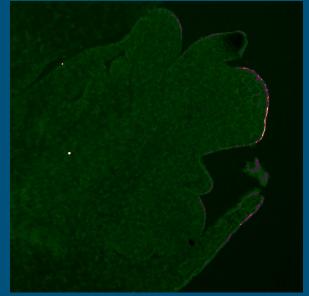
Computer Model for Classifying Cell Wall Antibody Staining

By Charles Maus

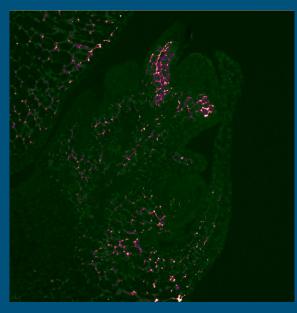
Localization of cell wall homogalacturonans can be visualized through immunofluorescence microscopy

LM20



Methylesterified HG

LM19



De-methylesterified HG

Raw microscope images can be modified to form data set

Download ImageMagick -

```
##Magick Downloaded (Used in Bash/Command Line)

Click to add a breakpoint aining \LM19\
magick mogrity -tormat jpg LM19*.tif

## Change color
magick LM19*.jpg -colorspace Gray LM19*BW.jpg

##Repeat for LM20

cd ...

cd LM20

magick mogrify -format jpg LM20*.tif

magick LM20*.jpg -colorspace Gray LM20*BW.jpg
```



There are python packages for image analysis and classification





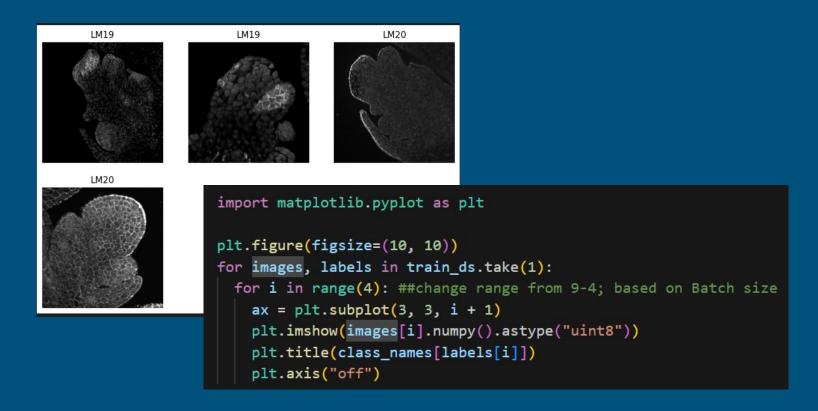
```
import matplotlib.pyplot as plt
import numpy as np
import PIL
import tensorflow as tf

from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import Sequential
import pathlib
```

We have to define the data set for the model

```
data_dir = "C:/Users/cccsm/praccomp2024/FinalProject/ImagesforModelTraining/ModelImages"
   pathlib.Path(data dir).with suffix('')
 ✓ 0.0s
WindowsPath('C:/Users/cccsm/praccomp2024/FinalProject/ImagesforModelTraining/ModelImages')
   batch size = 4 ## Should we do 1 at a time?
   img height = 1024
   img width = 1024
 ✓ 0.0s
   train_ds = tf.keras.utils.image_dataset_from_directory(
     data_dir,
     validation_split=0.2,
     subset="training",
     seed=123,
     image size=(img height, img width),
     batch size=batch size)
 ✓ 0.1s
Found 24 files belonging to 2 classes.
Using 20 files for training.
   val_ds = tf.keras.utils.image_dataset_from_directory(
     data dir,
     validation_split=0.2,
     subset="validation",
     seed=123,
     image_size=(img_height, img_width),
     batch size=batch size)
```

We can use matplotlib.pyplot to visualize what the model sees



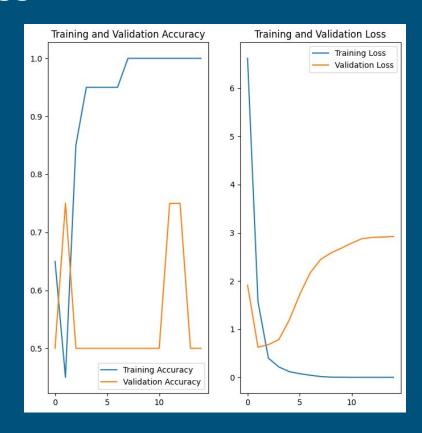
Once we have the data, it is compiled and run through the model

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	(None, 1024, 1024, 3)	0
conv2d (Conv2D)	(None, 1024, 1024, 16)	448
max_pooling2d (MaxPooling2D)	(None, 512, 512, 16)	0
conv2d_1 (Conv2D)	(None, 512, 512, 32)	4,640
max_pooling2d_1 (MaxPooling2D)	(None, 256, 256, 32)	0
conv2d_2 (Conv2D)	(None, 256, 256, 64)	18,496
max_pooling2d_2 (MaxPooling2D)	(None, 128, 128, 64)	0
flatten (Flatten)	(None, 1048576)	0
dense (Dense)	(None, 128)	134,217,856
dense_1 (Dense)	(None, 2)	258

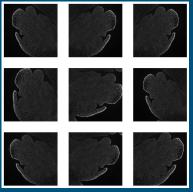
```
epochs=15
history = model.fit(
   train_ds,
   validation_data=val_ds,
   epochs=epochs
)
```

The model displays training success, but has limited validation success

```
acc = history.history['accuracy']
val acc = history.history['val accuracy']
loss = history.history['loss']
val loss = history.history['val loss']
epochs range = range(epochs)
plt.figure(figsize=(8, 8))
plt.subplot(1, 2, 1)
plt.plot(epochs range, acc, label='Training Accuracy')
plt.plot(epochs_range, val_acc, label='Validation Accuracy')
plt.legend(loc='lower right')
plt.title('Training and Validation Accuracy')
plt.subplot(1, 2, 2)
plt.plot(epochs range, loss, label='Training Loss')
plt.plot(epochs_range, val_loss, label='Validation Loss')
plt.legend(loc='upper right')
plt.title('Training and Validation Loss')
plt.show()
```



To account for validation issues, we can optimize and augment the data



```
model = Sequential([
   data_augmentation,
   layers.Rescaling(1./255),
   layers.Conv2D(16, 3, padding='same', activation='relu'),
   layers.MaxPooling2D(),
   layers.Conv2D(32, 3, padding='same', activation='relu'),
   layers.MaxPooling2D(),
   layers.Conv2D(64, 3, padding='same', activation='relu'),
   layers.MaxPooling2D(),
   layers.MaxPooling2D(),
   layers.Dropout(0.2),
   layers.Flatten(),
   layers.Dense(128, activation='relu'),
   layers.Dense(num_classes, name="outputs")
```

The new validation and training plot displays the success of this augmentation

Training and Validation Loss

Training Loss

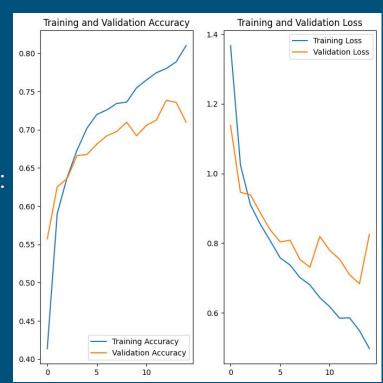
10

Validation Loss 12 0.9 10 My 0.8 Model: 0.7 0.6 2 0.5 0 Validation Accuracy

Training and Validation Accuracy

1.0

Expected:



Let's Test it!

```
LM20 path = "C:/Users/cccsm/praccomp2024/FinalProject/TestImages/NTestLM20bBW.jpg"
   img = tf.keras.utils.load img(
       LM20_path, target_size=(img_height, img_width)
   img array = tf.keras.utils.img to array(img)
   img_array = tf.expand_dims(img_array, 0) # Create a batch
   predictions = model.predict(img array)
   score = tf.nn.softmax(predictions[0])
   print(
       "This image most likely belongs to {} with a {:.2f} percent confidence."
       .format(class names[np.argmax(score)], 100 * np.max(score))
✓ 0.1s
                     0s 69ms/step
This image most likely belongs to LM20 with a 99.79 percent confidence.
   LM20 path = "C:/Users/cccsm/praccomp2024/FinalProject/TestImages/NTestLM20aBW.jpg"
   img = tf.keras.utils.load img(
      LM20 path, target size=(img height, img width)
  img_array = tf.keras.utils.img_to_array(img)
   img_array = tf.expand_dims(img_array, 0) # Create a batch
   predictions = model.predict(img array)
   score = tf.nn.softmax(predictions[0])
   print(
       "This image most likely belongs to {} with a {:.2f} percent confidence."
       .format(class_names[np.argmax(score)], 100 * np.max(score))
 ✓ 0.1s
                     — 0s 70ms/step
This image most likely belongs to LM20 with a 71.36 percent confidence.
```

Possible edits and ways to increase accuracy of classification & Future Applications

Additional Data - Increasing Data Set Size!

Randomizing Validation vs Training Images

Applying the model to other meristem types (SAMs, SPMs, etc.)

