



IBM Advance Data science Capstone project: Image classification of grape leaves diseases using machine and deep learning

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The goal of the Capstone project



1. Prepare the image classification models in order to classify grape leaves images into 4 different classes.

2. Deploy the model in Watson studio using Watson Machine learning repository and create the REST API.

3. Show how to use the image classification REST API in the real-life use case.



Presentation for
stakeholders



Introduction

Mr. Andrew's experience with grape diseases

Mr. Andrew is a 65-year-old owner of the Vineyard in South East of Slovakia. He was not in his vineyard for several days. Although he did not notice anything at the last visit, now he found out that one part of his vineyard was infected with the esca disease in a very large extent and in another part of the vineyard the other disease called mite spread out. He lost 30% of his grapes because he did not take a necessary action earlier.



Current problems of the Vineyard owners



Common questions

- How could I detect diseases in early stages and actively protect my Vineyard?
- How can I prevent the spread out of the grapevine disease?
- Can I do that with limited resources?



Too much time

- Manually identify the locations with grapevine diseases.
- Take necessary actions at the right place.
- Recover from the disease.

What if...



There is cloud
based solution
Save the Vineyard



Save The Vineyard

21. 5. 2018

class_4

Demo

class_4

Status: esca

Location: 48.411377, 21.802958

Leaflet



SMS notification with link to the application

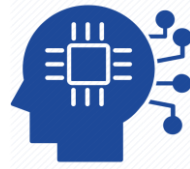
[https://save-the-vineyard-ui.eu-
de.mybluemix.net/](https://save-the-vineyard-ui.eu-de.mybluemix.net/)

Save the Vineyard's key features



Process Automation

**Automatic retrieval
of time, location and
image data.**



Machine Learning

**Visual recognition to
identify and classify
grape leaves
diseases.**

**Give initial feedback
about the diseases
spread.**



SMS notification

**SMS notification to
the Vineyard owner
in case of the grape
leaves disease.**



Data visualization

**Data visualization
with information
about location and
type of disease.**

High level application architecture



IBM Cloud
is used to keep
all components.



Watson IoT
Is used to capture
images and obtains
GPS coordinates.



Cloudant
is used to store
captured images.

Save the Vineyard



Choose a model:

4 class

Model	Class	Score
CNN	esca	0.634334445

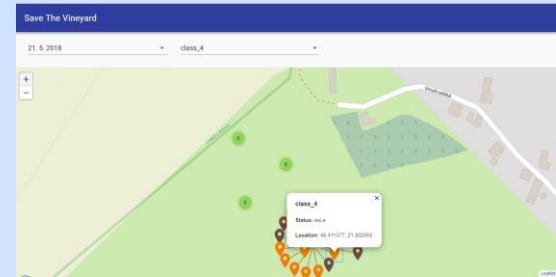
Upload a file

Use camera

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Client Innovation Center Slovakia - Košice

Image Classification REST API is used
to classify grape leaves diseases.



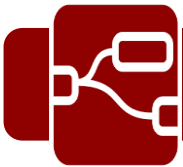
Web application is used to
visualize data after classification.



Twilio
is used to send alert via
sms to the Vineyard owner.



Cloudant
is used to store data
after classification.



Node Red is used for orchestration.



Presentation for
data scientist

Architectural choices

I used

- **for the raw data:** my own dataset of grape leaves.
- **for the data repository:** IBM Cloud object storage and Github repository.
- **for data exploration, data preprocessing and modeling:** Jupyter notebook with Python 3.5.
- **for the solution, the following Python libraries:**
 - NumPy
 - Pandas
 - Seaborn
 - Scikit learn
 - Xgboost
 - Keras
 - Watson-machine-learning-client

The dataset

The dataset contains 272 images.

The structure of the dataset:

- Test_set (48 images)
- Training_set (200 images)
- Validation_set (12 images)

The dataset is available:

https://github.com/RenataUjhaziova/dataset_WS_DvsEvsHvsM_512-512_git.git



Dry



Esca



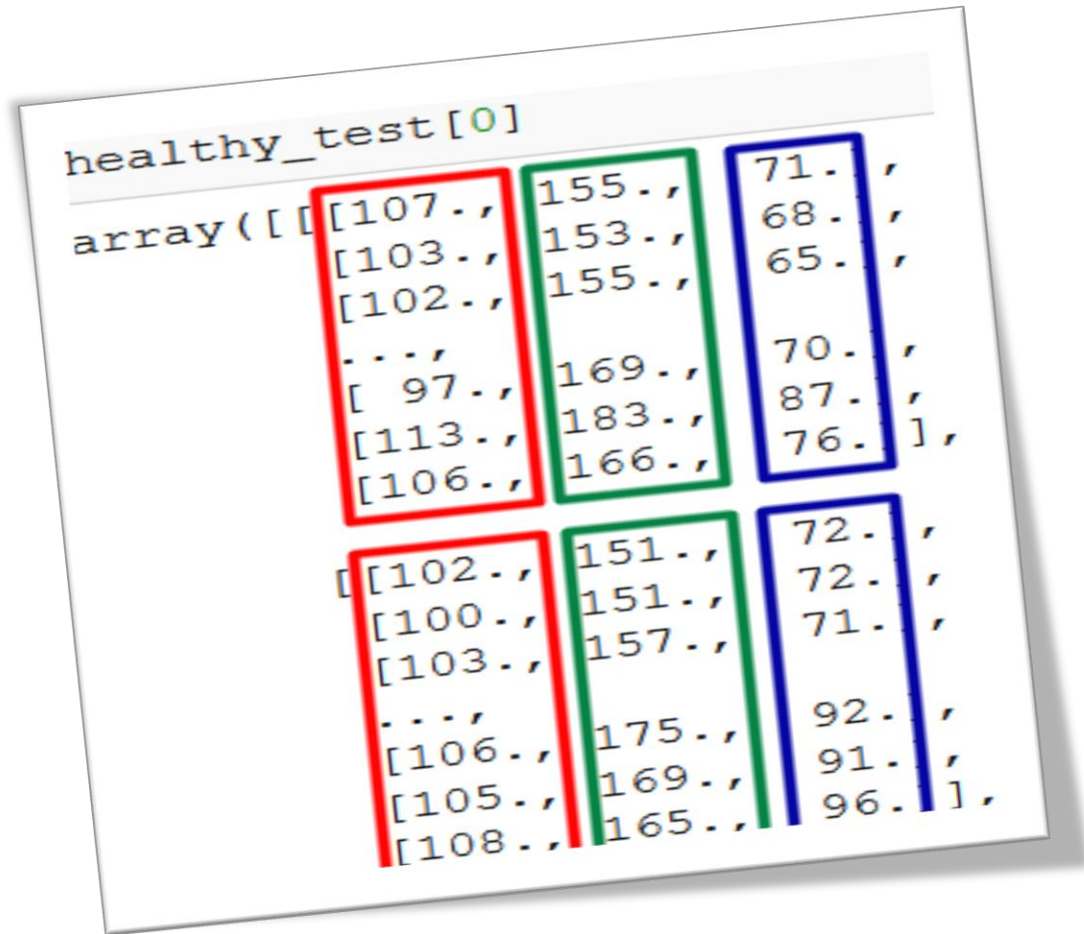
Healthy



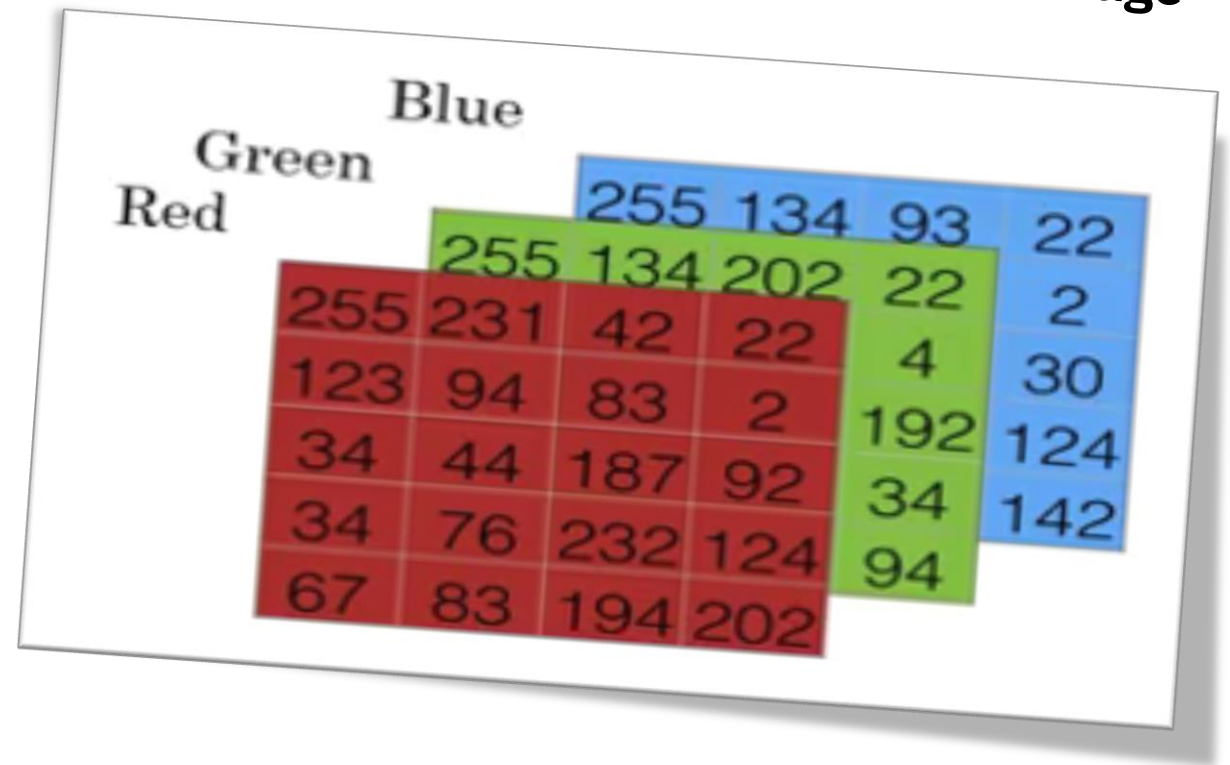
Mite

Data understanding

Color images are stored as **RGB values of pixels** (description of picture).

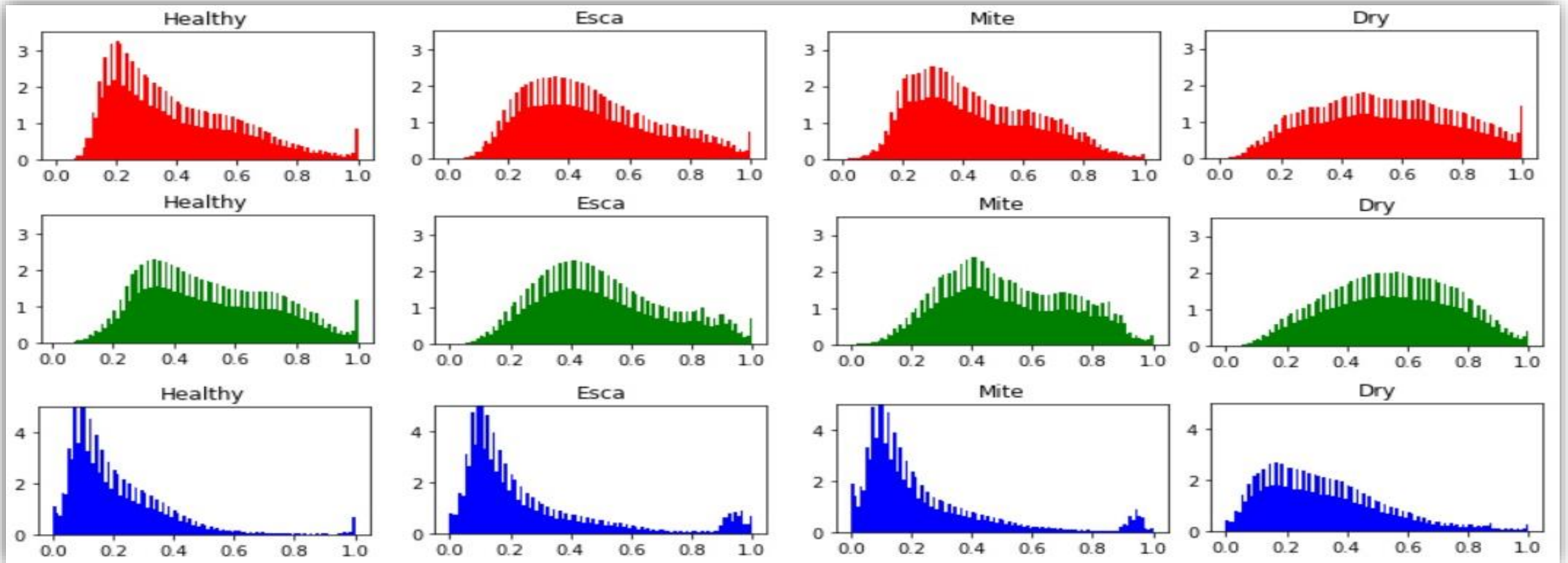


Pixel intensity of color channels of an image



Data exploration

Comparison of pixel color intensities across different classes



Feature extraction

There are different ways of extracting features from picture:

- extracting the **average color** in each of the three channels (RGB)
- extracting **dominant colors** from picture
- extracting features based on **histograms of pixels color intensities**

```
def append_to_df(img_array, df, label):  
    for image in img_array:  
        hist_b = np.histogram(image[:, :, 0], bins=30, density=True, range=(0,1))[0]  
        hist_g = np.histogram(image[:, :, 1], bins=30, density=True, range=(0,1))[0]  
        hist_r = np.histogram(image[:, :, 2], bins=30, density=True, range=(0,1))[0]  
        hist = np.append(np.append(hist_r, hist_g), hist_b)  
        df = df.append({'hist_data': hist, 'label': label}, ignore_index=True)  
    return df
```


Feature creation

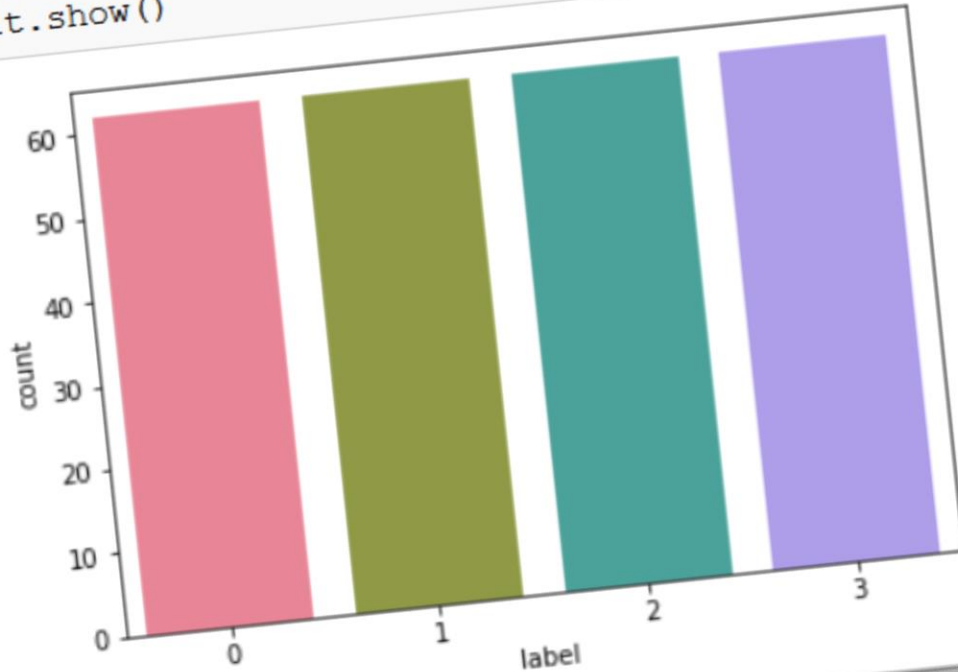
```
data = pd.DataFrame(columns=['hist_data', 'label'])
data = append_to_df(dry_train, data, 0)
data = append_to_df(dry_test, data, 0)
data = append_to_df(esca_train, data, 1)
data = append_to_df(esca_test, data, 1)
data = append_to_df(healthy_train, data, 2)
data = append_to_df(healthy_test, data, 2)
data = append_to_df(mite_train, data, 3)
data = append_to_df(mite_test, data, 3)
```

```
data.head(10)
```

	hist_data	label
0	[0.0048065185546875, 0.0128173828125, 0.050582...	0
1	[0.094757080078125, 0.2579498291015625, 0.8288...	0
2	[0.0450897216796875, 0.14041900634765625, 0.52...	0
3	[0.0597381591796875, 0.20885467529296875, 0.62...	0
4	[0.00400543212890625, 0.0405120849609375, 0.42...	0
5	[0.791015625, 1.9091033935546875, 3.6917495727...	0
6	[0.00560760498046875, 0.04703521728515625, 0.4...	0
7	[0.02529144287109375, 0.09029388427734375, 0.5...	0
8	[0.7715606689453125, 2.1530914306640625, 3.805...	0
9	[0.21881103515625, 0.4827117919921875, 1.17919...	0

Description of the dataset

```
# Classes distribution plot  
sns.countplot(x='label', data=data, palette='husl')  
plt.show()
```



```
# column names  
column_names = data.columns  
column_names  
  
Index(['hist_data', 'label'], dtype='object')
```

```
# dataset shape  
data.shape  
  
(248, 2)
```

```
# null values check  
data.isnull().sum()  
  
hist_data    0  
label        0  
dtype: int64
```

Model selection

Machine learning

KNN

XGBoost

Deep learning

ANN

CNN model

CNN using VGG16

Model creation and training: KNN

Train & test split: 75:25

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score
```

```
# Create the KNN classifier
KNN_model = KNeighborsClassifier()
```

```
# Train and evaluate.
KNN_model.fit(X_train, y_train)
```

```
# Select trained model.
y_pred_knn = KNN_model.predict(X_test)
```

```
# Check the accuracy of the trained model.
accuracy = accuracy_score(y_test, y_pred_knn)
print('Accuracy: %.2f%%' % (accuracy * 100.0))
```

Grid search & cross validation

```
# Create KNN pipeline, set up parameter grid.
KNN_model_gs = KNeighborsClassifier()
parameters = {'n_neighbors': [4, 6, 8, 10],
              'weights': ['uniform', 'distance'],
              'metric': ['euclidean', 'manhattan']}
```

```
# Search for the best parameters.
clf = GridSearchCV(estimator = KNN_model_gs,
                  param_grid = parameters,
                  verbose = 1,
                  cv = 5,
                  n_jobs = -1)
```

```
clf.fit(X_train, y_train)
```

```
# Display the accuracy of the best parameter combination
y_pred_cv = clf.best_estimator_.predict(X_test)
```

```
accuracy = accuracy_score(y_test, y_pred_cv)
print('Accuracy: %.2f%%' % (accuracy * 100.0))
```

Model creation and training: XGBoost

Train & test split: 75:25

```
# Import packages you need to create the XGBoost model.
from xgboost.sklearn import XGBClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import accuracy_score

# Create the XGB classifier - xgb_model.
xgb_model = XGBClassifier(n_estimators=200,
                          objective= 'multi:softmax')

# Train and evaluate.
xgb_model.fit(X_train, y_train, eval_metric=['mlogloss'],
              eval_set=[(X_train, y_train), (X_test, y_test)])

# Select trained model.
n_trees = 85
y_pred = xgb_model.predict(X_test, ntree_limit= n_trees)

# Check the accuracy of the trained model.
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f%%' % (accuracy * 100.0))
```

PCA for model tuning

```
# PCA
from sklearn.pipeline import Pipeline
from sklearn.decomposition import PCA

pca = PCA(n_components=10)
xgb_model_pca = XGBClassifier(n_estimators=n_trees)
pipeline = Pipeline(steps=[('pca', pca), ('xgb', xgb_model_pca)])

pipeline.fit(X_train, y_train)

y_pred = pipeline.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print('Accuracy: %.2f%%' % (accuracy * 100.0))
```

Model creation and training: ANN

Train & test split: 75:25

```
ANN_model = Sequential()
```

```
# Adding the input layer and the first hidden layer
ANN_model.add(Dense(output_dim = 45,
                    init = 'uniform',
                    activation = 'relu',
                    input_dim = 90))
```

```
# Adding the second hidden layer
ANN_model.add(Dense(output_dim = 45,
                    init = 'uniform',
                    activation = 'relu'))
```

```
# Adding the output layer
ANN_model.add(Dense(output_dim = 4,
                    init = 'uniform',
                    activation = 'softmax'))
```

```
# Compiling the ANN
ANN_model.compile(optimizer = 'adam',
                  loss = 'categorical_crossentropy',
                  metrics = ['accuracy'])
```

```
# Fitting the ANN to the Training set
ANN_model.fit(X_train, y_train, batch_size = 10,
              nb_epoch = 30,
              validation_data=(X_test, y_test),
              callbacks=[plot_learning])
```

```
score_test = ANN_model.evaluate(X_test, y_test, verbose=0)
```

```
print("Loss = ", score_test[0], ", Accuracy = ", score_test[1])
```

```
#predictions_test
predictions_test = ANN_model.predict(X_test)
```

```
y_pred_test = []
for i in range(len(predictions_test)):
    y_pred_test.append(np.argmax(predictions_test[i]))
print(y_pred_test)
```

```
y_test_labels = [ np.where(r==1)[0][0] for r in y_test ]
y_test_labels
```

```
ctr_test=0
for i in range(len(y_pred_test)):
    if y_pred_test[i] == y_test_labels[i]:
        ctr_test=ctr_test+1
res_test = ctr_test/len(y_pred_test)*100
print(res_test)
```


Model creation and training: ANN cross validation

Cross validation

```
from sklearn.model_selection import StratifiedKFold
```

```
seed = 7  
np.random.seed(seed)
```

```
kfold = StratifiedKFold(n_splits=10, shuffle=True,  
                        random_state=seed)
```

```
for train, test in kfold.split(X, y):  
    cv_model = Sequential()  
    cv_model.add(Dense(output_dim = 45,  
                       init = 'uniform',  
                       activation = 'relu',  
                       input_dim = 90))  
    cv_model.add(Dense(output_dim = 45,  
                       init = 'uniform',  
                       activation = 'relu'))  
    cv_model.add(Dense(output_dim = 4,  
                       init = 'uniform',  
                       activation = 'softmax'))  
  
    # Compiling the ANN model  
    cv_model.compile(optimizer = 'adam',  
                    loss = 'categorical_crossentropy',  
                    metrics = ['accuracy'])  
  
    # Fitting the ANN model  
    cv_model.fit(X_train, y_train, batch_size = 10,  
                nb_epoch = 30, verbose=1,  
                validation_data=(X_test, y_test))  
  
score_test_cv = cv_model.evaluate(X_test, y_test, verbose=0)  
print("Loss = ", score_test_cv[0], ", Accuracy = ", score_test_cv[1])
```

Model creation and training: CNN VGG16

Train & test split

```
vgg16_model = keras.applications.vgg16.VGG16()
vgg16_model.summary()

#This is a Keras Functional API need to convert to sequential type(vgg16_model)
#Iterate over the functional layers and add it as a stack
model = Sequential()
for layer in vgg16_model.layers[:-1]:
    model.add(layer)

#Since the model is already trained with certain weights,
# we dont want to change it. Let it be the same
for layer in model.layers:
    layer.trainable = False

# Compile the model
model.compile(Adam(lr=.00015),
              loss='categorical_crossentropy', metrics=['accuracy'])
```

```
model.fit_generator(train_batches, steps_per_epoch=20,
                    validation_data=test_batches,
                    validation_steps=12, epochs=20,
                    verbose=1, shuffle=False,
                    callbacks=[plot_learning])
```

```
scores_test = model.evaluate_generator(generator = test_batches_pred, steps=1)
print("Loss = ", scores_test[0], ", Accuracy = ", scores_test[1])
```

```
predictions_test = model.predict_generator(test_batches_pred, steps=1, verbose=0)
predictions_test
```

```
y_pred_test = []
for i in range(len(predictions_test)):
    y_pred_test.append(np.argmax(predictions_test[i]))
print(y_pred_test)
```

```
ctr_test=0
for i in range(len(y_pred_test)):
    if y_pred_test[i] == y_test[i]:
        ctr_test=ctr_test+1
res_test = ctr_test/len(y_pred_test)*100
print(res_test)
```

Model creation and training: CNN Sequential

Train & test split

```
# Initialising the CNN
```

```
model = Sequential()
```

```
# Step 1 - Convolution
```

```
model.add(Conv2D(filters = 32, kernel_size=(3,3),  
                 input_shape = input_shape,  
                 activation = 'relu'))
```

```
# Step 2 - Pooling
```

```
model.add(MaxPooling2D(pool_size = (2, 2)))
```

```
# Adding a second convolution layer
```

```
model.add(Conv2D(filters = 64, kernel_size=(3,3),  
                 activation = 'relu'))  
model.add(MaxPooling2D(pool_size = (2, 2)))  
model.add(Dropout(rate=0.20))
```

```
# Adding a third convolution layer
```

```
model.add(Conv2D(filters = 128, kernel_size=(3,3),  
                 activation = 'relu'))  
model.add(MaxPooling2D(pool_size = (2, 2)))  
model.add(Dropout(rate=0.20))
```

```
# Step 3 - Flattening
```

```
model.add(Flatten())
```

```
# Step 4 - Full connection
```

```
model.add(Dense(units = 128, activation = 'relu'))  
model.add(BatchNormalization())  
model.add(Dropout(rate=0.5))
```

```
# Step 5 - Final layer
```

```
model.add(Dense(units = num_classes,  
                 activation = 'softmax'))
```

```
model.fit_generator(train_batches, steps_per_epoch=7,  
                   validation_data=test_batches,  
                   validation_steps = 48,  
                   epochs=200, verbose=1, shuffle=False,  
                   callbacks=[plot_learning])
```

```
scores_test = model.evaluate_generator(generator = test_batches_pred, steps=1)  
print("Loss = ", scores_test[0], ", Accuracy = ", scores_test[1])
```


Model evaluation: ML models

Model name	Training method	Accuracy
KNN	Train & test set split	80.65%
	Grid search & cross validation	83.87%
XGBoost	Train & test set split	85.48%
	PCA for model tuning	88.71%

Model evaluation: DL models

Model name	Training method	Accuracy
ANN	Train & test set split	83.87%
	Cross validation	83.87%
CNN using VGG16	Train & test set split	79.16%
CNN model	Train & test set split	77.08%

List of deployed models in WML repository

Models

Watson Machine Learning models

NAME	STATUS	TYPE
XGBoost model for grape leaves disease classification	trained	scikit-learn-0.19
KNN model for grape leaves disease classification	trained	scikit-learn-0.19
ANN cv model for grape leaves disease classification v1-1	trained	tensorflow-1.5
CNN model for grape leaves disease classification 128-128 v3	trained	tensorflow-1.5
CNN model for grape leaves disease classification v1	trained	tensorflow-1.5

New Watson Machine Learning model

Deployments

NAME	TYPE	STATUS	ACTIONS
Predict grape leaves diseases	Web service	ready	
Predict grape leaves diseases KNN	Web service	ready	
Predict grape leaves diseases - CNN model final v1	Web service	ready	
Predict grape leaves diseases - CNN model final 128-128 v3	Web service	ready	
Predict grape leaves diseases - ANN cv model final v1-1	Web service	ready	

Models REST APIs

'redict grape leaves diseases

Overview Implementation Test

Implementation

Scoring End-point https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-326f7ff5deff/online

'redict grape leaves diseases KNN

Overview Implementation Test

Implementation

[View API Specification](#)

Scoring End-point https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-d220-4984-85e1-31cf24cd3369/deployments/77f737fc-8932-45bb-a991-b645fbc5e66b/online

'redict grape leaves diseases - CNN model final v1

Overview Implementation Test

Implementation

Scoring End-point https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-d220-4984-aff5055abab9/online

'redict grape leaves diseases - CNN model final 128-128 v3

Overview Implementation Test

Implementation

[View API Specification](#)

Scoring End-point https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-d220-4984-85e1-31cf24cd3369/deployments/f42ade46-aa26-4266-9028-1a52b01375ac/online

'redict grape leaves diseases - ANN cv model final v1-1

Overview Implementation Test

Implementation

[View API Specification](#)

Scoring End-point https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-d220-4984-85e1-31cf24cd3369/deployments/f9653920-f751-4726-847f-161b2099473e/online

Get the score using the model's REST API

```
img_file_name = "datasetWS_DvsEvshvsm_512-512_ext_set/esca.IMG_7508.jpg"
```

```
import numpy as np
from PIL import Image
```

```
img = Image.open(img_file_name)
img = img.resize((224, 224))
img = np.array(img)
img = img.astype('float32') / 255.0
img = img.reshape((1,224, 224,3))
type(img)
```

```
img_to_list = img.tolist()
img_to_list
```

```
scoring_payload = {"values": img_to_list}
#print(scoring_payload)
```

```
model_deployment_endpoint_url = 'https://us-south.ml.cloud.ibm.com/v3/wml_instances/985d7680-d220-4984-85e1-31cf24cd3369/deployments/c3374942-d0f1-477b-9cde-aff5055abab9/online'
```

```
parms = { "wml_credentials" : wml_credentials, "model_deployment_endpoint_url" : model_deployment_endpoint_url }
```

```
from watson_machine_learning_client import WatsonMachineLearningAPIClient
client = WatsonMachineLearningAPIClient( parms["wml_credentials"] )
model_result = client.deployments.score(model_deployment_endpoint_url, scoring_payload )
```

```
model_result
```

```
{'fields': ['prediction', 'prediction_classes', 'probability'],
 'values': [[[0.16954658925533295,
              0.44687438011169434,
              0.203651562333107,
              0.1799274981021881],
              1,
              [0.16954658925533295,
              0.44687438011169434,
              0.203651562333107,
              0.1799274981021881]]]]}
```

```
img_class = model_result["values"][0][1]
img_class
```

```
1
```



THANK YOU

A Newton's cradle is shown with five blue blocks hanging in a row, spelling out the word 'THANK'. To the right of these, there are three blue blocks hanging in a row, spelling out the word 'YOU'. The blocks are blue with white capital letters. The cradle is set against a plain white background.