```
#———- require(envimaR) # MANDANTORY: defining the root folder DO NOT change this
line rootDIR = "C:/Users/jomue/edu/geoAI"
source(file.path(envimaR::alternativeEnvi(root_folder =
rootDIR), "src/geo_AI_setup.R"), echo = TRUE) #read data
Koralle<-sf::st read("E:/Koralle/images/Coral 10m 2022.shp") Koralle Coral ras =
raster::stack("E:/Koralle/images/Coral_2018_new.tif") Coral_ras names(Coral_ras)<-
c("red", "green", "blue") Coral_ras<-subset(Coral_ras,c("red", "green", "blue")) Koralle =
sf::st_transform(Koralle, crs(Coral_ras)) Coral_extent <- raster::extent(Coral_ras) Koralle <-
sf::st_crop(Koralle[1], Coral_extent) Koralle # rasterize the coral rasterized_vector <-
raster::rasterize(Koralle, Coral ras[[1]]) # reclassify to 0 and 1
rasterized_vector[is.na(rasterized_vector[])] <- 0 rasterized_vector[rasterized_vector > 1]
<- 1 #save raster::writeRaster(rasterized vector,
("E:/Koralle/images/Coral_Mask_10_2018.tif"), overwrite = T) # divide to training and
testing extent e test <- raster::extent(3e+05, 7390240, 320000, 74500000) e train <-
raster::extent(320000, 7620000, 409800, 7500040)
coral_mask_train <- raster::crop(rasterized_vector, e_train) coral_dop_train <-</pre>
raster::crop(Coral ras, e train)
coral_mask_test <- raster::crop(rasterized_vector, e_test) coral_dop_test <-</pre>
raster::crop(Coral_ras, e_test)
raster::writeRaster(coral mask test, ("E:/Koralle/images/Coral Mask 10m 2018 test.tif"),
overwrite = T)
raster::writeRaster(coral dop test, ("E:/Koralle/images/Coral Dop 10m 2018 test.tif"),
overwrite = T)
raster::writeRaster(coral mask train,
("E:/Koralle/images/Coral Mask 10m 2018 train.tif"), overwrite = T)
raster::writeRaster(coral_dop_train, ("E:/Koralle/images/Coral_Dop_10m_2018_train.tif"),
overwrite = T)
subset ds <- function(input raster, model input shape, path, targetname = "", mask =
FALSE) { # determine next number of quadrats in x and y direction, by simple rounding
targetsizeX <- model input shape[1] targetsizeY <- model input shape[2] inputX <-
ncol(input raster) inputY <- nrow(input raster) # determine dimensions of raster so that #</pre>
it can be split by whole number of subsets (by shrinking it) while (inputX %% targetsizeX!
= 0) { inputX = inputX - 1 } while (inputY %% targetsizeY != 0) { inputY = inputY - 1 } #
determine difference diffX <- ncol(input_raster) - inputX diffY <- nrow(input_raster) -</pre>
inputY # determine new dimensions of raster and crop, # cutting evenly on all sides if
possible newXmin <- floor(diffX / 2) newXmax <- ncol(input raster) - ceiling(diffX / 2) - 1
newYmin <- floor(diffY / 2) newYmax <- nrow(input_raster) - ceiling(diffY / 2) - 1</pre>
rst_cropped <- suppressMessages(raster::crop( input_raster, raster::extent(input_raster,</pre>
newYmin, newYmax, newXmin, newXmax) )) agg <--</pre>
suppressMessages(raster::aggregate(rst cropped[[1]], c(targetsizeX, targetsizeY))) agg[] <-
```

```
suppressMessages(1:ncell(agg)) agg_poly <-
suppressMessages(raster::rasterToPolygons(agg)) names(agg_poly) <-"polis" if (mask)
{ lapply( seq_along(agg), FUN = function(i) { subs <- local({ e1 <-
raster::extent(agg_poly[agg_poly$polis == i,]) subs <-
suppressMessages(raster::crop(rst_cropped, e1)) }) writePNG(as.array(subs), target =
pasteO(path, targetname, i, ".png")) }) } else{ lapply( seq_along(agg), FUN = function(i)
{ subs <- local({ e1 <- raster::extent(agg_poly[agg_poly$polis == i,]) subs <-
suppressMessages(raster::crop(rst_cropped, e1)) # rescale to 0-1, for png export if (mask
== FALSE) { subs <- suppressMessages((subs - cellStats(subs, "min")) / (cellStats(subs,
"max") - cellStats(subs, "min"))) }}) writePNG(as.array(subs), target = pasteO(path,
targetname, i, ".png")) }) rm(subs, agg, agg_poly) gc() return(rst_cropped) } remove_files
<- function(df) { lapply( seq(1, nrow(df)), FUN = function(i) { local({ fil = df$list_masks[i] png = readPNG(fil) len = length(png) if (AllEqual(png)) { file.remove(df$list_dops[i]) file.remove(df$list_masks[i]) } else { } }) })}</pre>
```

# read training data

coral\_mask\_train <- raster::stack("E:/Koralle/images/Coral\_Mask\_10m\_2018\_train.tif") coral\_dop\_train <- raster::stack("E:/Koralle/images/Coral\_Dop\_10m\_2018\_train.tif") # set the size of each image model\_input\_shape = c(128, 128)

subset\_ds(input\_raster = coral\_mask\_train, path = "E:/Koralle/images/Cor\_2018/", mask = TRUE, model\_input\_shape = model\_input\_shape)

subset\_ds(input\_raster = coral\_dop\_train, path = "E:/Koralle/images/Dop\_2018/", mask = FALSE, model\_input\_shape = model\_input\_shape)

#### list all created files in both folders

list\_dops <- list.files("E:/Koralle/images/Dop\_2018/", full.names = TRUE, pattern = ".png") list\_masks <- list.files("E:/Koralle/images/Cor\_2018/", full.names = TRUE, pattern = ".png")

## create a data fram

```
df = data.frame(list_dops, list_masks)
remove_files(df)
```

# list the files again

files <- data.frame( img = list.files( file.path("E:/Koralle/images/Dop\_2018/"), full.names = TRUE, pattern = ".png"), mask = list.files( file.path("E:/Koralle/images/Cor\_2018/"), full.names = TRUE, pattern = ".png")) # split randomly into training and validation (not testing!!) data sets set.seed(7) data <- initial\_split(files, prop = 0.8)

# function to prepare your data set for all further processes

prepare ds <- function(files = NULL, train, predict = FALSE, subsets path = NULL, model input shape = c(256, 256), batch size = batch size, visual = FALSE) { if (!predict) { # function for random change of saturation, brightness and hue, # will be used as part of the augmentation spectral augmentation <- function(img) { img <- tfimage random brightness(img, max\_delta = 0.1) img <- tfima gerandom\_contrast(img, lower = 0.9, upper = 1.1) img <- tfimagerandom saturation(img, lower = 0.9, upper = 1.1) # make sure we still are between 0 and 1 img <- tf\$clip\_by\_value(img, 0, 1) } # create a tf\_dataset from the input data.frame # right now still containing only paths to images dataset <tensor slices dataset(files) # use dataset map to apply function on each record of the dataset # (each record being a list with two items: img and mask), the # function is list\_modify, which modifies the list items # 'img' and 'mask' by using the results of applying decode\_png on the img and the mask # -> i.e. pngs are loaded and placed where the paths to the files were (for each record in dataset) dataset <- dataset map(dataset, function(.x) list\_modify( .x, img = tf\\$imaged e c o de\_p ng \(\delta\)ior e a  $d_f$  i le \(\delta\)img)), mask = tf ima gedecode png(tfioread file(.x\$mask)) )) # convert to float32: # for each record in dataset, both its list items are modified # by the result of applying convert image dtype to them dataset <- dataset\_map(dataset, function(.x) list\_modify( .x, img = tf\$image  $convert_i mage_d t y peiimg, dtype = tff loat 32i, mask = tfimageconvert_i mage_d t y peii$ mask, dtype = tf\$float32) )) # data augmentation performed on training set only if (train) { # augmentation 1: flip left right, including random change of # saturation, brightness and contrast # for each record in dataset, only the img item is modified by the result # of applying spectral\_augmentation to it augmentation <- dataset\_map(dataset, function(.x) list modify(x, img = spectral augmentation(x)) #...as opposed to this, flipping is applied to img and mask of each record augmentation <- dataset map(augmentation, function(.x) list\_modify(.x, img =  $tfima qeflip_left_right(.xim qi, mask = tfimage$  $f li p_l e f t_r i g ht i mask)$  )) dataset\_augmented <- dataset\_concatenate(augmentation. dataset) # augmentation 2: flip up down, # including random change of saturation, brightness and contrast augmentation <- dataset map(dataset, function(.x) list modify(.x, img = spectral\_augmentation( $ximgiiaugmentation < -dataset_mapiimage$  $f li p_{\mu} p_{d} o w n \dot{c} img)$ , mask = tfi ma qeflip up down(.x\$mask) )) dataset augmented <dataset concatenate(augmentation, dataset augmented) # augmentation 3: flip left right AND up down, # including random change of saturation, brightness and contrast augmentation <- dataset\_map(dataset, function(.x) list\_modify(.x, img =</pre> spectral\_augmentation(.x\$img))) augmentation <- dataset\_map(augmentation, function(.x) list\_modify(.x, img = tfimageflip\_left\_right(.ximg $\dot{c}$ , mask=tfimageflip\_left\_ight $\dot{c}$ mask) )) augmentation <- dataset map(augmentation, function(.x) list modify(.x, img = tf  $imageflip\_up\_down(.ximgi, mask=tfimageflip_up_downimask)))$  dataset\_augmented <dataset concatenate(augmentation, dataset augmented) } # shuffling on training set only # unsauber if (!visual) { if (train) { dataset <- dataset shuffle(dataset augmented, buffer size = batch\_size \* 256) } # train in batches; batch size might need to be adapted depending on # available memory dataset <- dataset batch(dataset, batch size) } if (visual) { dataset <dataset augmented } # output needs to be unnamed dataset <- dataset map(dataset, unname) } else{ # make sure subsets are read in in correct order # so that they can later be

reassembled correctly # needs files to be named accordingly (only number) o <order(as.numeric(tools::file\_path\_sans\_ext(basename( list.files(subsets\_path) ))))
subset\_list <- list.files(subsets\_path, full.names = T)[o] dataset <tensor\_slices\_dataset(subset\_list) dataset <- dataset\_map(dataset, function(.x) tfima ge
decode\_png(tfioread\_file(.x))) dataset <- dataset\_map(dataset, function(.x) tfima ge
convert\_image\_dtype(.x, dtype = tf\$float32)) dataset <- dataset\_batch(dataset, batch\_size)
dataset <- dataset\_map(dataset, unname) } }

### one more parameter

batch\_size = 8

# prepare data for training

training\_dataset <- prepare\_ds( training(data), train = TRUE, predict = FALSE, model\_input\_shape = model\_input\_shape, batch\_size = batch\_size )

# also prepare validation data

validation\_dataset <- prepare\_ds( testing(data), train = FALSE, predict = FALSE, model\_input\_shape = model\_input\_shape, batch\_size = batch\_size )

# we first get a all our training data

it <- as\_iterator(training\_dataset) it <- iterate(it) # head(it)</pre>

we convert our data to an array and also subset our iterator e.g.

# with the 4th batch ([[4]]) of the images ([[1]])

im <-as.array(it[[4]][[1]]) # then we subset just take the first image out of our batch im <-im[1,,,] # and plot it plot(as.raster(im))



# and for the according mask it is almost the same

ma <-as.array(it[[4]][[2]]) ma <- ma[1,,,] plot(as.raster(ma))

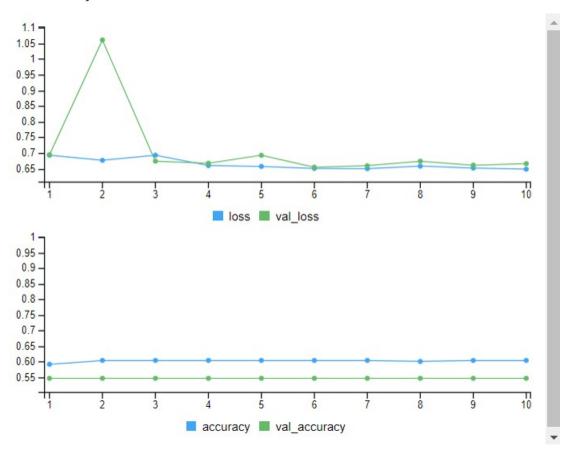


```
#U-Net # function to build a U-Net # of course it is possible to change the input shape
get_unet_128 <- function(input_shape = c(128, 128, 3), num_classes = 1) { inputs <-
layer input(shape = input shape) # 128 down1 <- inputs %>% layer conv 2d(filters = 64.
kernel_size = c(3, 3), padding = "same") %>% layer_activation("relu") %>%
layer conv 2d(filters = 64, kernel size = c(3, 3), padding = "same") %>%
layer activation("relu") down1 pool <- down1 %>% layer max pooling 2d(pool size = c(2.
2), strides = c(2, 2)) # 64 down2 <- down1_pool %>% layer_conv_2d(filters = 128,
kernel_size = c(3, 3), padding = "same") %>% layer_activation("relu") %>%
layer_conv_2d(filters = 128, kernel_size = c(3, 3), padding = "same") %>%
layer activation("relu") down2 pool <- down2 %>% layer max pooling 2d(pool size = c(2,
2), strides = c(2, 2)) # 32 down3 <- down2_pool %>% layer_conv_2d(filters = 256,
kernel size = c(3, 3), padding = "same") %>% layer activation("relu") %>%
layer conv 2d(filters = 256, kernel size = c(3, 3), padding = "same") %>%
layer_activation("relu") down3_pool <- down3 %>% layer_max_pooling_2d(pool_size = c(2,
2), strides = c(2, 2)) # 16 down4 <- down3 pool %>% layer conv 2d(filters = 512.
kernel_size = c(3, 3), padding = "same") %>% layer_activation("relu") %>%
layer conv 2d(filters = 512, kernel size = c(3, 3), padding = "same") %>%
layer_activation("relu") down4_pool <- down4 %>% layer_max_pooling_2d(pool_size = c(2,
2), strides = c(2, 2)) # # 8 center <- down4 pool %>% layer conv 2d(filters = 1024,
kernel_size = c(3, 3), padding = "same") %>% layer_activation("relu") %>%
layer conv 2d(filters = 1024, kernel size = c(3, 3), padding = "same") %>%
layer_activation("relu") # center up4 <- center %>% layer_upsampling_2d(size = c(2, 2))
%>% { layer_concatenate(inputs = list(down4, .), axis = 3) } %>% layer_conv_2d(filters =
512, kernel size = c(3, 3), padding = "same") %>% layer activation("relu") %>%
layer conv 2d(filters = 512, kernel size = c(3, 3), padding = "same") %>%
layer_activation("relu") %>% layer_conv_2d(filters = 512, kernel_size = c(3, 3), padding =
"same") %>% layer_activation("relu") # 16 up3 <- up4 %>% layer_upsampling_2d(size =
c(2, 2)) %>% { layer concatenate(inputs = list(down3, .), axis = 3) } %>%
layer_conv_2d(filters = 256, kernel_size = c(3, 3), padding = "same") %>%
layer_activation("relu") %>% layer_conv_2d(filters = 256, kernel_size = c(3, 3), padding =
"same") %>% layer activation("relu") %>% layer conv 2d(filters = 256, kernel size = c(3,
3), padding = "same") %>% layer activation("relu") # 32 up2 <- up3 %>%
layer_upsampling_2d(size = c(2, 2)) %>% { layer_concatenate(inputs = list(down2, .), axis =
3) \% \% layer_conv_2d(filters = 128, kernel_size = c(3, 3), padding = "same") \%>\%
layer activation("relu") %>% layer conv 2d(filters = 128, kernel size = c(3, 3), padding =
"same") %>% layer_activation("relu") %>% layer_conv_2d(filters = 128, kernel_size = c(3,
3), padding = "same") %>% layer_activation("relu") # # 64 up1 <- up2 %>%
layer_upsampling_2d(size = c(2, 2)) %>% { layer_concatenate(inputs = list(down1, .), axis =
3) } %>% layer_conv_2d(filters = 64, kernel_size = c(3, 3), padding = "same") %>%
layer activation("relu") %>% layer conv 2d(filters = 64, kernel size = c(3, 3), padding =
"same") %>% layer_activation("relu") %>% layer_conv_2d(filters = 64, kernel_size = c(3,
3), padding = "same") %>% layer_activation("relu") # 128 classify <- layer_conv_2d( up1,
filters = num_classes, kernel_size = c(1, 1), activation = "sigmoid") model <-
keras_model(inputs = inputs, outputs = classify) return(model) }
```

unet\_model <- get\_unet\_128() # compile the model unet\_model %>% compile( optimizer =
optimizer\_adam(learning\_rate = 0.0001), loss = "binary\_crossentropy", metrics =
"accuracy" )

## train the model

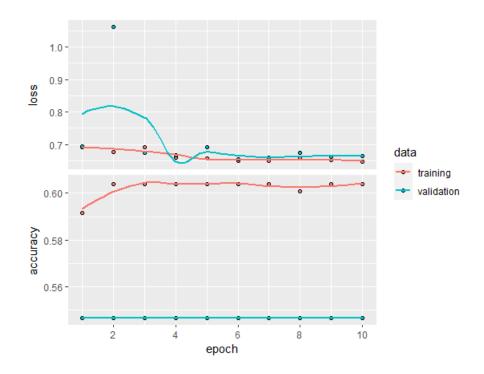
hist <- unet\_model %>% fit( training\_dataset, validation\_data = validation\_dataset, epochs = 10, verbose = 1)



#### save the model

unet\_model %>% save\_model\_hdf5(file.path("E:/Koralle/images/models/",
"unet\_corals\_2018.hdf5"))

unet\_model plot(hist)



#### load the test data

coral\_mask\_test <- stack("E:/Koralle/images/Coral\_Mask\_10m\_2018\_test.tif") coral\_dop\_test <- stack("E:/Koralle/images/Coral\_Dop\_10m\_2018\_test.tif") target\_rst <- subset\_ds( input\_raster = coral\_mask\_test, path = "E:/Koralle/images/Cor\_test\_2018/", mask = TRUE, model\_input\_shape = model\_input\_shape ) subset\_ds( input\_raster = coral\_dop\_test, path = "E:/Koralle/images/Dop\_test\_2018/", mask = FALSE, model\_input\_shape = model\_input\_shape ) # write the target\_rst to later rebuild your image writeRaster( target\_rst,

 $\label{lem:condition} file.path("E:/Koralle/images/models/model_test_2018/", "coral_mask_2018_test_target.tif"), overwrite = T)$ 

#list and prepare the files again test\_file <- data.frame( img = list.files( file.path("E:/Koralle/images/Dop\_test\_2018"), full.names = T, pattern = ".png"), mask = list.files( file.path("E:/Koralle/images/Cor\_test\_2018"), full.names = T, pattern = ".png"))

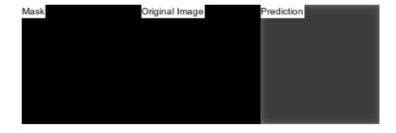
testing\_dataset <- prepare\_ds( test\_file, train =FALSE, predict = FALSE, model\_input\_shape = model\_input\_shape, batch\_size = batch\_size) # load a U-Net unet\_model <- load\_model\_hdf5(file.path("E:/Koralle/images/models/", "unet\_corals\_2018.hdf5"), compile = TRUE) # evaluate the model with test set ev <- unet\_model\$evaluate(testing\_dataset) # prepare\_data\_for\_prediction\_prediction\_dataset <-

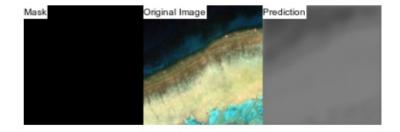
unet\_model\$evaluate(testing\_dataset) # prepare data for prediction prediction\_dataset <prepare\_ds( predict = TRUE, subsets\_path =</pre>

paste0(file.path("E:/Koralle/images/Dop\_test\_2018/")), model\_input\_shape =
model\_input\_shape, batch\_size = batch\_size ) # get sample of data from testing data
t\_sample <- floor(runif(n = 5, min = 1, max = nrow(test\_file))) # simple visual comparison</pre>

of mask, image and prediction for (i in t\_sample) { png\_path <- test\_file png\_path <- png\_path[i,] img <- image\_read(png\_path[, 1]) mask <- image\_read(png\_path[, 2]) pred <- image\_read(as.raster(predict(object = unet\_model, testing\_dataset)[i, , ,])) out <- image\_append(c( image\_annotate( mask, "Mask", size = 10, color = "black", boxcolor = "white" ), image\_annotate( img, "Original Image", size = 10, color = "black", boxcolor = "white" ), image\_annotate( pred, "Prediction", size = 10, color = "black", boxcolor = "white" ) )) plot(out) }







```
# function to rebuild your image rebuild img <- function(pred subsets, out path,
target_rst, model_name) { subset_pixels_x <- ncol(pred_subsets[1, , , ]) subset_pixels_y <-
nrow(pred_subsets[1,,,]) tiles_rows <- nrow(target_rst) / subset_pixels_y tiles_cols <-</pre>
ncol(target rst) / subset pixels x # load target image to determine dimensions
target_stars <- st_as_stars(target_rst, proxy = F) #prepare subfolder for output
result_folder <- paste0(out_path, model_name) if (dir.exists(result_folder))
{ unlink(result_folder, recursive = T) } dir.create(path = result_folder) # for each tile,
create a stars from corresponding predictions, # assign dimensions using original/target
image, and save as tif: for (crow in 1:tiles rows) { for (ccol in 1:tiles cols) { i <- (crow - 1) *
tiles_cols + (ccol - 1) + 1 dimx <- c(((ccol - 1) * subset_pixels_x + 1), (ccol *
subset_pixels_x)) dimy <- c(((crow - 1) * subset_pixels_y + 1), (crow * subset_pixels_y))
cstars <- st_as_stars(t(pred_subsets[i, , , 1])) attr(cstars, "dimensions")[[2]]$delta = -1 #set
dimensions using original raster st dimensions(cstars) <- st dimensions(target stars),
dimx[1]:dimx[2], dimy[1]:dimy[2]])[1:2] write_stars(cstars, dsn = paste0(result_folder,
"/out", i, ".tif")) } } starstiles <- as.vector(list.files(result_folder, full.names = T), mode =
"character") sf::gdal utils( util = "buildvrt", source = starstiles, destination =
paste0(result_folder, "/mosaic.vrt") ) sf::gdal_utils( util = "warp", source =
paste0(result_folder, "/mosaic.vrt"), destination = paste0(result_folder, "/mosaic.tif") ) }
#load target raster target rst <-
raster(file.path("E:/Koralle/images/models/model_test_2018/","coral_mask_2018_test_tar
get.tif")) # make the actual prediction pred_subsets <- predict(object = unet_model, x =
prediction dataset) # name your output path model name <- "unet abc 2018" # rebuild .tif
from each patch rebuild_img( pred_subsets = pred_subsets, out_path =
pasteO(file.path("E:/Koralle/images/prediction/", "/")), target_rst = target_rst,
model_name = model_name )
```