PRJ381: DESCRIPTION OF MODELING SCRIPT AND IETRAIONS

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Contents

Criterion 1: Knowledge of the Problem Domain

- **Understanding of the Problem Domain:** The project aims to develop a machine learning model to classify plant life stages (flower, bud, etc.) based on images of floating plants. This task is significant for environmental monitoring, especially for managing the spread of invasive plants.

- **Relevance of Methodologies and Techniques:** The team applied transfer learning using the EfficientNetB0 model to leverage pre-trained features, supporting faster and more effective learning.

- **Solution Addressing Core Issues:** By iteratively improving the data preprocessing and augmentation techniques, the team addressed core issues of model accuracy, gradually increasing it from 23% to 56%.

Initial Data Preparation:

Download and organizing script:

The main goal of this script is to download and organize the images into the appropriate folders.

(This script stayed the same throughout our model building process.)

The libraries we used for this script:

- **pandas:** This was used to read the data from the excel file.
- **requests:** Used to download the images from the URLs.
- **os:** To manage directories and file paths.
- **tqdm:** To show us a progress bar during the image downloading process.

download_and_organize.py > ...

```python
import pandas as pd
import os
import requests
from tqdm import tqdm

file_path = 'C:\\Users\\user-pc\\Documents\\PRJ381(2)\\data\\Aloe ferox PHENOLOGY.xlsx'
base_dir = 'Images'
classes = ['flower', 'bud', 'fruit', 'no_evidence']

for split in ['train', 'validation', 'test']:
    for cls in classes:
        os.makedirs(os.path.join(base_dir, split, cls), exist_ok=True)

def download_images(sheet_name, class_name):

    df = pd.read_excel(file_path, sheet_name=sheet_name)

    if 'image_url' not in df.columns:
        print(f"Sheet '{sheet_name}' does not contain an 'image_url' column.")
        return

    for index, row in tqdm(df.iterrows(), total=df.shape[0], desc=f"Downloading {class_name} images"):
        image_url = row['image_url']
        image_name = f"{class_name}_{index}.jpg"
        split = 'train'

        image_path = os.path.join(base_dir, split, class_name, image_name)

        try:
            response = requests.get(image_url, stream=True, timeout=10)
            if response.status_code == 200:
                with open(image_path, 'wb') as file:
                    for chunk in response.iter_content(1024):
                        file.write(chunk)
            else:
                print(f"Failed to download {image_url}: Status code {response.status_code}")
        except Exception as e:
            print(f"Failed to download {image_url}: {e}")

download_images('FLOWERS', 'flower')
download_images('BUDS', 'bud')
download_images('FRUIT', 'fruit')
download_images('No Evidence', 'no_evidence')
```

Steps in script:

Define paths:

- Specifies the path to the excel file that was provided to us.
- It defines the "base_dir" (Images) and classes (like "flower" and "bud") to organize the images into different categories.

Creation of base directories:

- We create folders for training, validation and testing splits for each class.

Downloading the images:

- The excel file gets read through to check for the "image_url" column and then downloads the images to the appropriate folders.
- If any of the images fails to download, it just prints an error message and then continues downloading the rest of the images.

Split Data Script:

In this script the images we downloaded gets split into training, validation and test sets.

(This script stayed the same throughout our model building process.)

<u>The libraries we used for this script:</u>

- **os and shutil:** For the file and directory operations.
- **random:** To shuffle the images for splitting.

split_data.py > ...

```python
import os
import shutil
import random

base_dir = 'Images'
train_dir = os.path.join(base_dir, 'train')
validation_dir = os.path.join(base_dir, 'validation')
test_dir = os.path.join(base_dir, 'test')

os.makedirs(validation_dir, exist_ok=True)
os.makedirs(test_dir, exist_ok=True)

val_split = 0.15
test_split = 0.15

for class_name in os.listdir(train_dir):
    class_path = os.path.join(train_dir, class_name)

    if os.path.isdir(class_path):
        os.makedirs(os.path.join(validation_dir, class_name), exist_ok=True)
        os.makedirs(os.path.join(test_dir, class_name), exist_ok=True)

        images = os.listdir(class_path)
        random.shuffle(images)

        total_images = len(images)
        val_size = int(total_images * val_split)
        test_size = int(total_images * test_split)

        val_images = images[:val_size]
        test_images = images[val_size:val_size + test_size]

        for image in val_images:
            src_path = os.path.join(class_path, image)
            dst_path = os.path.join(validation_dir, class_name, image)
            shutil.move(src_path, dst_path)

        for image in test_images:
            src_path = os.path.join(class_path, image)
            dst_path = os.path.join(test_dir, class_name, image)
            shutil.move(src_path, dst_path)

print("Images have been split into train, validation, and test sets.")
```

Steps in this script:

Defining paths:

- Defines the paths for the training, validation and testing directories.

Creation of the directories:

- This ensures that the directories for the validation and test sets exist.

Proportioning the validation and test sets:

- This specifies that 15% of the images is for validation (val_split) and 15% is for testing (test_split).

Splitting the images:

- The images get shuffled in each class folder to ensure that the images are in a random order.
- The images then get split into validation and test sets and gets moved to their respective folders using shutil.move().

What the different sets get used for:

- **Train Set:** Used to train the model, allowing it to learn patterns and features from the data.
- **Validation Set:** Used to evaluate the model during training to prevent overfitting and guide hyperparameter tuning.
- **Test Set:** Reserved for the final evaluation to assess the model’s generalization to new, unseen data.

Initial Preprocessing Script:

This script loads the images, applies data augmentation, normalizes them, and saves the pre-processed images.

The libraries we used for this script:

- **tensorflow:** To handle data loading, augmentation and processing.
- **os:** To handle the file paths.

PreProcessing.py > ...

```python
import tensorflow as tf
import os

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

preprocessed_base_dir = 'Preprocessed_Images'
train_save_dir = f'{preprocessed_base_dir}/train'
validation_save_dir = f'{preprocessed_base_dir}/validation'
test_save_dir = f'{preprocessed_base_dir}/test'

os.makedirs(train_save_dir, exist_ok=True)
os.makedirs(validation_save_dir, exist_ok=True)
os.makedirs(test_save_dir, exist_ok=True)

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

normalization_layer = tf.keras.layers.Rescaling(1.0 / 255)

data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.3),
    tf.keras.layers.RandomZoom(0.3),
    tf.keras.layers.RandomBrightness(0.3),
    tf.keras.layers.RandomContrast(0.3)
])

def save_preprocessed_images(dataset, save_dir, augment=False):
    for batch_index, (images, labels) in enumerate(dataset):
        augmented_images = data_augmentation(images) if augment else images
        normalized_images = normalization_layer(augmented_images)

        for i in range(len(normalized_images)):
            label = tf.argmax(labels[i]).numpy()
            label_dir = os.path.join(save_dir, str(label))
            os.makedirs(label_dir, exist_ok=True)
            file_path = os.path.join(label_dir, f'image_{batch_index * len(normalized_images) + i}.jpg')
            try:
                tf.keras.preprocessing.image.save_img(file_path, normalized_images[i])
            except Exception as e:
                print(f"Error saving image {file_path}: {e}")

save_preprocessed_images(train_dataset, train_save_dir, augment=True)

save_preprocessed_images(validation_dataset, validation_save_dir, augment=False)
save_preprocessed_images(test_dataset, test_save_dir, augment=False)

print(f"Preprocessed images saved in '{preprocessed_base_dir}' directory.")
```

Steps in this script:

Defining the paths:

- Defines the paths for the train, validation and test directories.
- New directories for saving the pre-processed images gets created (Preprocessed_Images).

Loading the datasets:

- The script uses '**image_dataset_from_directory ()'** to load the images from the train, validation and test directories.
- All the images are resized to (224, 224) pixels.
- The script loads the images in batches of 32 to efficiently train the model.

Normalization Layer:

- A rescaling layer gets applied to normalize the pixel values from [0, 255] to [0, 1] by dividing each value by 255.

Data gets Augmented:

- The following augmentation techniques are used to artificially expand the dataset by introducing variations and helps the model generalize better:
  - Random Flip
  - Random Rotation
  - Random Zoom
  - Random Brightness
  - Random Contrast

Save pre-processed images:

- The augmented images are saved in the "train" folder and the non-augmented images are saved in the "validation" and "test" folders.
- The script iterates through the dataset and saves each pre-processed image using '**tf. keras. preprocessing.image.save_img()'.**

Criterion 2: Handling Complexities and Uncertainties

– **Initial Results:** Initially, the model achieved a low training accuracy of 23%. Despite multiple epochs, the training accuracy gradually increased, but the validation accuracy remained stagnant at around 31%, with an official accuracy of 25% at the end of the initial run. This discrepancy suggested that the model was underfitting, meaning it was unable to learn sufficient features from the data.

Possible Reasons for Underfitting:

- **Dataset Size**: The dataset may be too small for a complex model like EfficientNet, which typically requires a large volume of data to generalize well.
- **Data Augmentation**: The data augmentation applied may have been too aggressive, potentially reducing the model's ability to learn essential features from the images.

```
Epoch 10/20
56/56 - 45s - 809ms/step - accuracy: 0.2649 - loss: 1.9316 - val_accuracy: 0.3079 - val_loss: 1.8539
Epoch 11/20
56/56 - 46s - 814ms/step - accuracy: 0.2598 - loss: 1.9711 - val_accuracy: 0.2507 - val_loss: 1.7542
Epoch 12/20
56/56 - 45s - 812ms/step - accuracy: 0.2818 - loss: 1.8791 - val_accuracy: 0.2779 - val_loss: 1.8282
Epoch 13/20
56/56 - 45s - 811ms/step - accuracy: 0.2750 - loss: 1.9266 - val_accuracy: 0.2534 - val_loss: 1.7920
Epoch 14/20
56/56 - 46s - 813ms/step - accuracy: 0.2649 - loss: 1.9139 - val_accuracy: 0.2316 - val_loss: 1.8385
Epoch 15/20
56/56 - 47s - 835ms/step - accuracy: 0.2626 - loss: 1.9142 - val_accuracy: 0.2507 - val_loss: 1.6994
Epoch 16/20
56/56 - 46s - 815ms/step - accuracy: 0.2716 - loss: 1.9223 - val_accuracy: 0.2316 - val_loss: 1.7776
Epoch 17/20
56/56 - 45s - 808ms/step - accuracy: 0.2699 - loss: 1.9039 - val_accuracy: 0.2180 - val_loss: 1.9389
Epoch 18/20
56/56 - 45s - 810ms/step - accuracy: 0.2626 - loss: 1.9309 - val_accuracy: 0.2316 - val_loss: 1.8255
Epoch 19/20
56/56 - 46s - 814ms/step - accuracy: 0.2683 - loss: 1.8753 - val_accuracy: 0.2289 - val_loss: 1.9818
Epoch 20/20
56/56 - 45s - 812ms/step - accuracy: 0.2507 - loss: 1.9180 - val_accuracy: 0.2289 - val_loss: 1.8102
12/12 ━━━━━━━━━━━━━━━━━━━━ 6s 474ms/step - accuracy: 0.2750 - loss: 1.7581
Test Accuracy: 0.25
```

– **Challenges and Uncertainties:** Initial underfitting due to a small dataset size and aggressive data augmentation posed a significant challenge, limiting the model's performance.

Second Iteration of the Model Training Script:

In the second iteration, adjustments were made to the model training script to improve accuracy and address underfitting. These changes reflect the team's adaptive approach to managing uncertainties and optimizing model performance.

ModelTraining.py > ...

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications import EfficientNetB0
import os

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

import warnings
warnings.filterwarnings("ignore")

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

batch_size = 16

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
).repeat()

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)
```

```python
num_train_samples = 1769
num_validation_samples = 376
steps_per_epoch = num_train_samples // batch_size
validation_steps = num_validation_samples // batch_size

data_augmentation = keras.Sequential([
    keras.layers.RandomFlip("horizontal"),
    keras.layers.RandomRotation(0.2),
    keras.layers.RandomZoom(0.2)
])
train_dataset = train_dataset.map(lambda x, y: (data_augmentation(x, training=True), y), num_parallel_calls=AUTOTUNE)

base_model = EfficientNetB0(input_shape=(224, 224, 3), include_top=False, weights='imagenet')
base_model.trainable = False

model = keras.Sequential([
    base_model,
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(128, activation='relu', kernel_regularizer=keras.regularizers.l2(0.001)),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(4, activation='softmax')
])

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

def scheduler(epoch, lr):
    if epoch < 10:
        return lr
    else:
        return float(lr * 0.95)
```

```python
lr_scheduler = keras.callbacks.LearningRateScheduler(scheduler, verbose=1)

history = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=30,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping, lr_scheduler]
)

base_model.trainable = True
fine_tune_at = len(base_model.layers) // 2
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history_fine = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=15,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping, lr_scheduler]
)

test_loss, test_accuracy = model.evaluate(test_dataset)
print(f"Test Accuracy: {test_accuracy:.2f}")

model.save('plant_lifecycle_classifier.keras')
```

<u>Different changes:</u>

Here follows the changes we made in our second iteration of the machine learning model:

Data Augmentation changes:

- In the initial model we used the “ImageDataGenerator” to apply various types of augmentation, like shear, zoom and horizontal flipping. This led to more aggressive augmentation.
- In the second iteration we used custom “Keras Sequential” augmentation with RandomFlip, RandomRotation(0.2) and RandomZoom(0.2). This strategy of augmentation is less aggressive.

Loading datasets:

- The second iteration uses “image_dataset_from_directory” from tensorflow to load the datasets instead of the “ImageDataGenerator”. This function creates “tf.data.Dataset” objects directly, which can be augmented, prefetched and mapped with greater control.

Prefetching for performance:

- In the initial version we did not use prefetching.

- In the second iteration we used prefetching so that the CPU can prepare the next batch while the GPU processes the current batch. This sped up the training time.

Batch size changes:

- We changed the batch size from 32 to 16. The reason for this is so the model can be a bit more stable when training.

Model architecture and changes to layers:

- In the second iteration we added an additional Batch Normalization layer before the output layer
- The second iteration still kept it's dropout rate of 0.5.
- We also added more layers and dropout to increase the complexity.

Fine Tuning:

- In the initial version we fine tuned all of the layers of the base model after the initial training.
- With the second iteration we just fine tuned the last half of the base model layers by unfreezing them.
- This change helped balance the use of pre-trained knowledge with some more specific tuning tailored for our dataset.

Early stopping and learning rate scheduler:

- In the second iteration we reduced the early stopping patience to only 10 epochs to prevent overfitting. This means that the training will stop earlier if the model is not improving.
- We added a learning rate scheduler that reduced the learning rate by multiplying by 0.95 after 10 epochs. This helps improve convergence and slows down the learning rate as the training progresses, which helps the model settle into local minima more effectively.

Steps per epoch calculation:

- In the initial version we used batches based on "ImageDataGenerator".
- In the second version we defined "steps_per_epoch" and "validation_steps" manually by calculating based on the number of samples and the batch size.
- We tried this approach to ensure that the entire dataset is utilized consistently. This can especially be useful if the dataset is not perfectly divisible by the batch size.

Results of the 2nd iteration:

The overall accuracy of the second iteration did improve quite a bit with the accuracy standing at 43% now.

Possible reasons for this inaccuracy:

- The model could possibly be overfitting. We can make this assumption because the validation accuracy fluctuated a lot and did not consistently improve.
- The reduced learning rate decrease might have been too aggressive during the fine tuning. This could be preventing the model from making substantial progress.

```
Epoch 13/30
110/110 ━━━━━━━━━━━━━━━━━━━━ 18s 163ms/step - accuracy: 0.4406 - loss: 1.7350 - val_accuracy: 0.4891 - val_loss: 1.4167 - learning_rate: 8.5737e-05

Epoch 14: LearningRateScheduler setting learning rate to 8.145062311086804e-05.
Epoch 14/30
110/110 ━━━━━━━━━━━━━━━━━━━━ 16s 143ms/step - accuracy: 0.4365 - loss: 1.7042 - val_accuracy: 0.6250 - val_loss: 1.2379 - learning_rate: 8.1451e-05

Epoch 1: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 1/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 48s 327ms/step - accuracy: 0.3116 - loss: 2.2382 - val_accuracy: 0.3995 - val_loss: 1.5680 - learning_rate: 1.0000e-05

Epoch 2: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 2/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 0s 286ms/step - accuracy: 0.3099 - loss: 2.21932024-10-27 21:13:26.679321: I tensorflow/core/framework/local_rendezvous.cc:404] Local rendezvous is aborting with status: OUT_OF_RANGE: End of sequence
         [[{{node IteratorGetNext}}]]
110/110 ━━━━━━━━━━━━━━━━━━━━ 31s 287ms/step - accuracy: 0.3100 - loss: 2.2190 - val_accuracy: 0.3750 - val_loss: 1.7685 - learning_rate: 1.0000e-05

Epoch 3: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 3/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 310ms/step - accuracy: 0.3135 - loss: 2.2901 - val_accuracy: 0.4266 - val_loss: 1.6741 - learning_rate: 1.0000e-05

Epoch 4: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 4/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 31s 283ms/step - accuracy: 0.3472 - loss: 2.1480 - val_accuracy: 0.5000 - val_loss: 1.4170 - learning_rate: 1.0000e-05

Epoch 5: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 5/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 309ms/step - accuracy: 0.3481 - loss: 2.0726 - val_accuracy: 0.4538 - val_loss: 1.5813 - learning_rate: 1.0000e-05

Epoch 6: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 6/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 32s 289ms/step - accuracy: 0.3578 - loss: 2.0529 - val_accuracy: 0.2500 - val_loss: 2.1561 - learning_rate: 1.0000e-05

Epoch 7: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 7/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 312ms/step - accuracy: 0.3640 - loss: 2.0844 - val_accuracy: 0.4538 - val_loss: 1.5392 - learning_rate: 1.0000e-05

Epoch 8: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 8/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 31s 285ms/step - accuracy: 0.3703 - loss: 2.0789 - val_accuracy: 0.5000 - val_loss: 1.5176 - learning_rate: 1.0000e-05

Epoch 9: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 9/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.3756 - loss: 2.0081 - val_accuracy: 0.4837 - val_loss: 1.4981 - learning_rate: 1.0000e-05

Epoch 10: LearningRateScheduler setting learning rate to 9.999999747378752e-06.
Epoch 10/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 31s 284ms/step - accuracy: 0.3901 - loss: 2.0548 - val_accuracy: 0.3750 - val_loss: 1.5725 - learning_rate: 1.0000e-05
24/24 ━━━━━━━━━━━━━━━━━━━━ 3s 138ms/step - accuracy: 0.4238 - loss: 1.6421
Test Accuracy: 0.43
```

Third Iteration of the Model Training Script:

In the third iteration, further refinements were made to the model training script. This continued iterative process highlights the team's commitment to overcoming challenges and improving the model's performance. The third iteration specifically targeted previous limitations and aimed to further stabilize the training process

ModelTraining.py > ...

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications import EfficientNetB0
import os

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

import warnings
warnings.filterwarnings("ignore")

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

batch_size = 16

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
).repeat()

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)

num_train_samples = 1769
num_validation_samples = 376
steps_per_epoch = num_train_samples // batch_size
validation_steps = num_validation_samples // batch_size

data_augmentation = keras.Sequential([
    keras.layers.RandomFlip("horizontal"),
    keras.layers.RandomRotation(0.2),
    keras.layers.RandomZoom(0.2)
])
train_dataset = train_dataset.map(lambda x, y: (data_augmentation(x, training=True), y), num_parallel_calls=AUTOTUNE)
```

```python
base_model = EfficientNetB0(input_shape=(224, 224, 3), include_top=False, weights='imagenet')
base_model.trainable = False

model = keras.Sequential([
    base_model,
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(128, activation='relu', kernel_regularizer=keras.regularizers.l2(0.001)),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(4, activation='softmax')
])

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

history = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=30,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping]
)

base_model.trainable = True
fine_tune_at = len(base_model.layers) // 2
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history_fine = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=15,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping]
)
```

```python
test_loss, test_accuracy = model.evaluate(test_dataset)
print(f"Test Accuracy: {test_accuracy:.2f}")

model.save('plant_lifecycle_classifier.keras')
```

Different changes:

Learning rate scheduler:

- In the third iteration we completely removed the learning rate scheduler. We did this to make the learning process a bit simpler, because the learning rate decrease in the second iteration might have been too aggressive.

Results of the 3rd iteration:

After removing the learning rate scheduler the model got an accuracy of 49%. Due to the model only improving with very minimal margins we decided to take a different approach and try to improve the preprocessing script.

```
Epoch 5/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.3093 - loss: 2.2688 - val_accuracy: 0.4348 - val_loss: 1.5611
Epoch 6/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 32s 287ms/step - accuracy: 0.3357 - loss: 2.1952 - val_accuracy: 0.3750 - val_loss: 1.5047
Epoch 7/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 316ms/step - accuracy: 0.3203 - loss: 2.2978 - val_accuracy: 0.4538 - val_loss: 1.5164
Epoch 8/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 31s 282ms/step - accuracy: 0.3537 - loss: 2.1635 - val_accuracy: 0.5000 - val_loss: 1.2844
Epoch 9/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 309ms/step - accuracy: 0.3504 - loss: 2.1295 - val_accuracy: 0.4565 - val_loss: 1.4873
Epoch 10/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 315ms/step - accuracy: 0.3954 - loss: 2.1167 - val_accuracy: 0.6250 - val_loss: 1.0040
Epoch 11/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 38s 343ms/step - accuracy: 0.3889 - loss: 2.0611 - val_accuracy: 0.4728 - val_loss: 1.4563
Epoch 12/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 318ms/step - accuracy: 0.3840 - loss: 2.0362 - val_accuracy: 0.3750 - val_loss: 1.5441
Epoch 13/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 38s 344ms/step - accuracy: 0.3989 - loss: 2.0564 - val_accuracy: 0.4864 - val_loss: 1.4333
Epoch 14/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 311ms/step - accuracy: 0.4131 - loss: 1.9724 - val_accuracy: 0.6250 - val_loss: 1.2280
Epoch 15/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 38s 345ms/step - accuracy: 0.3980 - loss: 1.9241 - val_accuracy: 0.5027 - val_loss: 1.4144
24/24 ━━━━━━━━━━━━━━━━━━━━ 4s 147ms/step - accuracy: 0.4418 - loss: 1.5221
Test Accuracy: 0.49
```

Fourth Iteration:

2nd Iteration of the Preprocessing Script:

In the fourth iteration, the team adjusted the preprocessing script to further enhance model performance. This iteration involved refining augmentation and normalization techniques, dynamically applying augmentation during each training epoch to introduce more variability. These changes aimed to improve training efficiency and boost model accuracy.

PreProcessing.py > ...

```python
import tensorflow as tf

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

normalization_layer = tf.keras.layers.Rescaling(1.0 / 255)

data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.2),
    tf.keras.layers.RandomZoom(0.2),
    tf.keras.layers.RandomBrightness(0.2),
    tf.keras.layers.RandomContrast(0.2)
])

AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.map(lambda x, y: (normalization_layer(data_augmentation(x, training=True)), y), num_parallel_calls=AUTOTUNE)

validation_dataset = validation_dataset.map(lambda x, y: (normalization_layer(x), y), num_parallel_calls=AUTOTUNE)
test_dataset = test_dataset.map(lambda x, y: (normalization_layer(x), y), num_parallel_calls=AUTOTUNE)

train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)

print("Train dataset:", train_dataset)
print("Validation dataset:", validation_dataset)
print("Test dataset:", test_dataset)
```

Different changes:

The saving of the preprocessed images:

- In the second iteration we decided to not save the images to the disk. We added this change to improve efficiency, thereby speeding up the overall workflow.

Applying augmentation and normalization:

- In the initial script data augmentation was only applied when saving the training images, and the images were only normalized after augmentation.
- However in the second script we applied dynamic augmentation and normalization. This augmentation style is model flexible, providing different augmented samples during each training epoch.
- We reduced the augmentation parameters to be less aggressive:
  - RandomRotation(0.2)
  - RandomZoom(0.2)
  - RandomBrightness(0.2)
  - RandomContrast(0.2)

Dataset prefetching:

- We added prefetching in the second iteration to improve the training speed, which ultimately enhanced the model's performance.

Results of the 4th iteration:

Applying a few changes to the preprocessing script did help improve the model's accuracy to 56%.

```
Epoch 7/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 313ms/step - accuracy: 0.4710 - loss: 1.5485 - val_accuracy: 0.5076 - val_loss: 1.3674
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 313ms/step - accuracy: 0.4710 - loss: 1.5485 - val_accuracy: 0.5076 - val_loss: 1.3674
Epoch 8/15
Epoch 8/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.4746 - loss: 1.5710 - val_accuracy: 0.5267 - val_loss: 1.3588
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.4746 - loss: 1.5710 - val_accuracy: 0.5267 - val_loss: 1.3588
Epoch 9/15
Epoch 9/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.4560 - loss: 1.5600 - val_accuracy: 0.5305 - val_loss: 1.3535
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 314ms/step - accuracy: 0.4560 - loss: 1.5600 - val_accuracy: 0.5305 - val_loss: 1.3535
Epoch 10/15
Epoch 10/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 321ms/step - accuracy: 0.4768 - loss: 1.4773 - val_accuracy: 0.5420 - val_loss: 1.3410
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 321ms/step - accuracy: 0.4768 - loss: 1.4773 - val_accuracy: 0.5420 - val_loss: 1.3410
Epoch 11/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 322ms/step - accuracy: 0.4547 - loss: 1.5374 - val_accuracy: 0.5534 - val_loss: 1.3380
Epoch 12/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 322ms/step - accuracy: 0.4547 - loss: 1.5374 - val_accuracy: 0.5534 - val_loss: 1.3380
Epoch 12/15
Epoch 12/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 309ms/step - accuracy: 0.4682 - loss: 1.5334 - val_accuracy: 0.5534 - val_loss: 1.3338
Epoch 13/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 313ms/step - accuracy: 0.4995 - loss: 1.4296 - val_accuracy: 0.5382 - val_loss: 1.3310
Epoch 14/15
Epoch 14/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 35s 316ms/step - accuracy: 0.5095 - loss: 1.4375 - val_accuracy: 0.5496 - val_loss: 1.3178
Epoch 15/15
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 312ms/step - accuracy: 0.4921 - loss: 1.4595 - val_accuracy: 0.5496 - val_loss: 1.3184
110/110 ━━━━━━━━━━━━━━━━━━━━ 34s 312ms/step - accuracy: 0.4921 - loss: 1.4595 - val_accuracy: 0.5496 - val_loss: 1.3184
17/17 ━━━━━━━━━━━━━━━━━━━━ 2s 143ms/step - accuracy: 0.5529 - loss: 1.3357
Test Accuracy: 0.56
```

Final Model Training and Preprocessing Scripts:

After implementing several additional techniques and adjustments, the team reached a model accuracy of 56%. Despite efforts to improve further, this was the highest accuracy achieved with the available data and adjustments. The results from this final model align with the 4th iteration’s findings, demonstrating the team's commitment to refining the model amidst limitations.

Model training script:

ModelTraining.py > ...

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications import EfficientNetB0
import os

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

import warnings
warnings.filterwarnings("ignore")

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

batch_size = 16

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
).repeat()

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=batch_size,
    label_mode='categorical'
)

AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)

num_train_samples = 1769
num_validation_samples = 376
steps_per_epoch = num_train_samples // batch_size
validation_steps = num_validation_samples // batch_size

data_augmentation = keras.Sequential([
    keras.layers.RandomFlip("horizontal"),
    keras.layers.RandomRotation(0.2),
    keras.layers.RandomZoom(0.2)
])
train_dataset = train_dataset.map(lambda x, y: (data_augmentation(x, training=True), y), num_parallel_calls=AUTOTUNE)
```

```python
base_model = EfficientNetB0(input_shape=(224, 224, 3), include_top=False, weights='imagenet')
base_model.trainable = False

model = keras.Sequential([
    base_model,
    keras.layers.GlobalAveragePooling2D(),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(128, activation='relu', kernel_regularizer=keras.regularizers.l2(0.001)),
    keras.layers.BatchNormalization(),
    keras.layers.Dropout(0.5),
    keras.layers.Dense(4, activation='softmax')
])

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=10,
    restore_best_weights=True
)

history = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=30,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping]
)

base_model.trainable = True
fine_tune_at = len(base_model.layers) // 2
for layer in base_model.layers[:fine_tune_at]:
    layer.trainable = False

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history_fine = model.fit(
    train_dataset,
    validation_data=validation_dataset,
    epochs=15,
    steps_per_epoch=steps_per_epoch,
    validation_steps=validation_steps,
    callbacks=[early_stopping]
)
```

```python
test_loss, test_accuracy = model.evaluate(test_dataset)
print(f"Test Accuracy: {test_accuracy:.2f}")

model.save('plant_lifecycle_classifier.keras')
```

Preprocessing script:

PreProcessing.py > ...

```python
import tensorflow as tf

base_dir = 'Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

train_dataset = tf.keras.utils.image_dataset_from_directory(
    train_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

validation_dataset = tf.keras.utils.image_dataset_from_directory(
    validation_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

test_dataset = tf.keras.utils.image_dataset_from_directory(
    test_dir,
    image_size=(224, 224),
    batch_size=32,
    label_mode='categorical'
)

normalization_layer = tf.keras.layers.Rescaling(1.0 / 255)

data_augmentation = tf.keras.Sequential([
    tf.keras.layers.RandomFlip('horizontal'),
    tf.keras.layers.RandomRotation(0.2),
    tf.keras.layers.RandomZoom(0.2),
    tf.keras.layers.RandomBrightness(0.2),
    tf.keras.layers.RandomContrast(0.2)
])

AUTOTUNE = tf.data.AUTOTUNE
train_dataset = train_dataset.map(lambda x, y: (normalization_layer(data_augmentation(x, training=True)), y), num_parallel_calls=AUTOTUNE)

validation_dataset = validation_dataset.map(lambda x, y: (normalization_layer(x), y), num_parallel_calls=AUTOTUNE)
test_dataset = test_dataset.map(lambda x, y: (normalization_layer(x), y), num_parallel_calls=AUTOTUNE)

train_dataset = train_dataset.prefetch(buffer_size=AUTOTUNE)
validation_dataset = validation_dataset.prefetch(buffer_size=AUTOTUNE)
test_dataset = test_dataset.prefetch(buffer_size=AUTOTUNE)

print("Train dataset:", train_dataset)
print("Validation dataset:", validation_dataset)
print("Test dataset:", test_dataset)
```

- **Mitigation Strategies:** The project addressed these complexities by modifying augmentation techniques and fine-tuning specific layers of the EfficientNet model. Adding batch normalization layers and changing batch sizes helped stabilize the training process, tackling overfitting risks.

- **Risk Mitigation and Contingency: Early** stopping and reduced learning rate scheduling were implemented to manage overfitting and improve convergence, especially with an unstable validation accuracy in the second iteration.

Criterion 3: Application of Specialized Skills

- **Model Training and Evaluation:**

  Initial Model training script:

  This script is responsible for creating the actual machine learning model using the pre-processed images. This script also evaluates the performance of the model. Transfer learning was used to leverage pre-trained features from EfficientNet, thereby speeding up and improving the model's accuracy.

  The libraries we used for this script:

  - **tensorflow, keras, EfficientNetB0, ImageDataGenerator:** For building, training and evaluating the model.

ModelTraining.py > ...

```python
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras.applications import EfficientNetB0
from tensorflow.keras.preprocessing.image import ImageDataGenerator
import os

os.environ['TF_CPP_MIN_LOG_LEVEL'] = '2'

base_dir = 'Preprocessed_Images'
train_dir = f'{base_dir}/train'
validation_dir = f'{base_dir}/validation'
test_dir = f'{base_dir}/test'

batch_size = 32

datagen = ImageDataGenerator(rescale=1./255,
                             rotation_range=40,
                             width_shift_range=0.2,
                             height_shift_range=0.2,
                             shear_range=0.2,
                             zoom_range=0.2,
                             horizontal_flip=True,
                             fill_mode='nearest')

train_datagen = datagen.flow_from_directory(train_dir, target_size=(224, 224), batch_size=batch_size, class_mode='categorical')
validation_datagen = datagen.flow_from_directory(validation_dir, target_size=(224, 224), batch_size=batch_size, class_mode='categorical')
test_datagen = datagen.flow_from_directory(test_dir, target_size=(224, 224), batch_size=batch_size, class_mode='categorical')

base_model = EfficientNetB0(weights='imagenet', include_top=False, input_shape=(224, 224, 3))

base_model.trainable = False

x = base_model.output
x = tf.keras.layers.GlobalAveragePooling2D()(x)
x = tf.keras.layers.Dense(128, activation='relu', kernel_regularizer=keras.regularizers.l2(0.001))(x)
x = tf.keras.layers.BatchNormalization()(x)
x = tf.keras.layers.Dropout(0.5)(x)
x = tf.keras.layers.Dense(4, activation='softmax')(x)

model = tf.keras.Model(inputs=base_model.input, outputs=x)

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-4),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

early_stopping = keras.callbacks.EarlyStopping(
    monitor='val_loss',
    patience=20,
    restore_best_weights=True
)

history = model.fit(train_datagen, epochs=30, validation_data=validation_datagen, verbose=2, callbacks=[early_stopping])

base_model.trainable = True
for layer in base_model.layers[:len(base_model.layers) // 2]:
    layer.trainable = False

model.compile(optimizer=keras.optimizers.AdamW(learning_rate=1e-5),
              loss='categorical_crossentropy',
              metrics=['accuracy'])

history_fine = model.fit(train_datagen, epochs=20, validation_data=validation_datagen, verbose=2, callbacks=[early_stopping])

loss, accuracy = model.evaluate(test_datagen)
print(f"Test Accuracy: {accuracy:.2f}")

model.save('plant_lifecycle_classifier.keras')
```

Steps in this script:

The suppression of the warnings:

- During the installation of Tensorflow and Python something must have went wrong because we keep getting warnings when importing them.
- We wrote code to suppress the warnings to avoid excessive console logs.

Defining the paths:

- This script uses the preprocessed images from the “Preprocessed_Images” folder.

Data generators:

- The script uses ImageDataGenerator to generate batches of image data with real time data augmentation.

- Random transformations like rotation, width/height shift, shear, zoom, etc. are used.

Loading EfficientNetB0:

- A pre-trained EfficientNetB0 model which has been trained on a large dataset (ImageNet) gets loaded. This model helps to quickly build an effective model sine it has already learned useful features.
- The “Include Top = False” part removes the classification layer, so we can add a custom head for our four classes.

Adding custom layers:

- We add a GlobalAveragePooling layer followed by several dense layers with dropout and batch normalization.
- The final layer has four output nodes with softmax activation to output probabilities for each of the four classes.

Compile the model:

- The script uses the AdamW optimizer with a learning rate of 1e-4.
- The loss function is categorical crossentropy, which is suitable for multi-class classification problems.

Early stopping callback:

- This callback stops training if the validation loss stops improving fro 20 epochs, preventing overfitting.

Training the model:

- The model gets trained for a total of 30 epochs using “train_datagen” and evaluates it using “validation_datagen”.

Fine-tuning the model:

- This unfreezes the base model layers, making them trainable.
- The model gets compiles with a lower learning rate (1e-5) to adjust the features learned by the EfficientNet base.
- The model gets fine-tuned for an additional 20 epochs.

Evaluating the model:

- The model gets evaluated on the test dataset and the accuracy gets printed.

Saving the model:

- The model gets saved to the “plant_lifecycle_classifier.keras” file.

– **Specialized Skills and Tools:** The team applied skills in TensorFlow, Keras, and transfer learning techniques with EfficientNetB0. Tools like `*ImageDataGenerator*` and TensorFlow’s `*image_dataset_from_directory*` helped manage real-time data augmentation.
– **Application of Skills to Project:** The team’s iterative adjustments in model training scripts demonstrate a proactive approach to problem-solving. Fine-tuning techniques and custom augmentation were particularly effective.
– **Innovation and Effectiveness:** Customizing the augmentation techniques and leveraging prefetching to optimize CPU/GPU coordination are innovative, optimizing the model’s performance within data limitations.

Criterion 4: Ethical Considerations

- **Ethical Implications**: Potential ethical implications include responsible use of plant images and adherence to data privacy standards.
- **Ensuring Ethical Conduct:** Ensuring that all data usage complies with relevant privacy and copyright laws, especially if the images are sourced from external platforms, is essential.
- **Cultural Diversity and Social Impact:** Acknowledging the socio-environmental impact of plant monitoring, this project supports broader environmental awareness.

Criterion 5: Information Presentation and Communication

- **Effective Communication:** The team organized documentation and detailed steps for each phase of the project, which is essential for clear communication with stakeholders.
- **Audience Tailoring:** Clear language was used in documentation to explain complex concepts, which aids stakeholders' understanding regardless of technical knowledge.

Criterion 6: Understanding of System Interactions

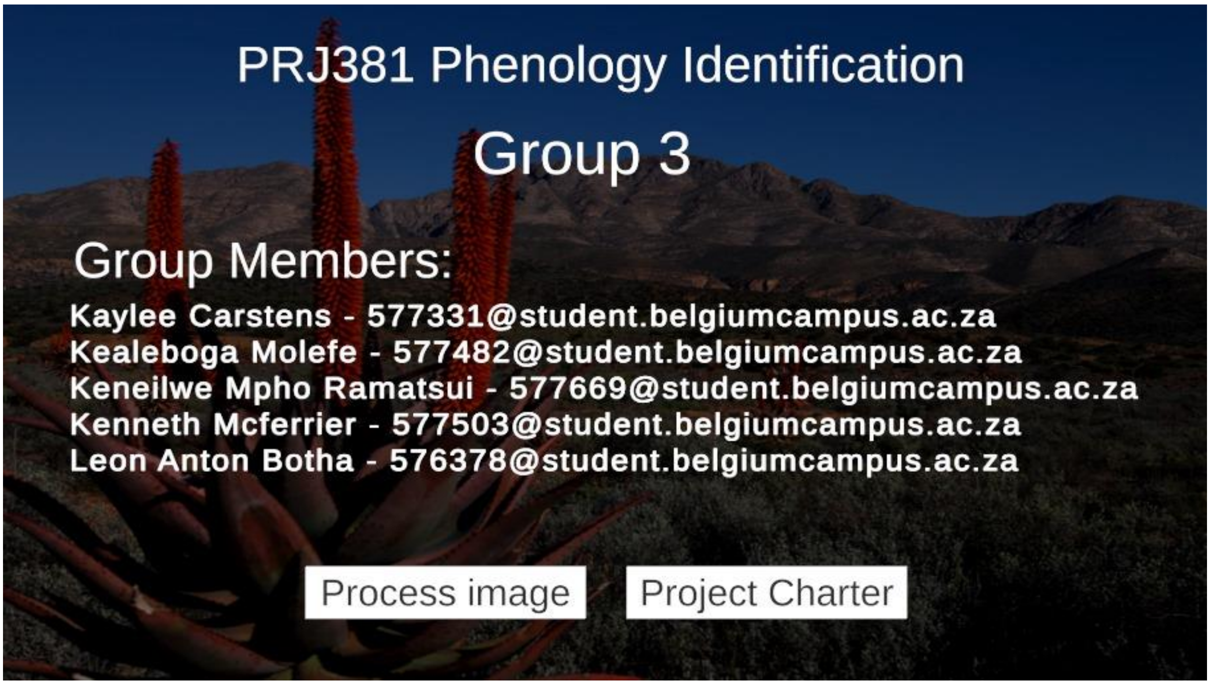
- **System Interactions:** The project's neural network model interacts with cloud-masked Landsat imagery, TensorFlow data augmentation libraries, and custom data loaders.
- **Dependencies and Interdependencies:** Proper handling of dependencies, such as TensorFlow libraries and EfficientNet model integration, was crucial for successful training.
- **Managing Interactions:** Dataset prefetching and the `image_dataset_from_directory` method enabled smoother handling of large data flows, ensuring consistent performance.
- **Data Handling and Organization**: The download and organizing script establishes the structure for data processing by creating directories and managing file paths. The use of os for directory management and *tqdm* for progress tracking supports seamless data organization and interaction with other systems. This organization enables efficient access and integration of data into subsequent processing and model training scripts.

Criterion 7: Accountability and Responsibility

- **Roles and Responsibilities:**
- **Time Leader:**
- **Time Management and Resource Allocation:** The team's structured approach to iterations suggests strong time management, optimizing resources by reusing pre-trained models and gradually adjusting model parameters to achieve higher accuracy.
- **Issue Resolution:** Problems such as overfitting and underfitting were promptly addressed through systematic testing and modifications across each iteration.

UI Design:

<u>Home page:</u>

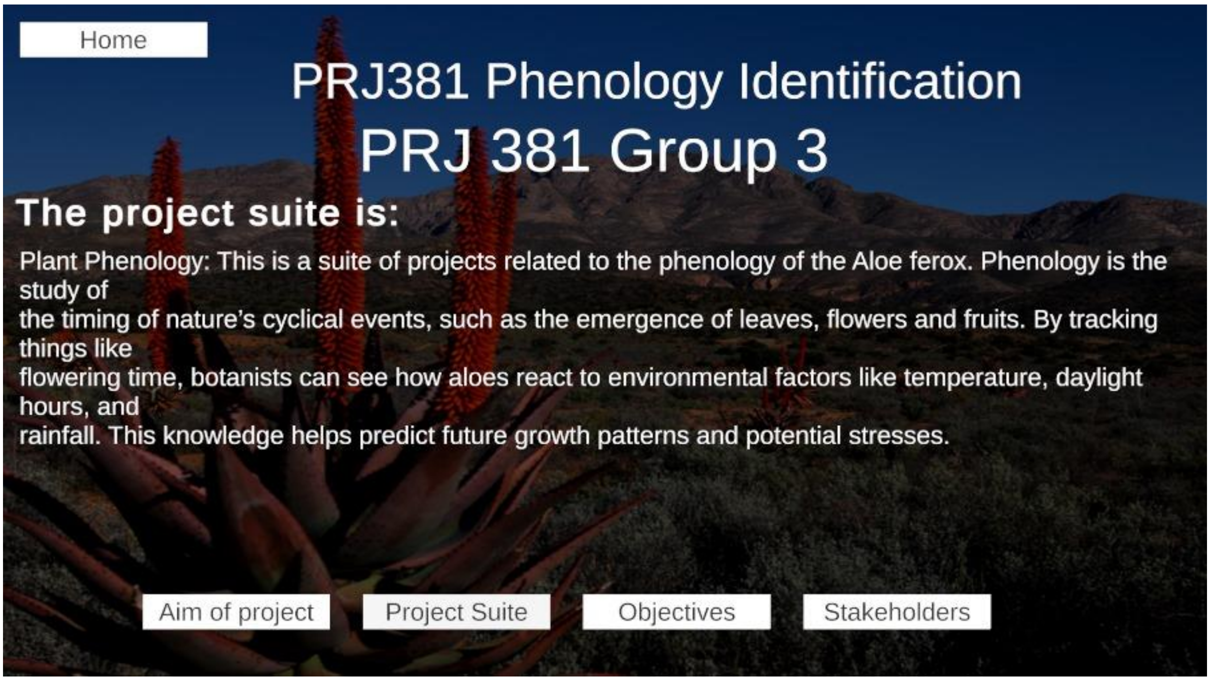


<u>Project Charter:</u>

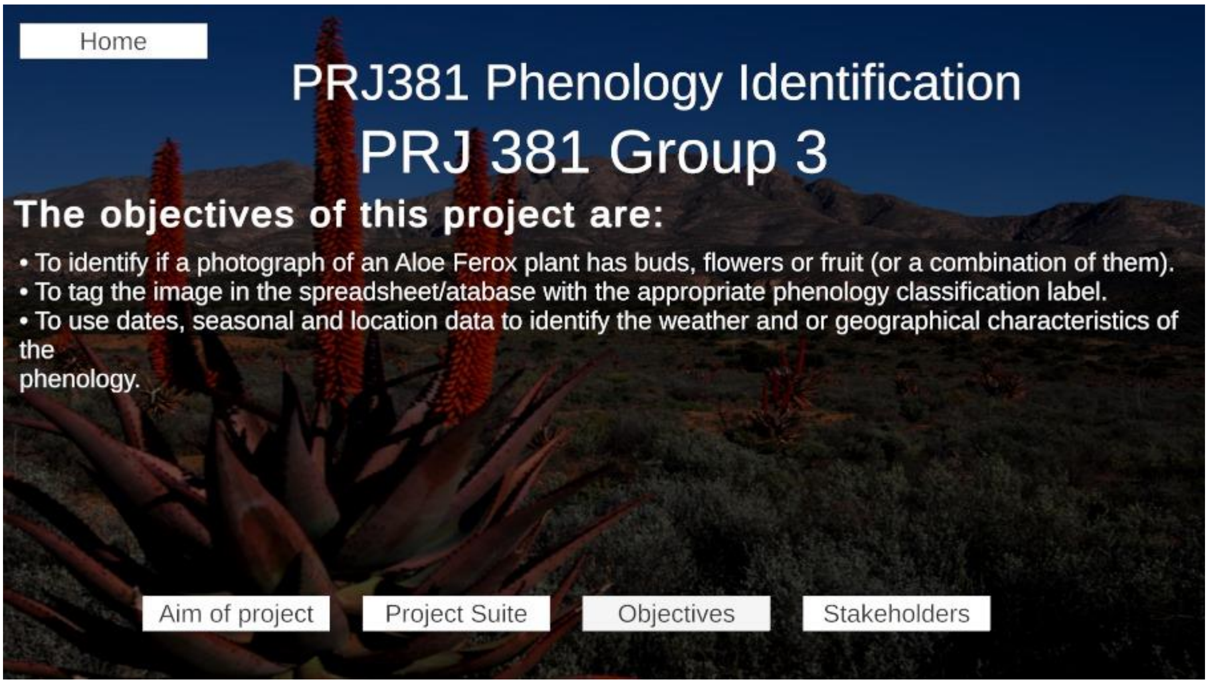
This is a simple page to sums up what we had to do for the project

Aim:

Project Suite:



Objectives:



Stakeholders:

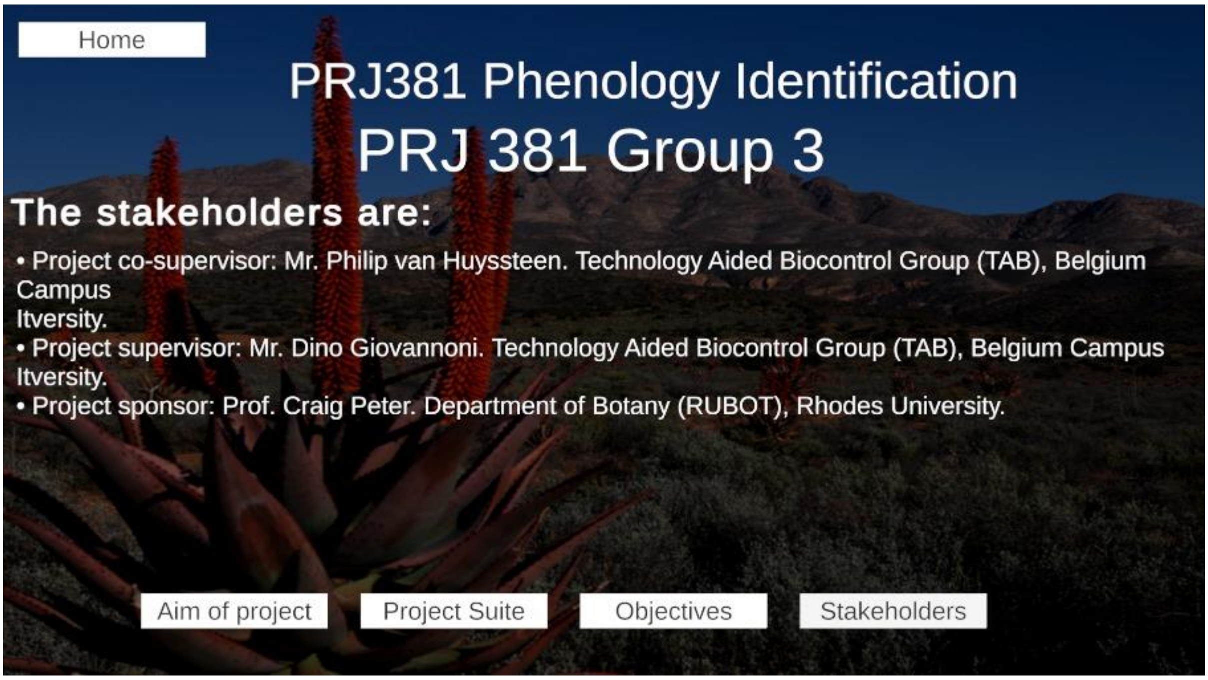
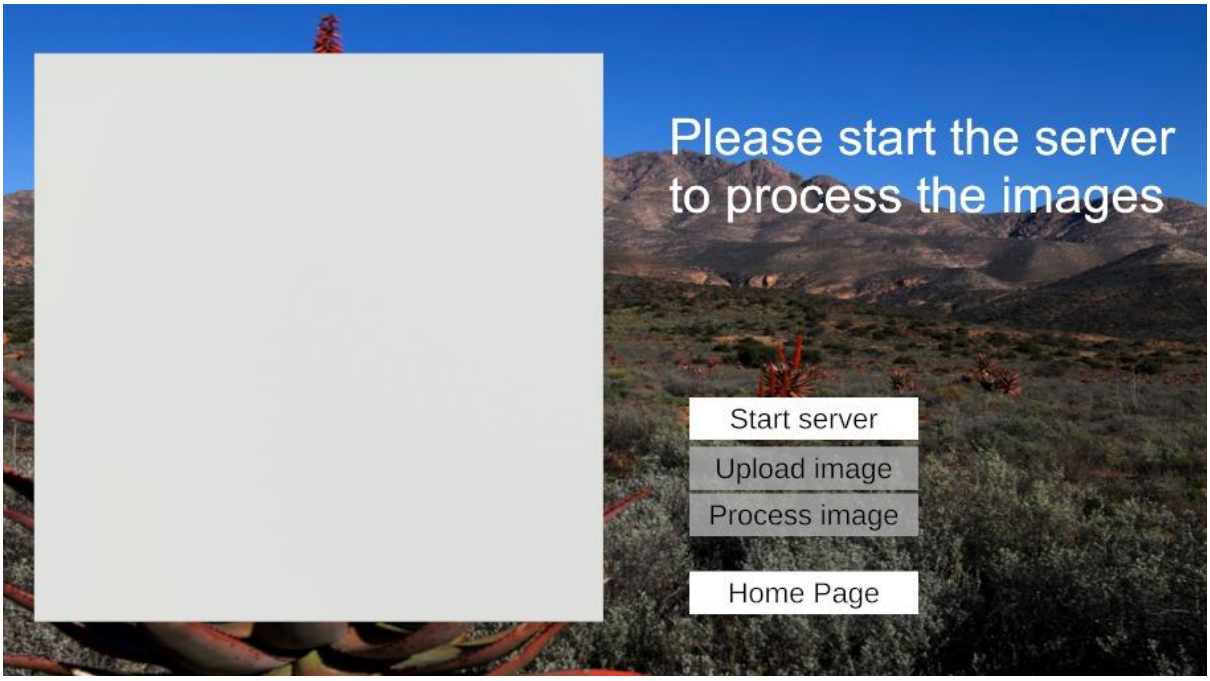


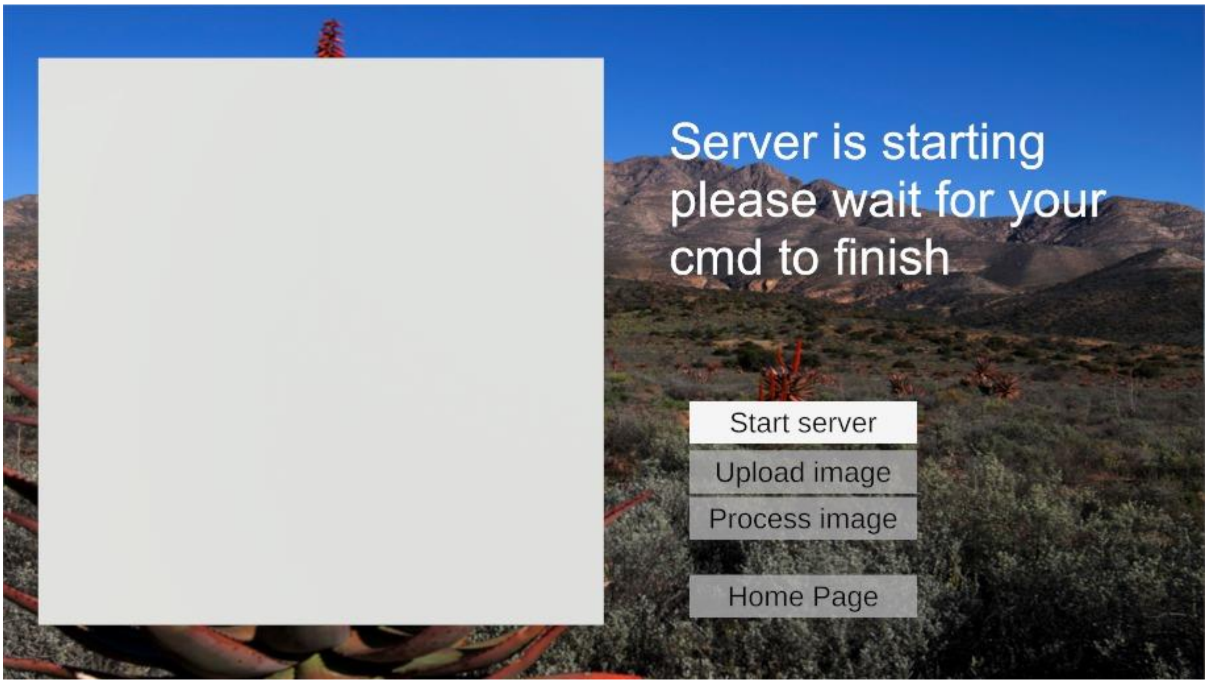
Image processing:

Server startup:

We start with all buttons disabled as the user will first need to start the server before the image processing can happen



As the server starts up we disable the home button to prevent interruptions and give text feedback to the user to know what to wait for before continueing



Once the server is up and running we enabled the buttons to upload a image

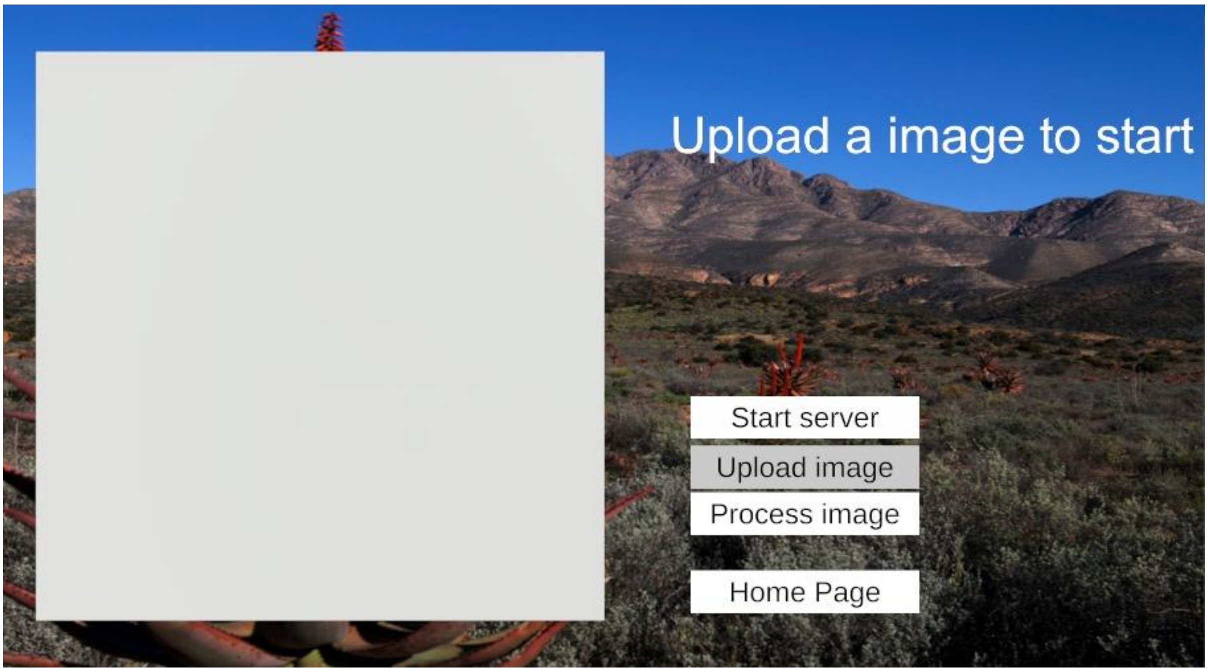


Image upload:

After the image is uploaded the user can Process the image this will send a command through the server that we started to send the image data to the model that we trained and give us a class and a confidency level

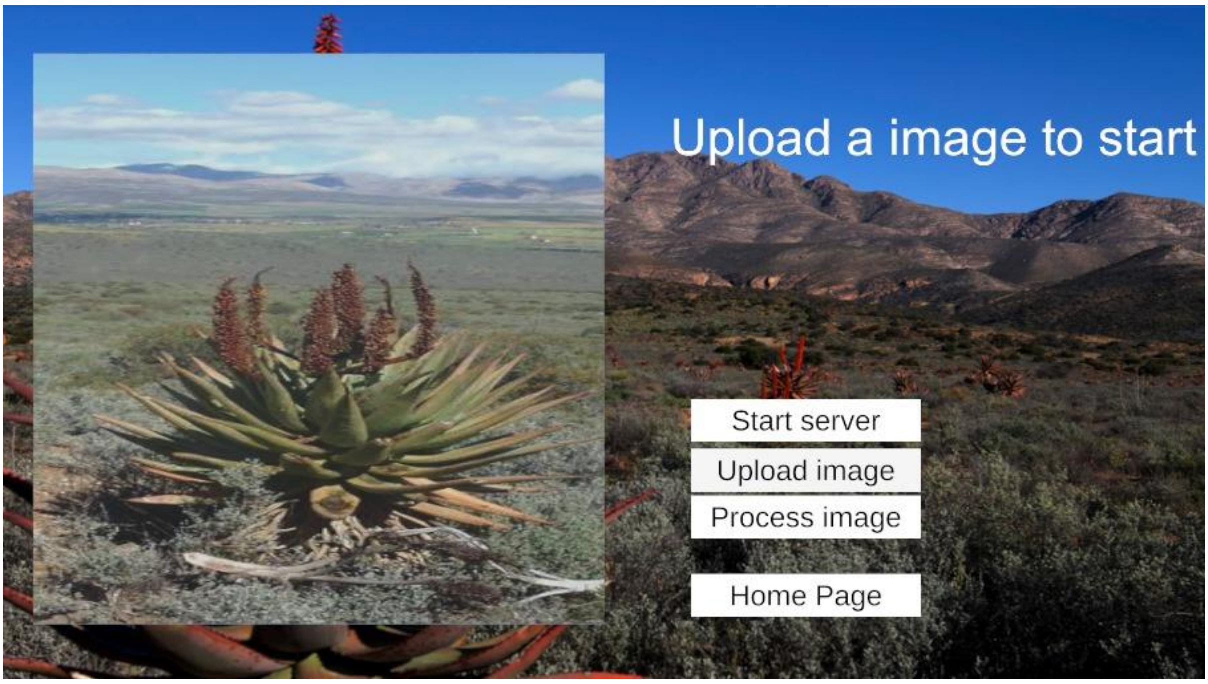
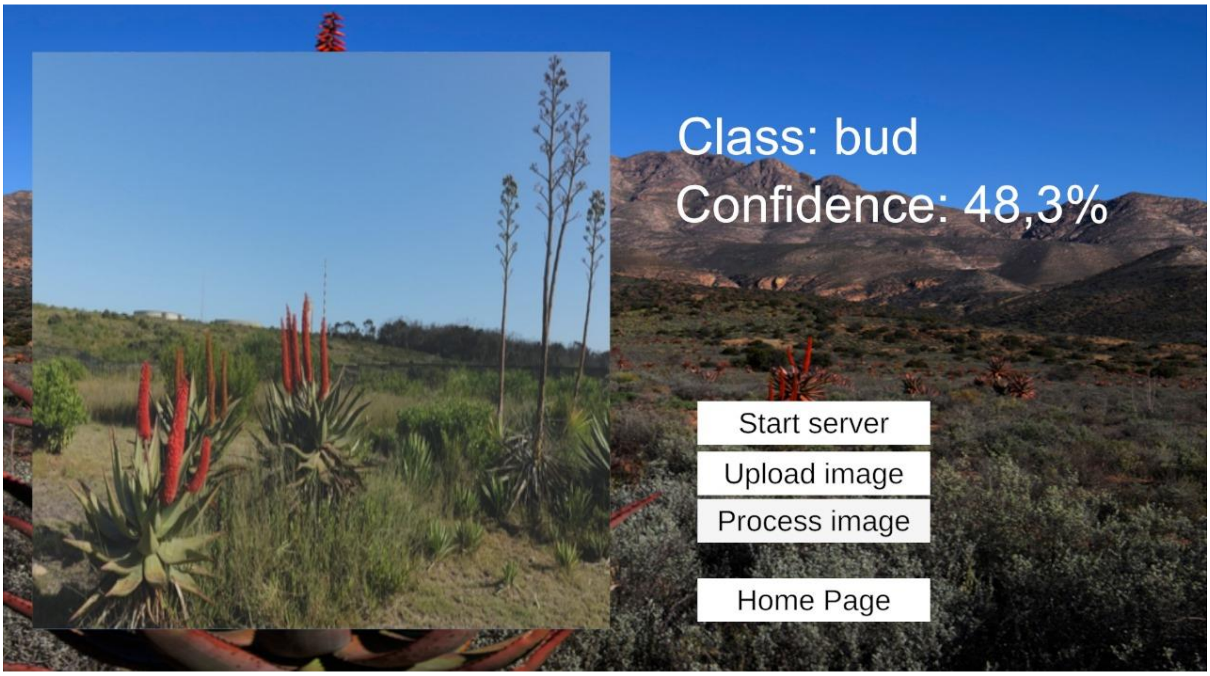


Image processing:

After the image is uploaded the server will respond and the results are uploaded to the UI via the server


Class: bud
Confidence: 48,3%
Start server
Upload image
Process image
Home Page