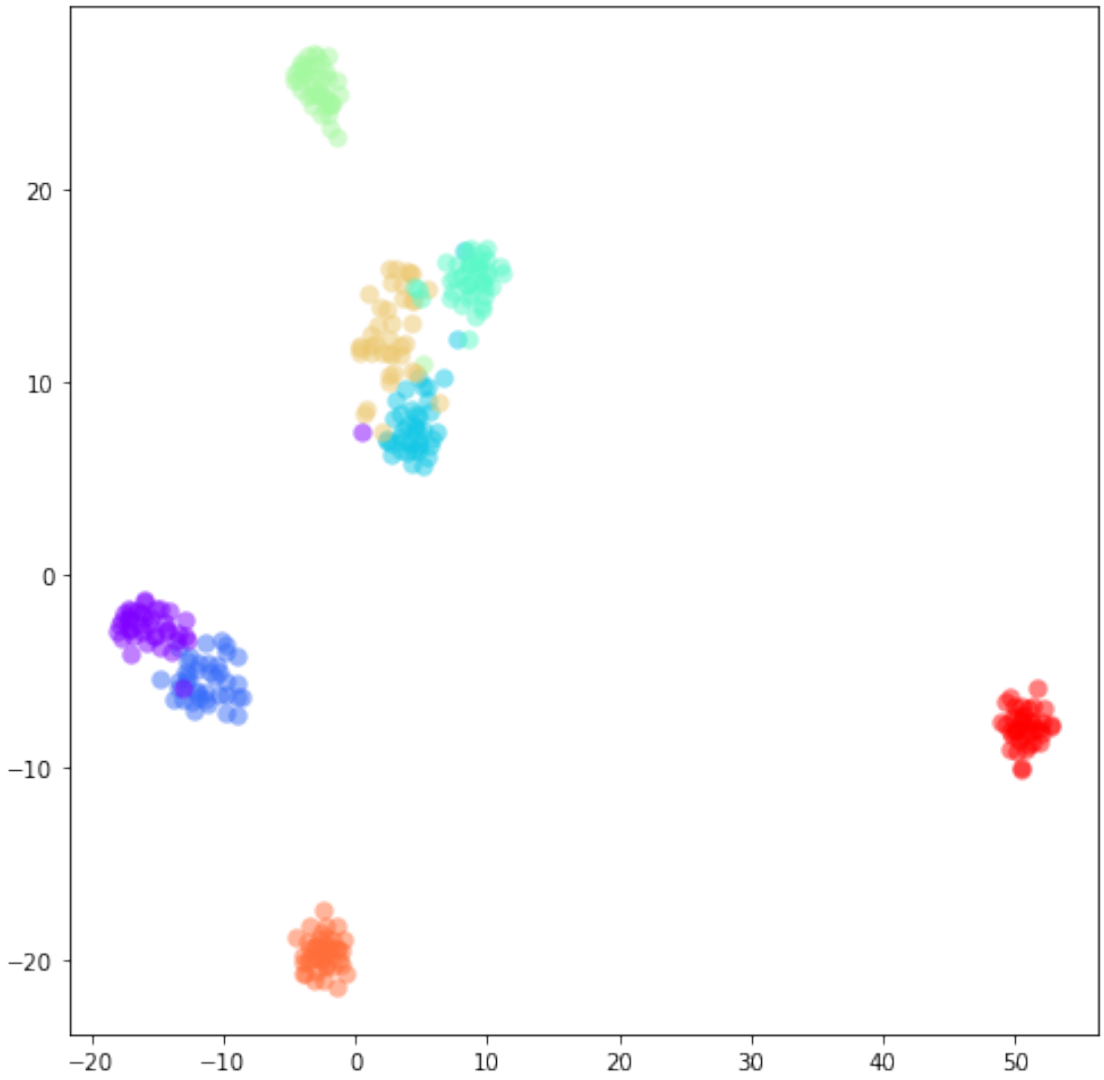
```
features.shape =  (320, 154)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_baseline_resnet.pdf
```



34 Projecting with baseline MobileNet

[39]:
```
model = keras.models.load_model("models/baseline_mobilenet/main.saved_model")


images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()

print("features.shape = ", features.shape)

plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of baseline MobileNet model",

                    legend_location = "best",

                    savename = "fig_2d_proj_baseline_mobilenet.pdf"
                )

del model
```

```
features.shape =  (320, 154)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_baseline_mobilenet.pdf
```



35 Projecting with contrastive simple model

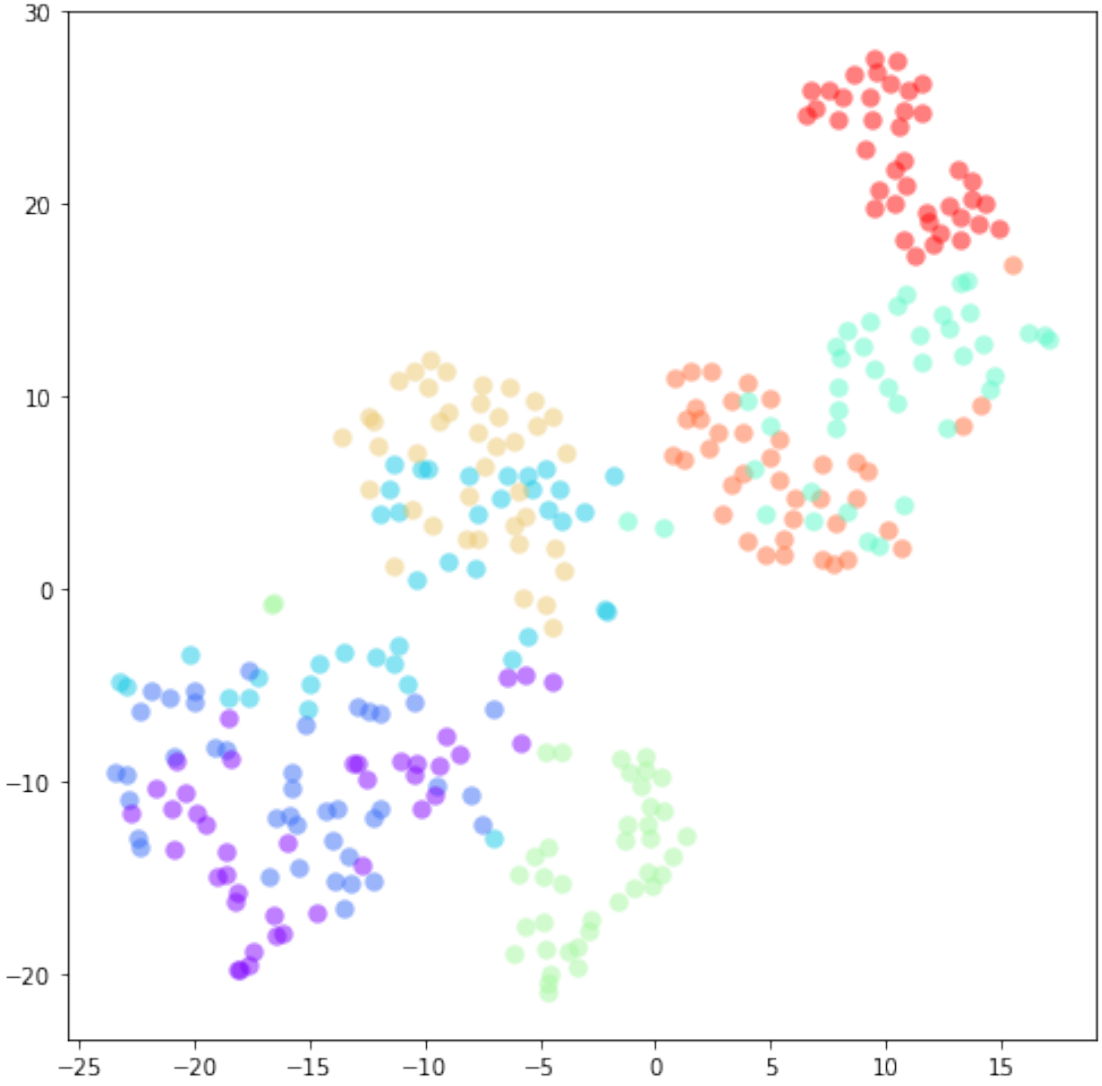
[40]:
```
model = keras.models.load_model("models/contrastive_simple/main.saved_model")


images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()

print("features.shape = ", features.shape)
```

```
plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of contrastive simple model",

                    legend_location = "best",

                    savename = "fig_2d_proj_contrastive_simple.pdf"
                )

del model
```

```
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28597044)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28595399) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28595421) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28597909) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference__wrapped_model_28593803) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28597080)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28597934) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_17_layer_call_a
nd_return_conditional_losses_28596758) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_17_layer_call_a
nd_return_conditional_losses_28596552) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_17_layer_call_a
nd_return_conditional_losses_28596442) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_17_layer_call_a
nd_return_conditional_losses_28596648) with ops with custom gradients. Will
likely fail if a gradient is requested.
```

```
features.shape =  (320, 512)
projections.shape =  (320, 2)
```

```
saved to:  figures/fig_2d_proj_contrastive_simple.pdf
```



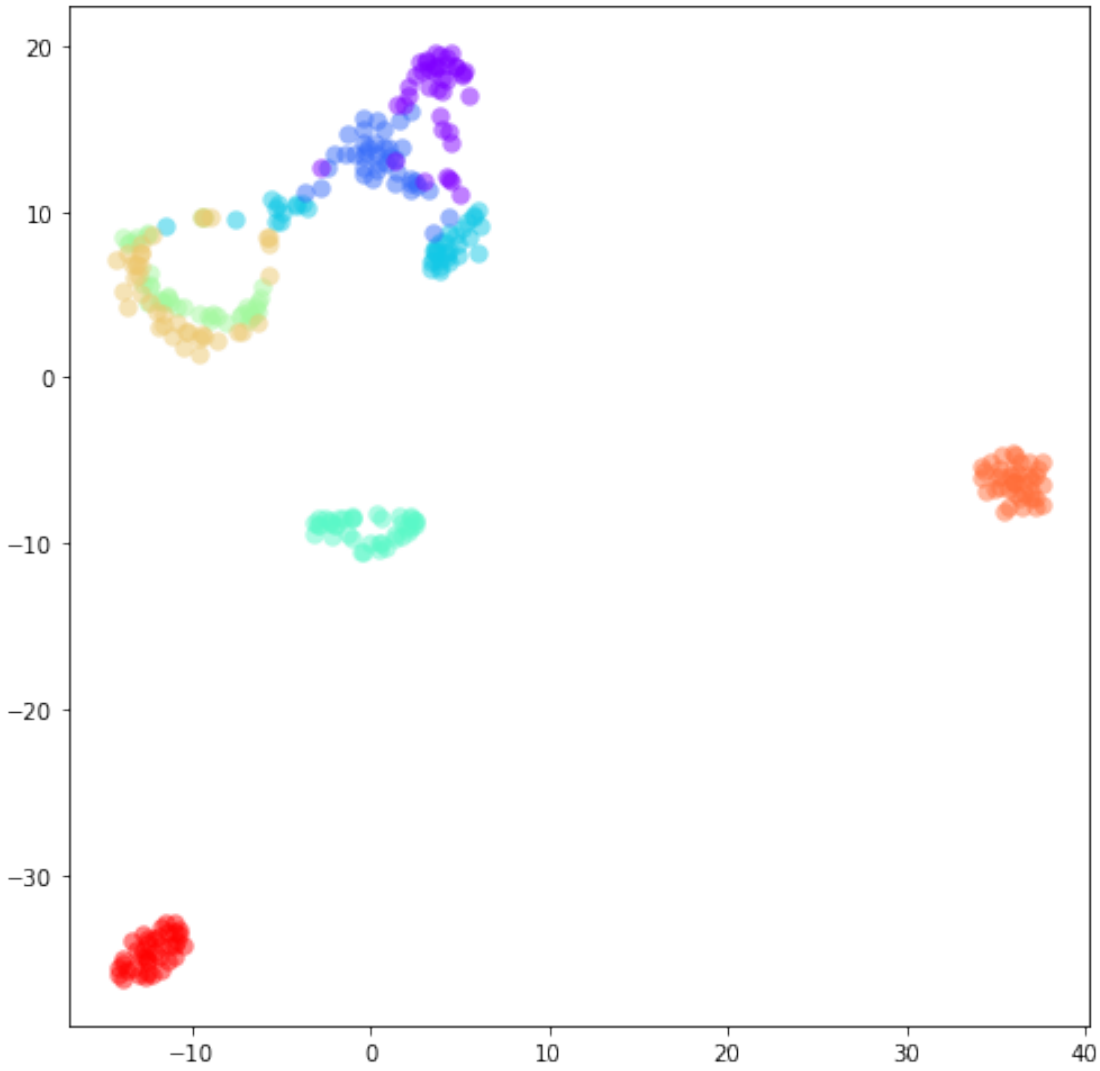
36 Projecting with contrastive VGG16

[41]:
```
model = keras.models.load_model("models/contrastive_vgg16/main.saved_model")


images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
features = features_.numpy()
```

```
print("features.shape = ", features.shape)

plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of contrastive VGG16 model",

                    legend_location = "best",

                    savename = "fig_2d_proj_contrastive_vgg16.pdf"
                )

del model
```

```
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28646246) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_18_layer_call_a
nd_return_conditional_losses_28645444) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28645550)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_18_layer_call_a
nd_return_conditional_losses_28645042) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28643701) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_18_layer_call_a
nd_return_conditional_losses_28645176) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28646271) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28643723) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_18_layer_call_a
nd_return_conditional_losses_28645310) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28645514)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference__wrapped_model_28642081) with ops
with custom gradients. Will likely fail if a gradient is requested.
```

```
features.shape =  (320, 512)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_contrastive_vgg16.pdf
```



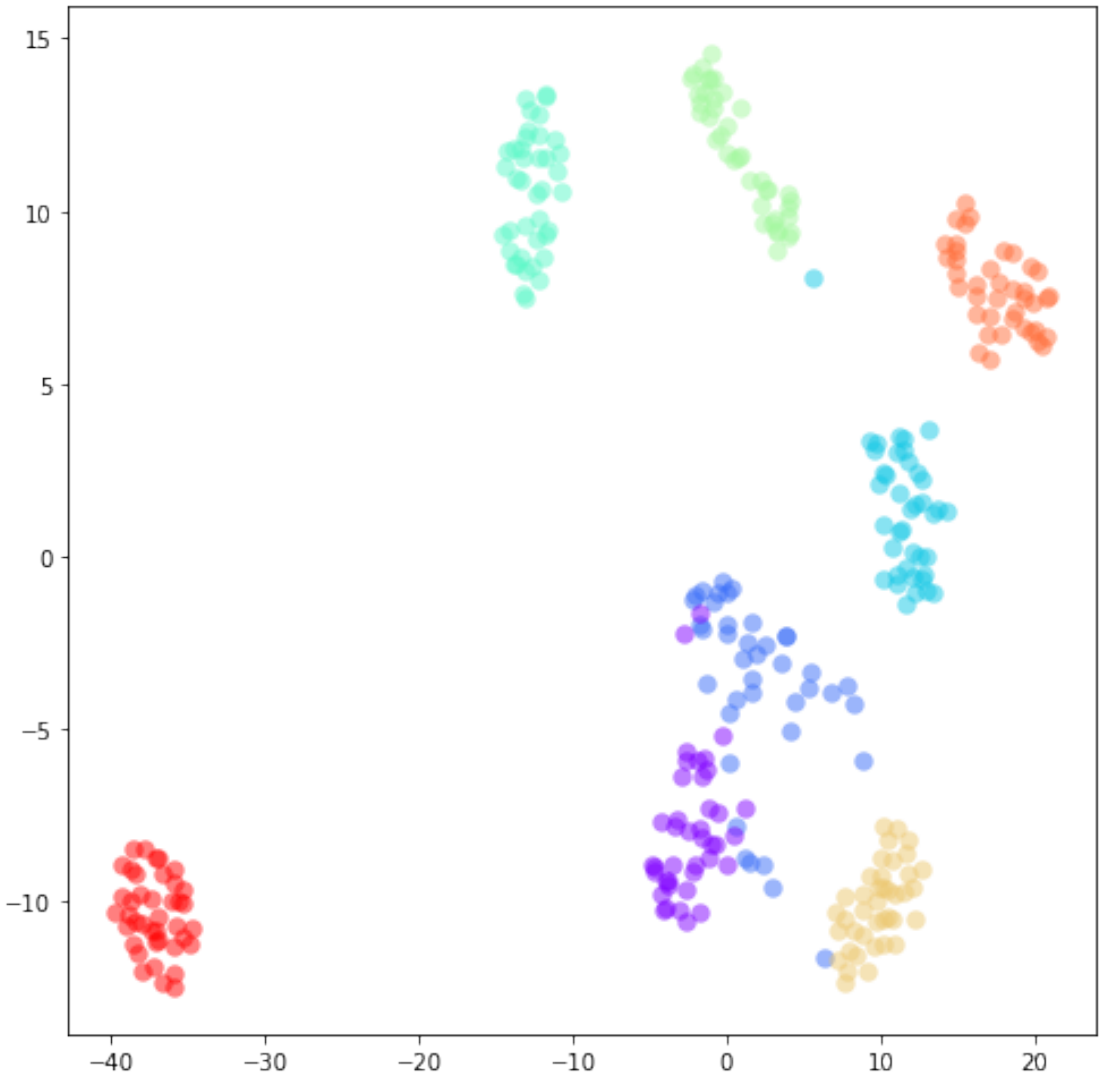
37 Projecting with contrastive ViT

[42]:
```
model = keras.models.load_model("models/contrastive_vit/main.saved_model")


images_ = images.astype("float32")
images_ = tf.convert_to_tensor(images_)

features_ = model(images_)
```

```
features = features_.numpy()

print("features.shape = ", features.shape)

plot_projections(
                    features = features,
                    labels = labels,

                    title = "The 2D projection of contrastive ViT model",

                    legend_location = "best",

                    savename = "fig_2d_proj_contrastive_vit.pdf"
                )

del model
```

```
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28707845) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_19_layer_call_a
nd_return_conditional_losses_28711287) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28713155)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_66_layer_call_and_return_conditional_losses_28706061) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_65_layer_call_and_return_conditional_losses_28713910) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_67_layer_call_and_return_conditional_losses_28714234) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_65_layer_call_and_return_conditional_losses_28705887) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference__wrapped_model_28704921) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_68_layer_call_and_return_conditional_losses_28706277) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_69_layer_call_and_return_conditional_losses_28714558) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_64_layer_call_and_return_conditional_losses_28705845) with
```

```
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_69_layer_call_and_return_conditional_losses_28706319) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_66_layer_call_and_return_conditional_losses_28714189) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_19_layer_call_a
nd_return_conditional_losses_28710785) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_19_layer_call_a
nd_return_conditional_losses_28711838) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_64_layer_call_and_return_conditional_losses_28713865) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_2_layer_call_and_
return_conditional_losses_28714727) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_contrastive_model_19_layer_call_a
nd_return_conditional_losses_28710234) with ops with custom gradients. Will
likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28714702) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_projhead_output_layer_call_and_return_conditional_losses_28713119)
with ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_model_1_layer_call_and_return_conditional_losses_28712530) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_model_1_layer_call_and_return_conditional_losses_28713049) with ops
with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function (__inference_projhead_hidden_1_layer_call_and_
return_conditional_losses_28707823) with ops with custom gradients. Will likely
fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_68_layer_call_and_return_conditional_losses_28714513) with
ops with custom gradients. Will likely fail if a gradient is requested.
WARNING:absl:Importing a function
(__inference_dense_67_layer_call_and_return_conditional_losses_28706103) with
ops with custom gradients. Will likely fail if a gradient is requested.

features.shape =  (320, 512)
projections.shape =  (320, 2)
saved to:  figures/fig_2d_proj_contrastive_vit.pdf
```



38 Conclusions

[ ]: