Python Scripts to process hyperspectral images

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Key Words: Hyperspectral imaging, Spectra, Classification model, Random forest

Part 1: Scripts used to process hyperspectral images

Importing libraries

```python
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import cv2
from spectral.io import envi
```

Importing images

```python
folder_path = r"path to hyperspectral images (.raw and .hdr)"
## Image dimensions
# x : x dimension (if it differs from one image to another, take the min)
# y : y dimension (all our images are 640)
# z : z dimension, number of spectral variables (in all our images this is 244)
target_shape = (x, y, z)

# List for storing imported data
data_list = []

# Loop to browse files in folder
for file_name in os.listdir(folder_path):
    # Checks if the file is an .hdr file
    if file_name.endswith(".hdr"):
        # Recovers base name without extension
        base_name = file_name[:-4]  # Remove ".hdr"

        # Correspondence with .raw file
        raw_file = base_name + ".raw"
        raw_path = os.path.join(folder_path, raw_file)
        hdr_path = os.path.join(folder_path, file_name)

        # Checks whether the corresponding .raw file exists
        if os.path.exists(raw_path):
            try:
                # Load hyperspectral data
                data = envi.open(hdr_path, raw_path)
                data_nparr = np.array(data.load(), dtype=np.float16)

                if data_nparr.shape != target_shape:
                    print(f"Original dimensions of {file_name} : {data_nparr.shape}")

                    if data_nparr.shape[0] > target_shape[0]:
                        data_nparr = data_nparr[:target_shape[0], :, :]
                        print(f"Image {file_name} resized to {data_nparr.shape}")

                    elif data_nparr.shape[0] < target_shape[0]:
                        print(f"Error : {file_name} is too small to fit.")
                        continue  # Go to next image

                # Adds adjusted data to the list
                data_list.append(data_nparr)
                print(f"Successfully imported : {file_name} & {raw_file}")

            except Exception as e:
                print(f"Error when importing {file_name} & {raw_file} : {e}")
        else:
            print(f"Missing RAW file for : {file_name}")
```

Reflectance correction

1. Importing white and black references

```python
dark_ref = envi.open('black reference .hdr path', 'black reference .raw path')
white_ref = envi.open('blache reference .hdr path', 'blache reference .raw path')
white_nparr = np.array(white_ref.load(), dtype=np.float16)
dark_nparr = np.array(dark_ref.load(), dtype=np.float16)
```

```python
# Resizing references
example_shape = data_list[0].shape

white_nparr_resized = np.zeros(example_shape, dtype=white_nparr.dtype)
for band in range(white_nparr.shape[2]):
    white_nparr_resized[:, :, band] = cv2.resize(white_nparr[:, :, band],(example_shape[1], example_shape[0]),interpolation=cv2.INTER_NEAREST)

dark_nparr_resized = np.zeros(example_shape, dtype=dark_nparr.dtype)
for band in range(dark_nparr.shape[2]):
    dark_nparr_resized[:, :, band] = cv2.resize(dark_nparr[:, :, band],(example_shape[1], example_shape[0]),interpolation=cv2.INTER_NEAREST)
```

2. Apply correction to each image in data_list

```python
corrected_images = []  # List for storing corrected images

# Loop to browse each image in data_list
for i, data_nparr in enumerate(data_list):
    # checking dimensions
    if data_nparr.shape != white_nparr_resized.shape:
        print(f"Error: Incompatible image dimensions {i}.")
        continue

    # Correction
    corrected_nparr = np.divide(
        np.subtract(data_nparr, dark_nparr_resized),
        np.subtract(white_nparr_resized, dark_nparr_resized)
    )
    corrected_nparr = np.clip(corrected_nparr, 0, 1)
    corrected_images.append(corrected_nparr)
```

Binarization, creation of a binary masks

```python
binary_masks = []  # List for storing binary masks
thresholds = []  # List for storing Otsu thresholds

# Define a small core so that the effect is not intense
kernel = np.ones((3, 3), np.uint8)  # 3x3 core
# Loop to scroll through each corrected image
for i, corrected_image in enumerate(corrected_images):
    # Select band 41 (index 40 as NumPy uses indices starting from 0)
    gray_image = corrected_image[:, :, 40]

    # Normalize image (make sure values are between 0 and 255 for cv2)
    gray_image_normalized = (gray_image * 255).astype(np.uint8)

    # Apply Otsu's binarization method
    otsu_threshold, binary_mask = cv2.threshold(gray_image_normalized, 0, 255, cv2.THRESH_BINARY + cv2.THRESH_OTSU)

    # Apply erosion (light effect so as not to be too intense)
    binary_mask_eroded = cv2.erode(binary_mask, kernel, iterations=2)

    # Apply dilatation (light effect to restore shapes)
    binary_mask_final = cv2.dilate(binary_mask_eroded, kernel, iterations=2)

    # Add binary mask to list
    binary_masks.append(binary_mask_final)
    thresholds.append(otsu_threshold)
```

Application of binary masks, and creation of segmented hyperspectral cubes

```python
masked_cubes = []  # List for storing hidden hyperspectral cubes

# Browse each corrected image and its bitmask
for i, (corrected_image, binary_mask) in enumerate(zip(corrected_images, binary_masks)):
    cube_images = []  # Temporary list for masked bands in this image

    # Apply the binary mask to all spectral bands
    for band_idx in range(corrected_image.shape[2]):
        # Extract the current spectral band
        current_band = corrected_image[:, :, band_idx]

        # Apply binary mask (black mask zones set pixels to 0)
        masked_band = np.where(binary_mask == 255, current_band, 0)

        # Add hidden band to temporary list
        cube_images.append(masked_band)

    # Convert the list of masked images into a hyperspectral cube
    cube_hyperspectral = np.stack(cube_images, axis=-1)
    masked_cubes.append(cube_hyperspectral)  # Add hidden cube to main list
```

Extraction of average spectra

```python
# Define the boundaries of the three regions in the images
regions = [{"ymin": , "ymax": , "label": "p"},  # Proximal
           {"ymin": , "ymax": , "label": "m"},  # Central
           {"ymin": , "ymax": , "label": "d"},  # Distal
]

# List of labels for the DataFrame to be trained between [], (If you know or prefer indexes for the samples, to train them, otherwise without labels will be from 1 sample to n sample)
labels = []

# Initialiser une structure pour stocker les spectres moyens de toutes les images
all_spectra = []

# Loop through each hyperspectral image
for idx, cube_hyperspectral in enumerate(masked_cubes):
    image_spectra = {}  # Dictionary to store the spectra of this image

    # Calculate the average spectrum for each region
    for region in regions:
        ymin, ymax, label = region["ymin"], region["ymax"], region["label"]

        # Extract sub-region from hyperspectral image
        subregion = cube_hyperspectral[ymin:ymax, :, :]

        # Create a mask to exclude values equal to 0
        mask = (subregion > 0)
        # Calculate the average spectrum
        spectre_moyen = np.zeros(cube_hyperspectral.shape[2])
        for band_idx in range(cube_hyperspectral.shape[2]):
            spectre_moyen[band_idx] = np.mean(subregion[:, :, band_idx][mask[:, :, band_idx]])

        # Store the average spectrum in the dictionary
        image_spectra[label] = spectre_moyen

    # Add the average spectra of this image to the main list
    all_spectra.append(image_spectra)

# Structuring data for the DataFrame
data = []
for idx, image_spectra in enumerate(all_spectra):
    for region_label, spectre in image_spectra.items():
        # Create a complete label based on image and region
        full_label = f'_G{idx+1:03d}FR{1 if idx < 6 else 2}{region_label}'
        data.append(spectre)

# Creating the DataFrame
Spectra = pd.DataFrame(data, index=labels)
```

Saving mean spectra

```python
file_path = r"path to file to save.xlsx"

# Create folder if none exists
os.makedirs(os.path.dirname(file_path), exist_ok=True)

# Save DataFrame in Excel
Spectra.to_excel(file_path, index=True)
```

Part 2: Scripts used to develop the classification model
(from importing data to saving the classification model)

Importing libraries

```python
import os
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from imblearn.over_sampling import SMOTE
import seaborn as sns
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, confusion_matrix, f1_score, matthews_corrcoef, precision_score
from sklearn.model_selection import train_test_split
import joblib
```

Data import

```python
# Set file path
file_path = r"path to template/12_dataset-HSI-WAB-boiled-cassava-CIAT-CIRAD-may2024-v250331.xlsx"

# Load the "Spectra" sheet and extract spectral data
df_spectra = pd.read_excel(file_path, sheet_name="Spectra", header=0, index_col=0)

# Select spectral data columns (index = 14 as Python starts at 0)
df_spectra = df_spectra.iloc[:, 14:]

# Load the "Laboratory data" sheet and extract response Y by name
df_Y = pd.read_excel(file_path, sheet_name="Laboratory data", header=0, index_col=0)
# Select "WAB (%) at 30 min" column
df_Y = df_Y[["WAB (%) at 30 min"]]
```

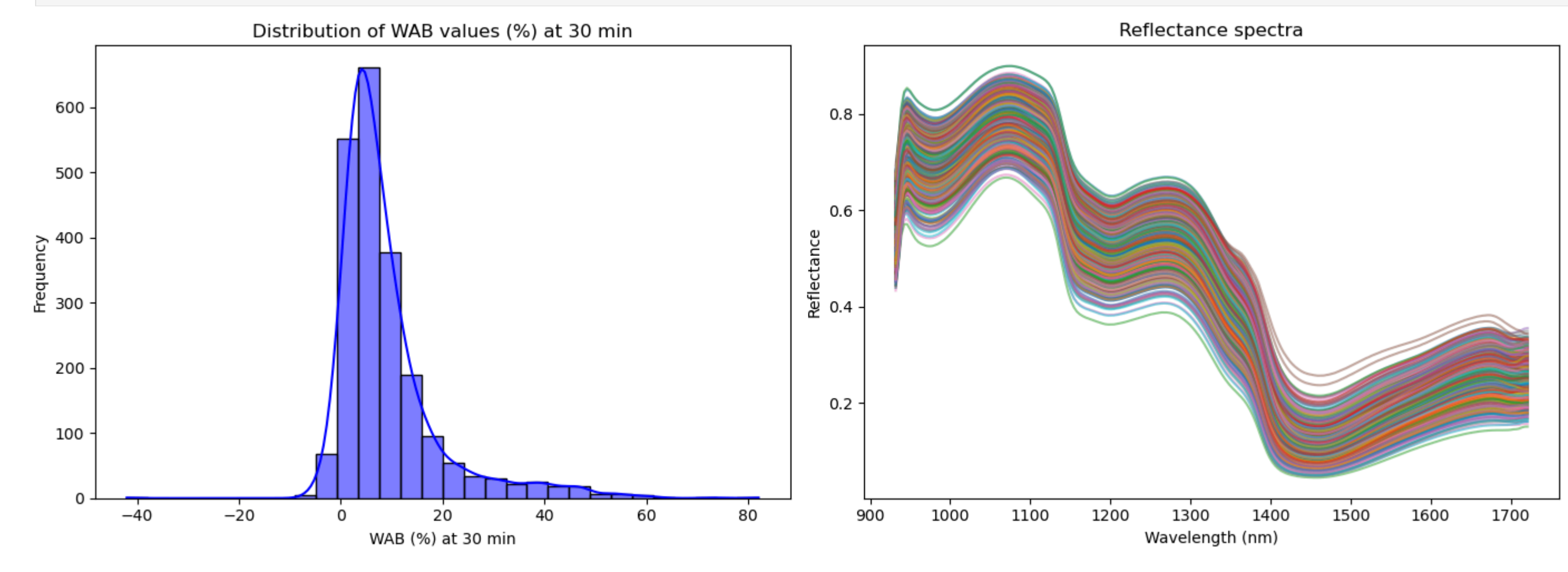
Data visualization (spectra and histogram of WAB value distribution)

```python
# Create figure with 2 side-by-side subplots
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Histogram of WAB values
sns.histplot(df_Y["WAB (%) at 30 min"], bins=30, kde=True, ax=axes[0], color="blue")
axes[0].set_title("Distribution of WAB values (%) at 30 min")
axes[0].set_xlabel("WAB (%) at 30 min")
axes[0].set_ylabel("Frequency")

# Reflectance spectra
axes[1].plot(df_spectra.columns.astype(float), df_spectra.T, alpha=0.5)
axes[1].set_title("Reflectance spectra")
axes[1].set_xlabel("Wavelength (nm)")
axes[1].set_ylabel("Reflectance")

# Ajuster l'espacement entre les graphiques
plt.tight_layout()
plt.show()
```




```python
# Descriptive statistics
statistiques = df_Y["WAB (%) at 30 min"].describe()
print(statistiques)
```

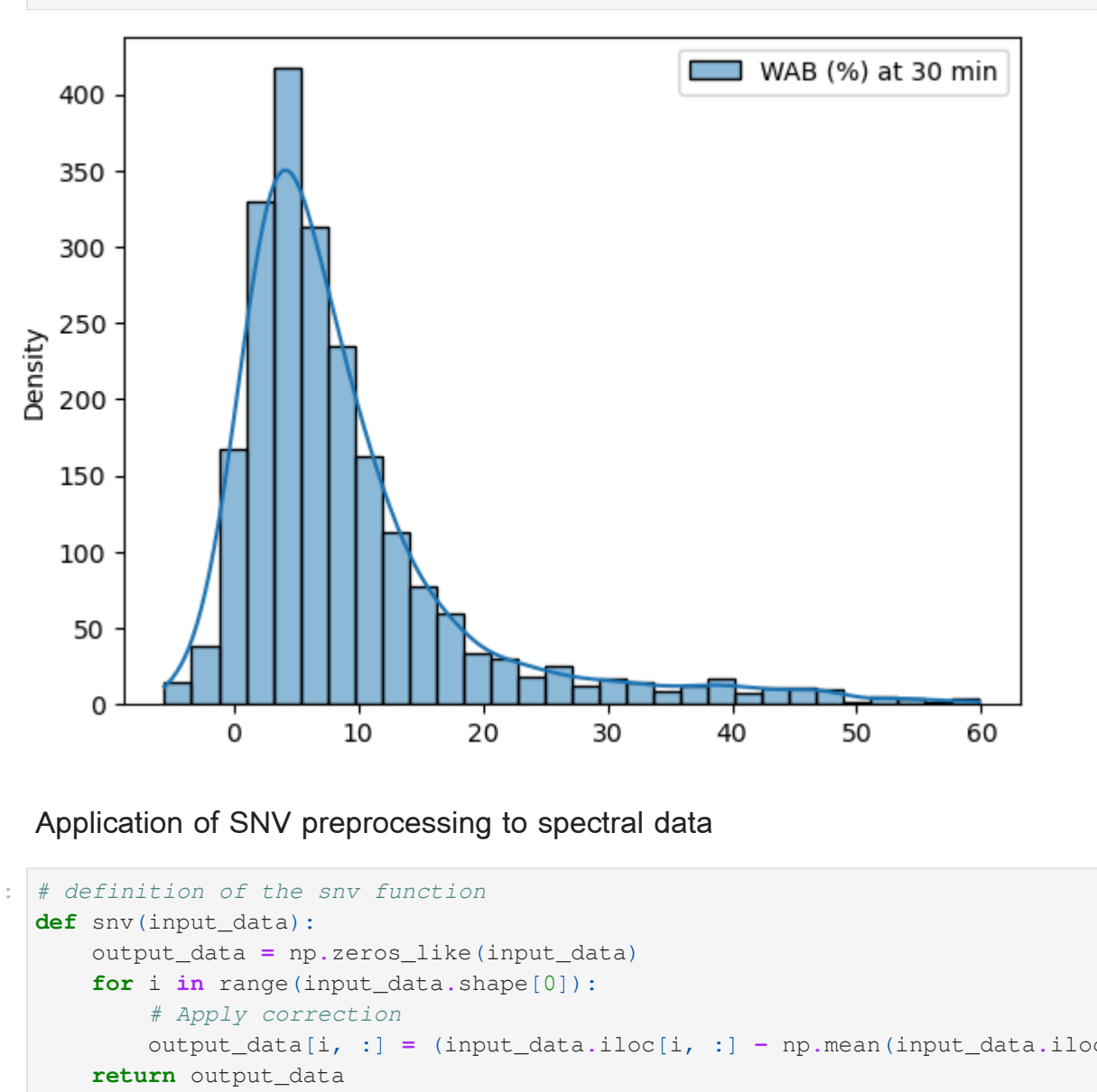
```
count    2175.000000
mean        9.103202
std        10.219647
min       -42.031464
25%         3.157459
50%         6.188119
75%        11.221271
max        82.064976
Name: WAB (%) at 30 min, dtype: float64
```

outliers elimination

```python
filtered_indexes = df_Y[(df_Y["WAB (%) at 30 min"] >= -20) & (df_Y["WAB (%) at 30 min"] <= 60)].index

# Apply filtering to both DataFrames
Y_df_filtered = df_Y.loc[filtered_indexes]
df_filtered = df_spectra.loc[filtered_indexes]

# Display of distribution after filtering
sns.histplot(Y_df_filtered, bins=30, kde=True)
plt.ylabel("Density")
plt.show()
```



Application of SNV preprocessing to spectral data

```python
# definition of the snv function
def snv(input_data):
    output_data = np.zeros_like(input_data)
    for i in range(input_data.shape[0]):
        # Apply correction
        output_data[i, :] = (input_data.iloc[i, :] - np.mean(input_data.iloc[i, :])) / np.std(input_data.iloc[i, :])
    return output_data
```

```python
df_snv = snv(df_filtered)
```

Define target variable (class)

```python
Y_df_filtered['Quality_Class'] = np.where(Y_df_filtered["WAB (%) at 30 min"] < 12, 0, 1)
```

data oversampling with the SMOTE method

```python
# Define explanatory variables (X) and target (y)
X = df_snv
y = Y_df_filtered['Quality_Class'].values  # Classes (0 or 1)

smote = SMOTE(random_state=42) # to fix the random effect
X_resampled, y_resampled = smote.fit_resample(X, y)
```

Split data into train/test (80% training, 20% test)

```python
X_train, X_test, y_train, y_test = train_test_split(X_resampled, y_resampled, test_size=0.2, random_state=42, stratify=y_resampled)
```

Randomforest Classifier model training

```python
RFc = RandomForestClassifier(n_estimators = 200, max_depth = 30, min_samples_split = 10, min_samples_leaf = 4, max_features = 'sqrt', random_state=42)
RFc.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier(max_depth=30, min_samples_leaf=4, min_samples_split=10,
                       n_estimators=200, random_state=42)
```

Model performance parameters

Function for calculating specificity and sensitivity

```python
def specificity_sensitivity(y_true, y_pred):
    tn, fp, fn, tp = confusion_matrix(y_true, y_pred).ravel()
    specificity = tn / (tn + fp) if (tn + fp) != 0 else 0
    sensitivity = tp / (tp + fn) if (tp + fn) != 0 else 0
    return specificity * 100, sensitivity * 100
```

```python
# Predictions on training and test sets
y_train_pred = RFc.predict(X_train)
y_test_pred = RFc.predict(X_test)
# Calculating metrics for the train set
accuracy_train = accuracy_score(y_train, y_train_pred) * 100
specificity_train, sensitivity_train = specificity_sensitivity(y_train, y_train_pred)
precision_train = precision_score(y_train, y_train_pred) * 100
f1_train = f1_score(y_train, y_train_pred) * 100
mcc_train = matthews_corrcoef(y_train, y_train_pred) * 100
# Calculating metrics for the test set
accuracy_test = accuracy_score(y_test, y_test_pred) * 100
specificity_test, sensitivity_test = specificity_sensitivity(y_test, y_test_pred)
precision_test = precision_score(y_test, y_test_pred) * 100
f1_test = f1_score(y_test, y_test_pred) * 100
mcc_test = matthews_corrcoef(y_test, y_test_pred) * 100
# Metrics table creation
metrics_df = pd.DataFrame({
    "Metrics": ["Accuracy", "Specificity", "Sensitivity", "Precision", "F1-Score", "MCC"],
    "Train (%)": [accuracy_train, specificity_train, sensitivity_train, precision_train, f1_train, mcc_train],
    "Test (%)": [accuracy_test, specificity_test, sensitivity_test, precision_test, f1_test, mcc_test]})

# Round to 2 decimal places
metrics_df = metrics_df.round(2)

# Final table display
print("\n🔹 Performance summary table :")
print(metrics_df)
```

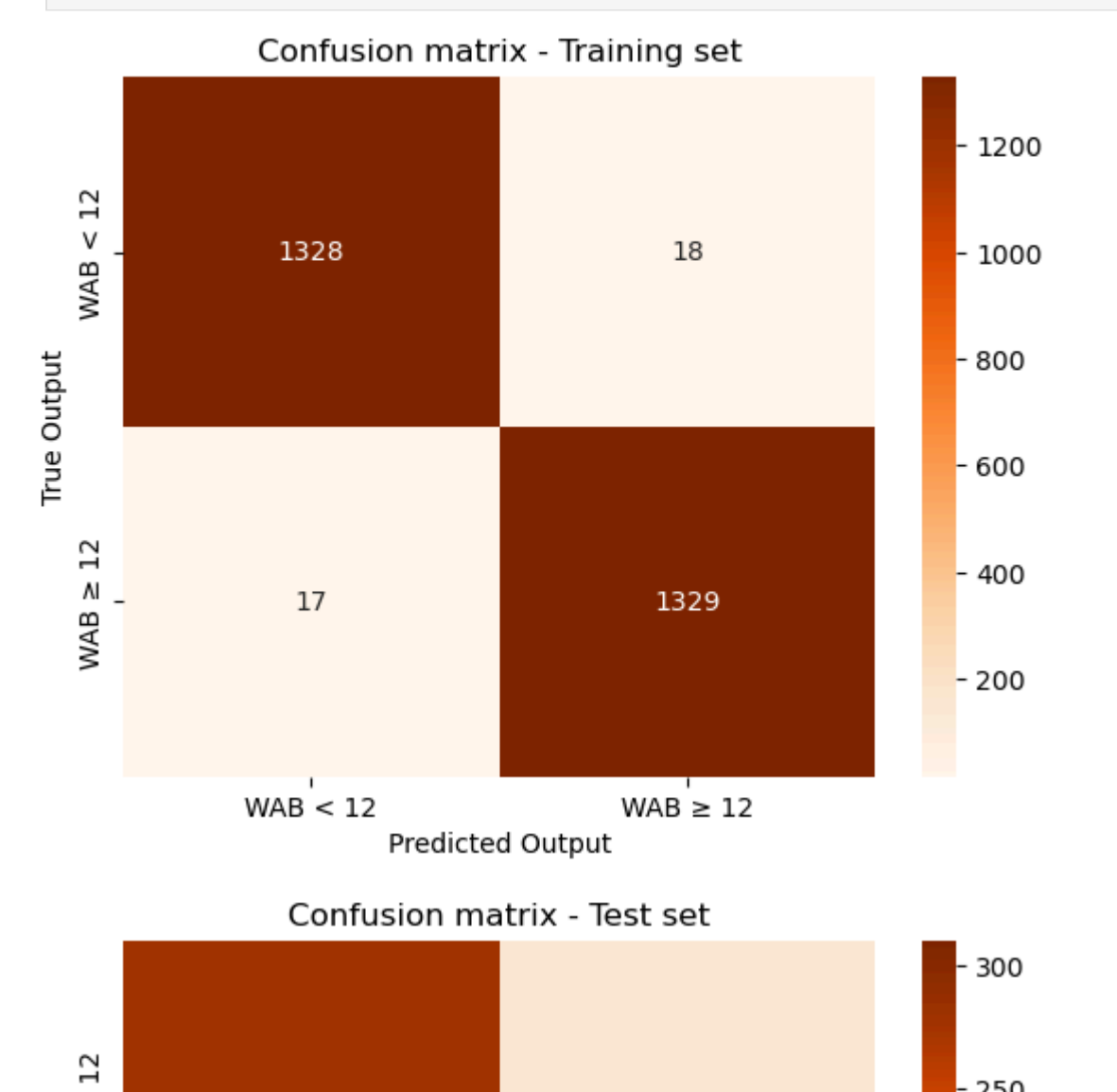
```
🔹 Performance summary table :
       Metrics  Train (%)  Test (%)
0     Accuracy      98.70     87.54
1  Specificity      98.66     83.09
2  Sensitivity      98.74     91.99
3    Precision      98.66     84.47
4     F1-Score      98.70     88.07
5          MCC      97.40     75.37
```

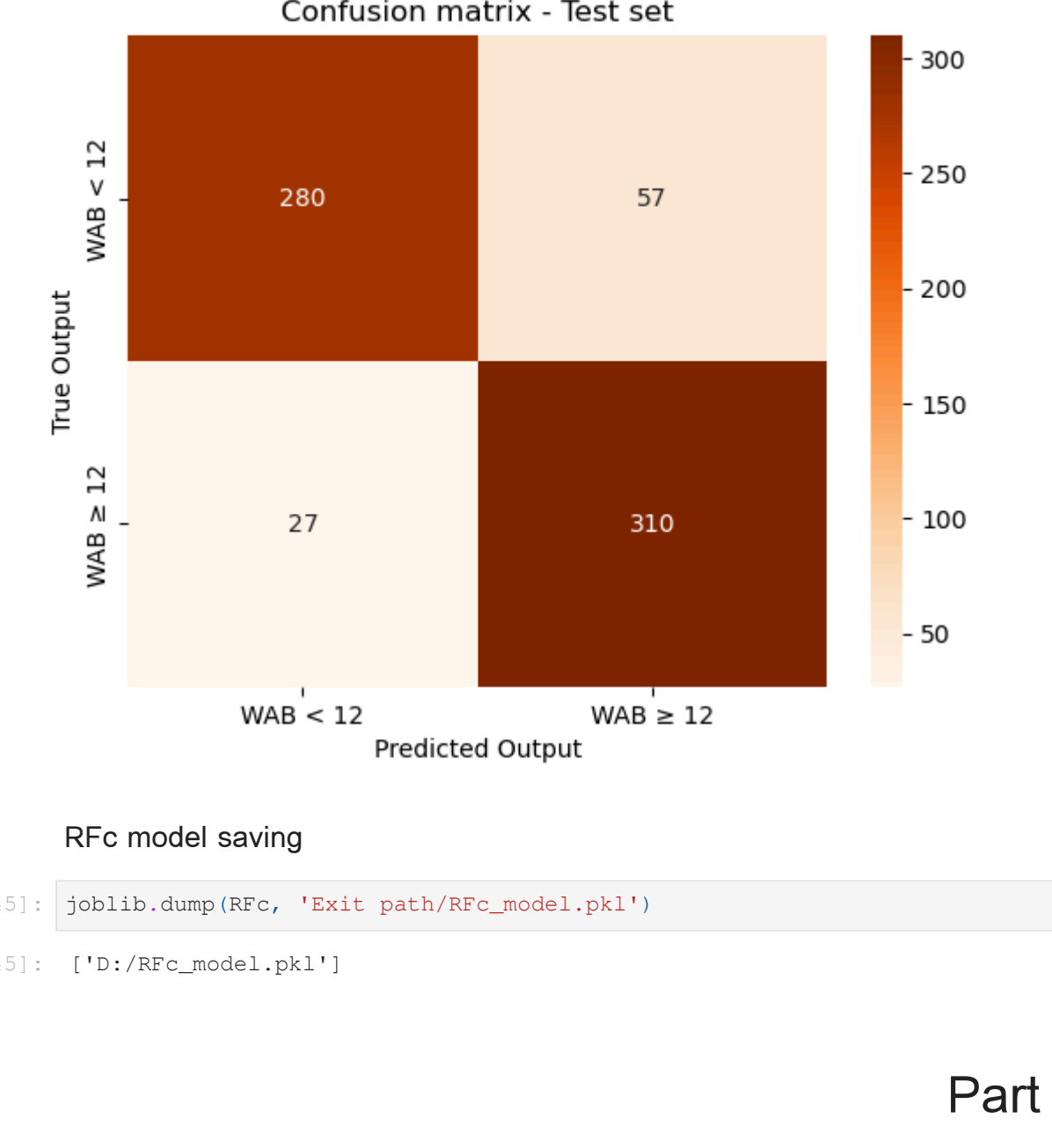
```python
conf_matrix_train = confusion_matrix(y_train, y_train_pred)
conf_matrix_test = confusion_matrix(y_test, y_test_pred)
# Function to display confusion matrices with seaborn
def plot_confusion_matrix(cm, labels, title):
    sns.heatmap(cm, annot=True, fmt='d', xticklabels=labels, yticklabels=labels, cmap='Oranges')
    plt.xlabel("Predicted Output")
    plt.ylabel("True Output")
    plt.title(title)
    plt.show()

# Class labels
labels = ["WAB < 12", "WAB ≥ 12"]

# Train set
plot_confusion_matrix(conf_matrix_train, labels, "Confusion matrix - Training set")

# Test set
plot_confusion_matrix(conf_matrix_test, labels, "Confusion matrix - Test set")
```





RFc model saving

```python
joblib.dump(RFc, 'Exit path/RFc_model.pkl')
```

```
['D:/RFc_model.pkl']
```

Part 3: Creating classification maps

importing the classification model

```python
# Import model
RFc_loaded = joblib.load('path/RFc_model.pkl')
```

```python
# Number of images to be processed
num_images = len(masked_cubes)

# Loop over all hyperspectral images
for i, cube_hyperspectral in enumerate(masked_cubes):
    # Hyperspectral cube dimensions
    height, width, num_bands = cube_hyperspectral.shape

    # Creation of ROI mask to detect valid pixels
    roi_mask = np.any(cube_hyperspectral > 0, axis=2)  # True for valid pixels

    # Initialization of the prediction map with NaN as background
    prediction_map = np.full((height, width), np.nan, dtype=np.float32)

    # Extraction of valid pixels for prediction
    selected_pixels = cube_hyperspectral[roi_mask].reshape(-1, num_bands)

    selected_pixelssnv = snv(selected_pixels)  # SNV filtering

    # Prediction with the trained model
    predicted_classes = RFc_loaded.predict(selected_pixelssnv).flatten()

    # Placement of predictions on the map only at valid pixels
    prediction_map[roi_mask] = predicted_classes
    # Classification card display
```

```
plt.figure(figsize=(10, 5))
plt.imshow(color_map, cmap="Purp", vmin=0, vmax=3)  # Blue = Class 0, Green = Class 1

# Add a white border and an intermediate color
cbar = plt.colorbar(ticks=[0, 1, 2, 3])
cbar.ax.set_yticklabels(["Red 1", "Red 2", "Red 3", "Red 4"])
plt.axis('off')  # Hide axes
plt.show()
```