National College of Ireland

Analysis of cloud environment for implementing machine leaning comparative to local server

MSc Research Project
Cloud Computing

Devaraj Devegowda
Student ID: 20125429

School of Computing
National College of Ireland

Supervisor: Sean Heeney

National College of Ireland

MSc Project Submission Sheet

School of Computing

Student Name:	Devaraj Devegowda		
Student ID:	20125429		
Programme:	Msc cloud computing	**Year:**	2022
Module:	Msc Research project		
Lecturer:	Sean Heeney		
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I hereby certify that the information contained in this (my submission) is information pertaining to research I conducted for this project. All information other than my own contribution will be fully referenced and listed in the relevant bibliography section at the rear of the project.
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Date: 28/04/2022

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Configuration Manual

Devaraj Devegowda
20125429

1 Introduction

This research consists of two development platforms for developing the machine learning. Local machine development and AWS cloud. In local machine learning models are built using Jupyter notebook. And web application is developed in online IDE Cloud 9. SageMaker is used for same ML models.

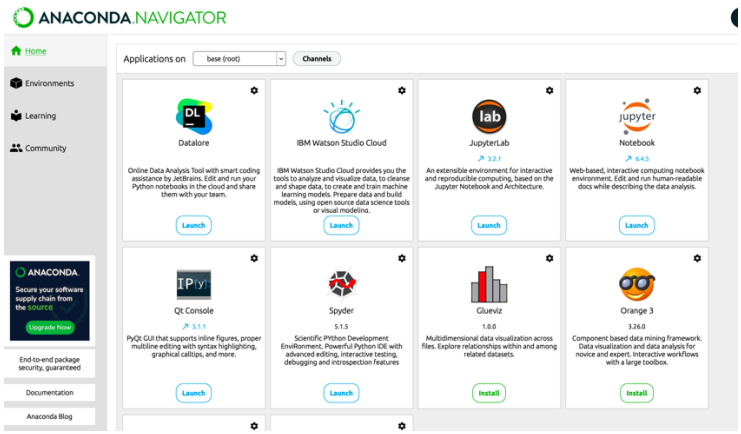
1.1 Before you begin

Before starting the project make installed below developer tools.

- Git bash: how to install is available athttps://www.educative.io/edpresso/how-to-install-git-bash-in-windows
- Pyhton SDK : https://realpython.com/installing-python/
- Anaconda for Jupyter Notebook: https://www.datacamp.com/community/tutorials/installing-anaconda-windows
- JMeter: https://www.simplilearn.com/tutorials/jmeter-tutorial/jmeter-installation

2 Machine learning implementation

Open the Anaconda navigator click on the jupyter notebook (Annaconda Jupyter, 2022)



After that jupyter notebook opens in default location

2.1 Crop recommendation

In [1]:
```
# Importing libraries

from __future__ import print_function
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import classification_report
from sklearn import metrics
from sklearn import tree
import warnings
#For interactivity
from ipywidgets import interact
warnings.filterwarnings('ignore')
```

In [2]:
```
PATH = 'Crop_recommendation.csv'
df = pd.read_csv(PATH)
```

In [3]:
```
df.head()
```

Out[3]:

	N	P	K	temperature	humidity	ph	rainfall	label
0	90	42	43	20.879744	82.002744	6.502985	202.935536	rice
1	85	58	41	21.770462	80.319644	7.038096	226.655537	rice
2	60	55	44	23.004459	82.320763	7.840207	263.964248	rice
3	74	35	40	26.491096	80.158363	6.980401	242.864034	rice
4	78	42	42	20.130175	81.604873	7.628473	262.717340	rice

At first we are importing all the necessary libraries and data set. Data set is stored in df variable.

```
In [10]: #Checking the Statistics for all the crops
         print("Average Ratio of nitrogen in the soil : {0: .2f}".format(df['N'].mean()))
         print("Average Ratio of Phosphorous in the soil : {0: .2f}".format(df['P'].mean()))
         print("Average Ratio of Potassium in the soil : {0: .2f}".format(df['K'].mean()))
         print("Average temperature in Celsius : {0: .2f}".format(df['temperature'].mean()))
         print("Average Relative Humidity in % is : {0: .2f}".format(df['humidity'].mean()))
         print("Average pH value of the soil : {0: .2f}".format(df['ph'].mean()))
         print("Average Rain fall in mm : {0: .2f}".format(df['rainfall'].mean()))

         Average Ratio of nitrogen in the soil :  50.55
         Average Ratio of Phosphorous in the soil :  53.36
         Average Ratio of Potassium in the soil :  48.15
         Average temperature in Celsius :  25.62
         Average Relative Humidity in % is :  71.48
         Average pH value of the soil :  6.47
         Average Rain fall in mm :  103.46
```

Above shows that nitrogen,Phosphorous and potassium should be around 50%

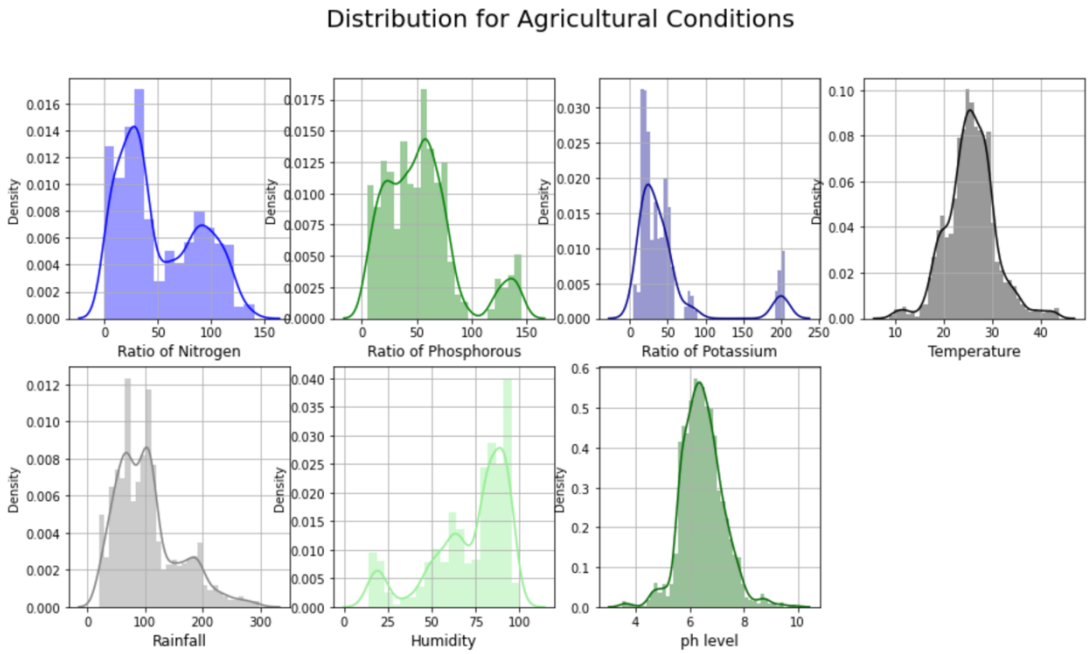
Temperature should be around 25°C and Humidity around 70%

Rain fall should be around 100mm and PH should be arount 7

```
In [11]: df['label'].value_counts()

Out[11]: rice           100
         maize          100
         jute           100
         cotton         100
         coconut        100
         papaya         100
         orange         100
         apple          100
         muskmelon      100
         watermelon     100
         grapes         100
         mango          100
         banana         100
         pomegranate    100
         lentil         100
         blackgram      100
         mungbean       100
         mothbeans      100
         pigeonpeas     100
         kidneybeans    100
         chickpea       100
         coffee         100
         Name: label, dtype: int64
```

Above functions shows the number crops in data set.

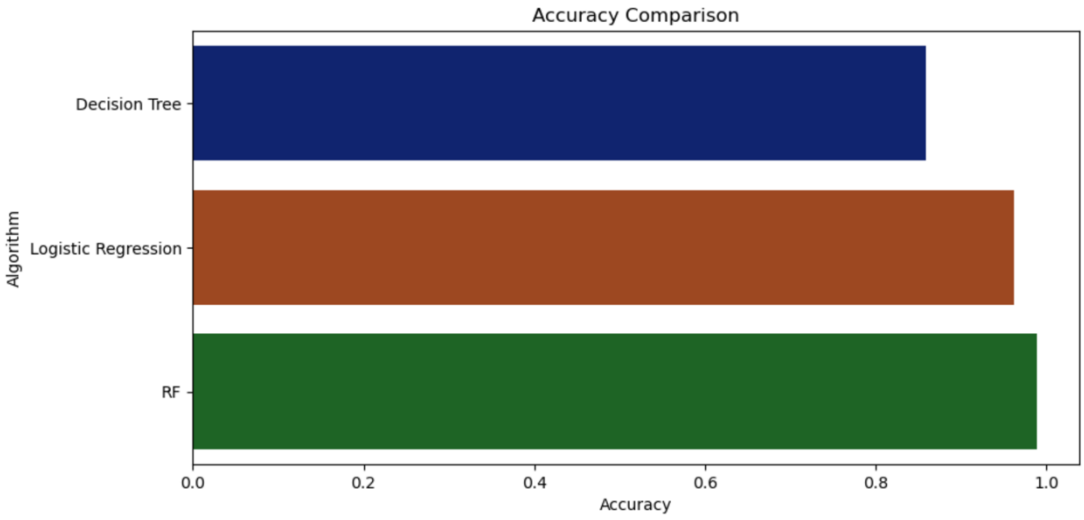


Above Graph shows us many hidden patterns like many crops need Phosphorous and Potassium at very high level.

Before the doing the modelling data is divided into two one is training and other for testing. In our dataset we are using 20 percent for testing and 80 percent for training.

We are using three different Modelling Classification algorithms

1. Decision Tree
2. Logistic Regression
3. Random Forest



From the above output we can see that random forest gives more accuracy so we will use random forest for predicting the crop. Sample output is given below.

In [33]:
```
accuracy_models = dict(zip(model, acc))
for k, v in accuracy_models.items():
    print (k, '-->', v)
```

```
Decision Tree --> 0.8590909090909091
Logistic Regression --> 0.9621212121212122
RF --> 0.9893939393939394
```

Making a prediction

In [34]:
```
data = np.array([[50,18, 67, 23.603016, 60.3, 6.7, 140.91]])
prediction = RF.predict(data)
print(prediction)
```

```
['pomegranate']
```

In [35]:
```
data = np.array([[83, 45, 60, 28, 70.3, 7.0, 150.9]])
prediction = RF.predict(data)
print(prediction)
```

```
['jute']
```

2.2 Crop yield prediction

At first, we imported important libraries and dataset. In this modelling we are using four different datasets which are

1. Yield.csv
2. Temperature.csv
3. Rainfall.csv
4. Pesticides.csv

In [1]:
```
import numpy as np
import pandas as pd
```

In [2]:
```
df_yield = pd.read_csv('yield.csv')
df_yield.shape
```

Out[2]: (56717, 12)

In [3]:
```
df_yield.head()
```

Out[3]:

	Domain Code	Domain	Area Code	Area	Element Code	Element	Item Code	Item	Year Code	Year	Unit	Value
0	QC	Crops	2	Afghanistan	5419	Yield	56	Maize	1961	1961	hg/ha	14000
1	QC	Crops	2	Afghanistan	5419	Yield	56	Maize	1962	1962	hg/ha	14000
2	QC	Crops	2	Afghanistan	5419	Yield	56	Maize	1963	1963	hg/ha	14260
3	QC	Crops	2	Afghanistan	5419	Yield	56	Maize	1964	1964	hg/ha	14257
4	QC	Crops	2	Afghanistan	5419	Yield	56	Maize	1965	1965	hg/ha	14400

```
In [6]: # drop unwanted columns.
df_yield = df_yield.drop(['Year Code','Element Code','Element','Year Code','Area Code','Domain Code','Domain','Unit'
df_yield.head()
```

Out[6]:

	Area	Item	Year	hg/ha_yield
0	Afghanistan	Maize	1961	14000
1	Afghanistan	Maize	1962	14000
2	Afghanistan	Maize	1963	14260
3	Afghanistan	Maize	1964	14257
4	Afghanistan	Maize	1965	14400

Removing all other columns which are not needed.

Rainfall

.

```
In [9]: df_rain = pd.read_csv('rainfall.csv')
df_rain.head()
```

Out[9]:

	Area	Year	average_rain_fall_mm_per_year
0	Afghanistan	1985	327
1	Afghanistan	1986	327
2	Afghanistan	1987	327
3	Afghanistan	1989	327
4	Afghanistan	1990	327

Now we need to merge the rainfall data with yield data.

In [15]:
```
# merge yield dataframe with rain dataframe by year and area columns
yield_df = pd.merge(df_yield, df_rain, on=['Year','Area'])
```

Now, we view the final shape of the dataframe and info of values:

In [16]:
```
yield_df.shape
```

Out[16]:
```
(25385, 5)
```

In [17]:
```
yield_df.head()
```

Out[17]:

	Area	Item	Year	hg/ha_yield	average_rain_fall_mm_per_year
0	Afghanistan	Maize	1985	16652	327.0
1	Afghanistan	Potatoes	1985	140909	327.0
2	Afghanistan	Rice, paddy	1985	22482	327.0
3	Afghanistan	Wheat	1985	12277	327.0
4	Afghanistan	Maize	1986	16875	327.0

Final dataset is shown below.

Data Exploration

yield_df is the final obtained dataframe;

In [33]:
```
yield_df.groupby('Item').count()
```

Out[33]:

Item	Area	Year	hg/ha_yield	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp
Cassava	2045	2045	2045	2045	2045	2045
Maize	4121	4121	4121	4121	4121	4121
Plantains and others	556	556	556	556	556	556
Potatoes	4276	4276	4276	4276	4276	4276
Rice, paddy	3388	3388	3388	3388	3388	3388
Sorghum	3039	3039	3039	3039	3039	3039
Soybeans	3223	3223	3223	3223	3223	3223
Sweet potatoes	2890	2890	2890	2890	2890	2890
Wheat	3857	3857	3857	3857	3857	3857
Yams	847	847	847	847	847	847

Data Preprocessing

In [41]:
```
from sklearn.preprocessing import OneHotEncoder
```

In [42]:
```
yield_df_onehot = pd.get_dummies(yield_df, columns=['Area',"Item"], prefix = ['Country',"Item"])
features=yield_df_onehot.loc[:, yield_df_onehot.columns != 'hg/ha_yield']
label=yield_df['hg/ha_yield']
features.head()
```

Out[42]:

	Year	average_rain_fall_mm_per_year	pesticides_tonnes	avg_temp	Country_Albania	Country_Algeria	Country_Angola	Country_Argentina	Country_Armenia
0	1990	1485.0	121.0	16.37	1	0	0	0	0
1	1990	1485.0	121.0	16.37	1	0	0	0	0
2	1990	1485.0	121.0	16.37	1	0	0	0	0
3	1990	1485.0	121.0	16.37	1	0	0	0	0
4	1990	1485.0	121.0	16.37	1	0	0	0	0

5 rows × 115 columns

Scaling dataset

In [46]:
```
from sklearn.preprocessing import MinMaxScaler
scaler=MinMaxScaler()
features=scaler.fit_transform(features)
```

After dropping year column in addition to scaling all values in features, the resulting array will look something like this :

In [47]:
```
features
```

Out[47]:
```
array([[4.49670743e-01, 3.28894097e-04, 5.13458262e-01, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [4.49670743e-01, 3.28894097e-04, 5.13458262e-01, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [4.49670743e-01, 3.28894097e-04, 5.13458262e-01, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       ...,
       [1.90028222e-01, 6.93361288e-03, 6.28960818e-01, ...,
        0.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [1.90028222e-01, 6.93361288e-03, 6.28960818e-01, ...,
        1.00000000e+00, 0.00000000e+00, 0.00000000e+00],
       [1.90028222e-01, 6.93361288e-03, 6.28960818e-01, ...,
        0.00000000e+00, 1.00000000e+00, 0.00000000e+00]])
```

Training data

The training and test datasets will be separated from the original dataset. Because training the model usually necessitates as many data points as feasible, the data is usually split inequitably. For train/test, the most typical splits are 70/30 or 80/20.

Below code shows how to split data set

from sklearn.model_selection import train_test_split

train_data, test_data, train_labels, test_labels = train_test_split(features, label, test_size=0.3, random_state=42)

2.2.1 Model Comparison & Selection

In [51]:
```
from sklearn.metrics import r2_score
def compare_models(model):
    model_name = model.__class__.__name__
    fit=model.fit(train_data,train_labels)
    y_pred=fit.predict(test_data)
    r2=r2_score(test_labels,y_pred)
    return([model_name,r2])
```

In [52]:
```
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn import svm
from sklearn.tree import DecisionTreeRegressor

models = [
    GradientBoostingRegressor(n_estimators=200, max_depth=3, random_state=0),
     RandomForestRegressor(n_estimators=200, max_depth=3, random_state=0),
    svm.SVR(),
   DecisionTreeRegressor()
]
```

In [53]:
```
model_train=list(map(compare_models,models))
```

In [54]:
```
print(*model_train, sep = "\n")
```

```
['GradientBoostingRegressor', 0.8965768919264416]
['RandomForestRegressor', 0.6842532317855172]
['SVR', -0.19543203867357395]
['DecisionTreeRegressor', 0.9603891419978052]
```

In [61]:
```
clf=DecisionTreeRegressor()
model=clf.fit(train_data,train_labels)

test_df["yield_predicted"]= model.predict(test_data)
test_df["yield_actual"]=pd.DataFrame(test_labels)["hg/ha_yield"].tolist()
test_group=test_df.groupby("Item")
test_group.apply(lambda x: r2_score(x.yield_actual,x.yield_predicted))
```

Out[61]:
```
Item
Cassava                 0.925671
Maize                   0.885694
Plantains and others    0.813427
Potatoes                0.910657
Rice, paddy             0.892735
Sorghum                 0.802142
Soybeans                0.818423
Sweet potatoes          0.840371
Wheat                   0.921280
Yams                    0.925841
dtype: float64
```

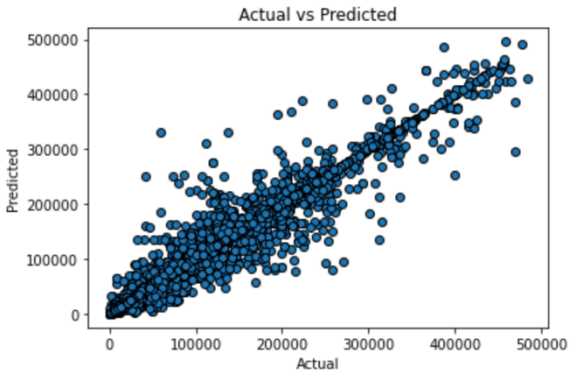
Actual values vs Predicted value

```
In [62]: # So let's run the model actual values against the predicted ones

         fig, ax = plt.subplots()

         ax.scatter(test_df["yield_actual"], test_df["yield_predicted"],edgecolors=(0, 0, 0))

         ax.set_xlabel('Actual')
         ax.set_ylabel('Predicted')
         ax.set_title("Actual vs Predicted")
         plt.show()
```



3 Web application development and deployment

Web application is built python 3 flask framework. Code for the whole application is available at https://github.com/devaraj-ncirl/Crop_recommendation (GitHub, 2022)

To clone the above project use the following command

git clone ” https://github.com/devaraj-ncirl/Crop_recommendation”

Create cloud 9 online IDE with python 3 installation

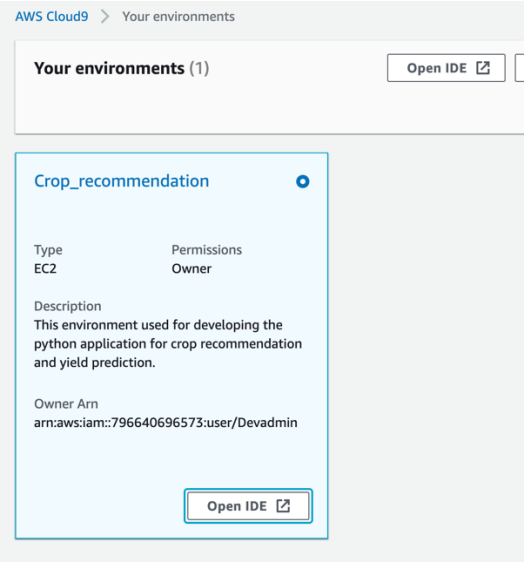


Figure 1: Cloud9 IDE

Clone web application using git command

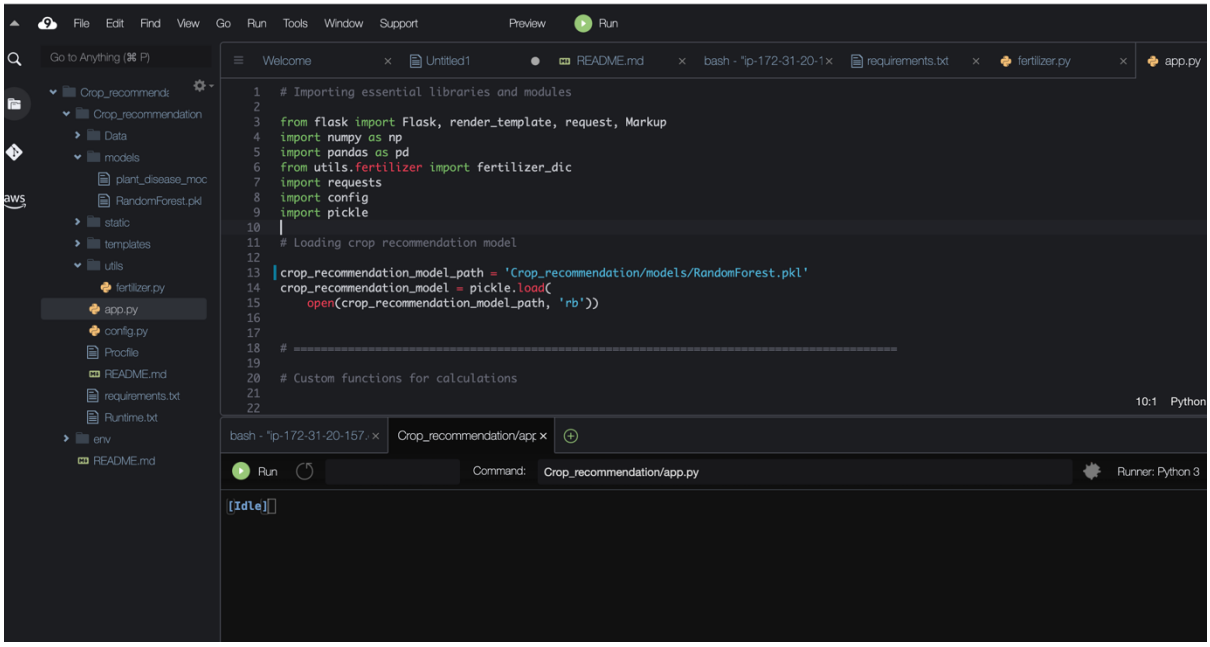


Figure2: cloud 9 IDE with Code

If there are any changes in code commit the code first then push it.

To commit code: git commit -m “message”
To push code: git push -origin master

After the full development of application, it is deployed to Elastic Beanstalk

3.1 Elastic beanstalk

Create Python environment in Elastic beanstalk use t2.mciro instance.

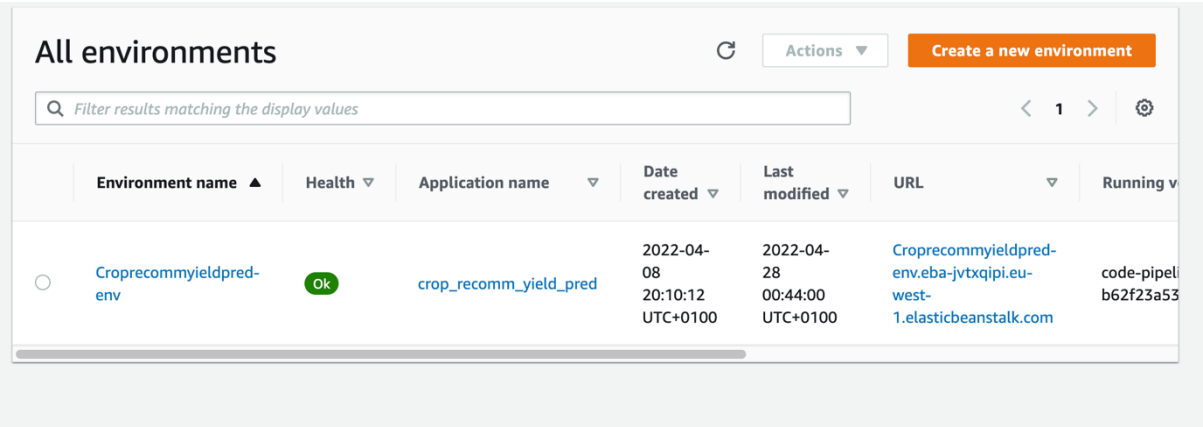


Figure 3: Python environment in elastic Beanstalk

3.2 Code Pipeline

Create code pipeline CI/CD integration (AWS, 2022)

Create source using GitHub

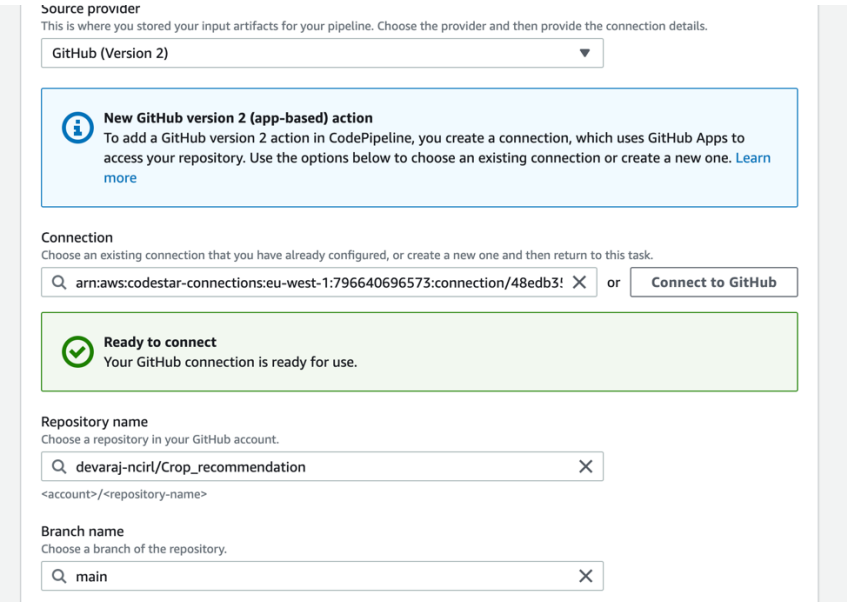


Figure 4: Code pipeline setup

Connect to crop recommendation repo and select main branch

Later on deploy stage select already created Elastic bean stalk enviornment.

At the end it should look like below diagram

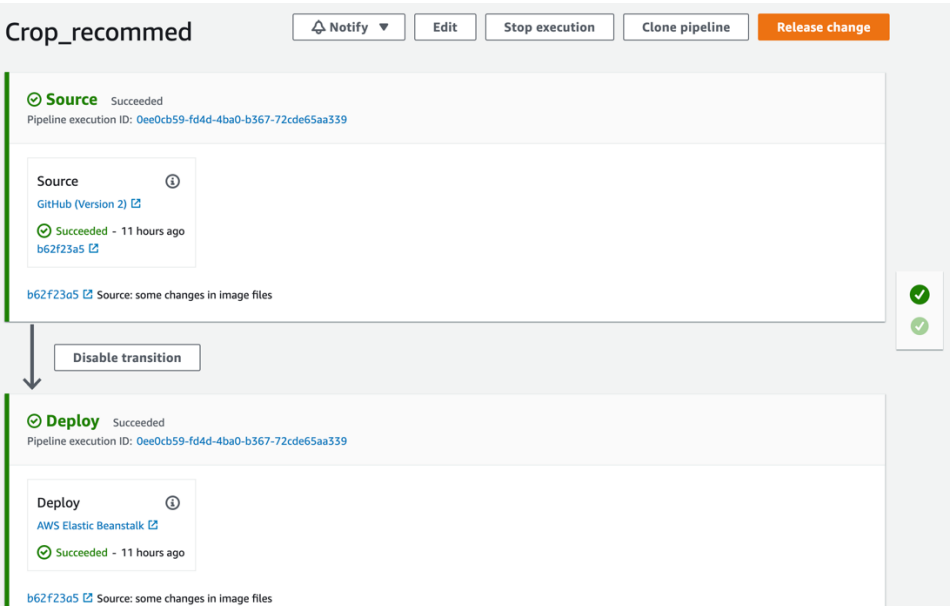


Figure 5: code pipeline success stage

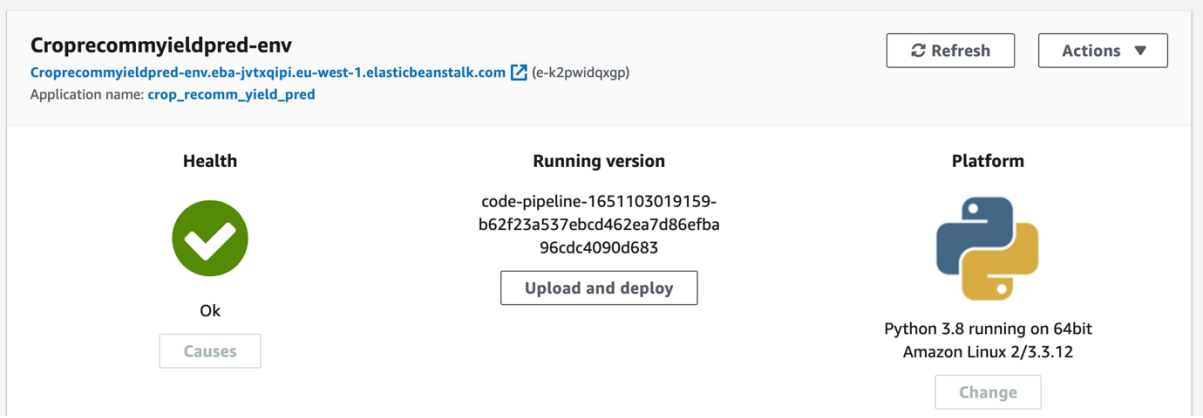


Figure6: Successful deployment in Elastic beanstalk

After that once we click on web application it should display the homepage

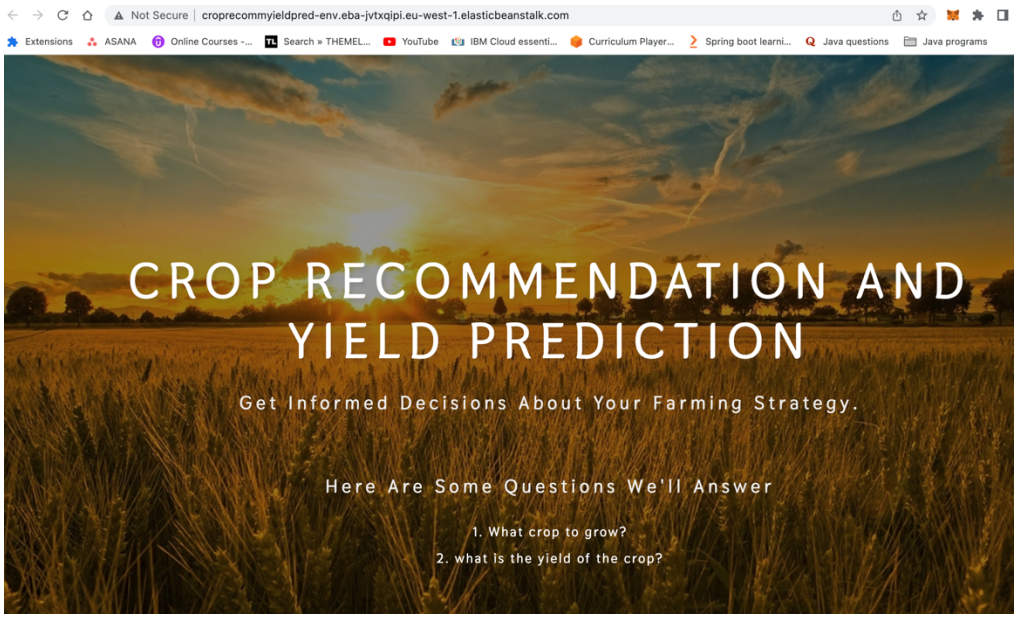


Figure 7 : Home page of Web application

3.3 Web application working

Web application consist of two main features crop recommendation and yield prediction

In home page nav bar click on crop recommend button form will be given to fill details

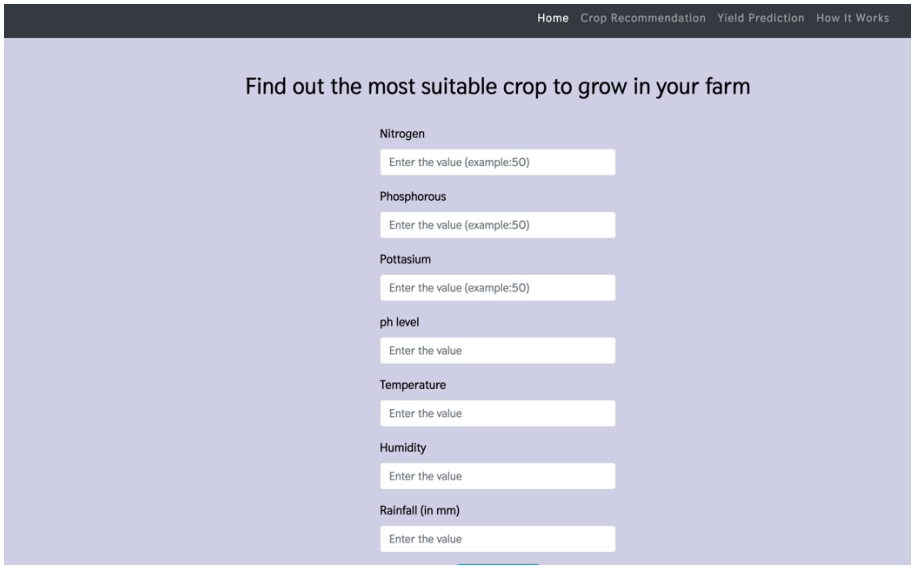


Figure 8 : Form of input data

After filling all the details click on submit button it should give predicted output.

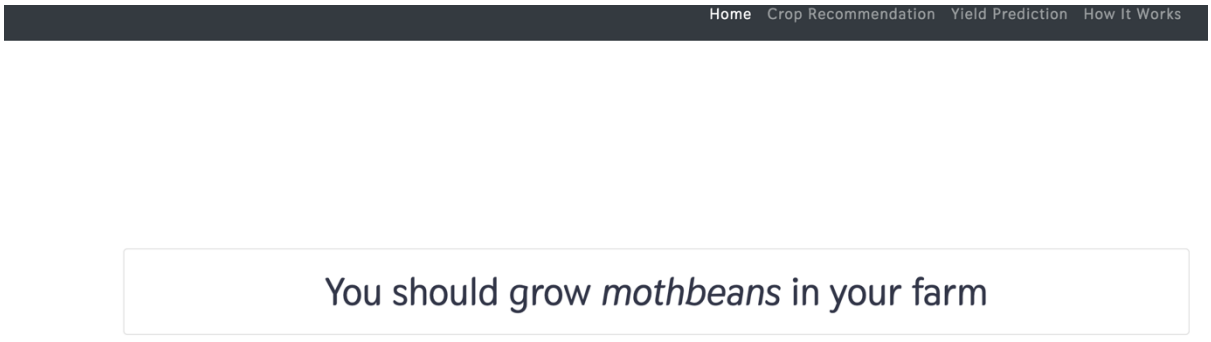


Figure 9: predicted output

same way you can do with crop yield prediction.

4 Machine learning using AWS SageMaker

Create SageMaker Studio

Create Note instance for Machine learning model development ml.t2.meduim (AWS, 2022)

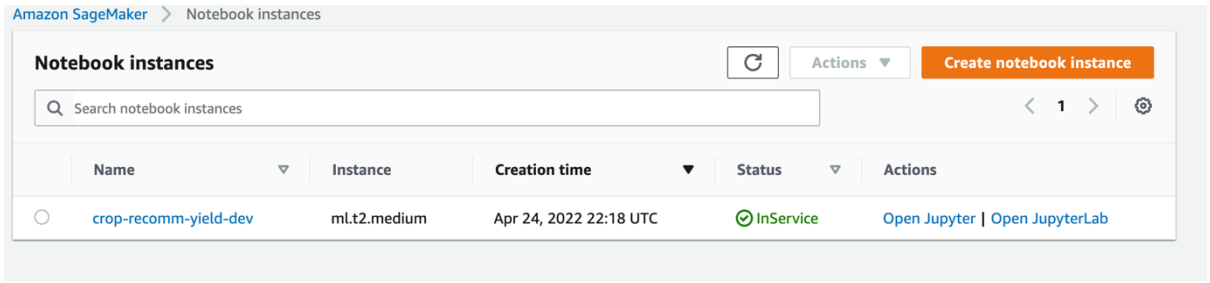


Figure 10: Notebook instance

Next step open Jupyter Notebook

Write the code Crop recommendation algorithm in Sage maker note book

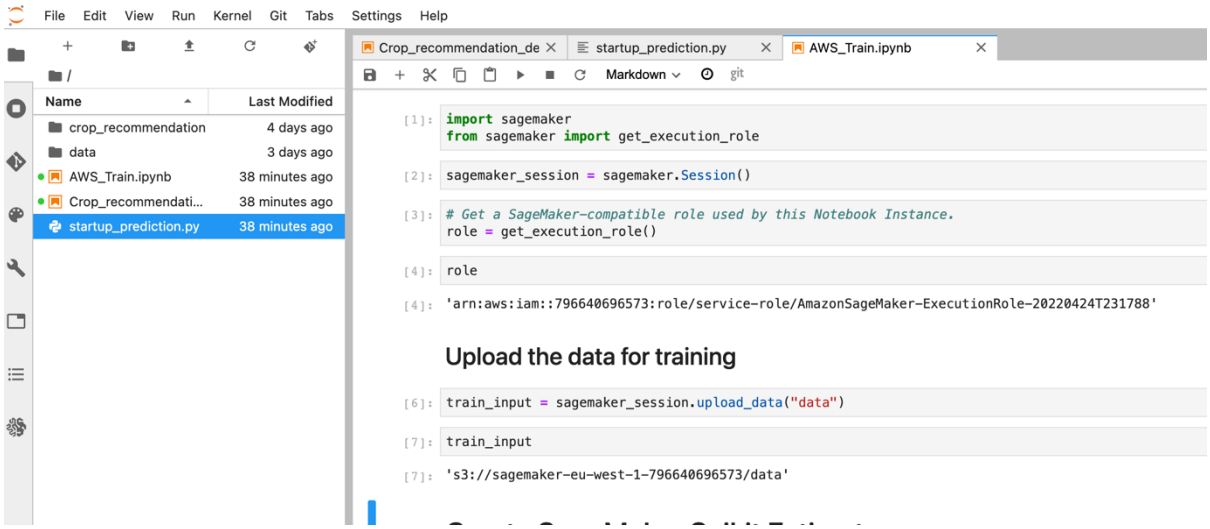


Figure 11: Notebook overview

Load the trained data to S3 bucket

Trian the model using sklearn container

```
[8]: from sagemaker.sklearn.estimator import SKLearn

script_path = 'startup_prediction.py'

sklearn = SKLearn(
    entry_point=script_path,
    instance_type="ml.m4.xlarge",
    framework_version="0.20.0",
    py_version="py3",
    role=role,
    use_spot_instances=True,
    max_run=300,
    max_wait=600)
    sagemaker_session=sagemaker_session)
```

Train SKLearn Estimator on Startup data

```
[9]: sklearn.fit({'train': train_input})
2022-04-25 09:15:48 Starting - Starting the training job...ProfilerReport-1650878148: InProgress
...
2022-04-25 09:16:31 Starting - Preparing the instances for training......
2022-04-25 09:17:34 Downloading - Downloading input data...
2022-04-25 09:18:12 Training - Downloading the training image......
2022-04-25 09:19:12 Uploading - Uploading generated training model2022-04-25 09:19:03,222 sagemaker-containers IN
ported framework sagemaker_sklearn_container.training
2022-04-25 09:19:03,226 sagemaker-training-toolkit INFO     No GPUs detected (normal if no gpus installed)
2022-04-25 09:19:03,238 sagemaker_sklearn_container.training INFO     Invoking user training script.
2022-04-25 09:19:03,721 sagemaker-training-toolkit INFO     No GPUs detected (normal if no gpus installed)
2022-04-25 09:19:03,746 sagemaker-training-toolkit INFO     No GPUs detected (normal if no gpus installed)
2022-04-25 09:19:03,771 sagemaker-training-toolkit INFO     No GPUs detected (normal if no gpus installed)
2022-04-25 09:19:03,790 sagemaker-training-toolkit INFO     Invoking user script
Training Env:
{
```

Deploy the model

```
deployment = sklearn.deploy(initial_instance_count=1, instance_type="ml.m4.xlarge")
```

```
------!
```

```
deployment.endpoint_name
```

```
'sagemaker-scikit-learn-2022-04-25-09-20-00-666'
```

```
result=deployment.predict([[21,21, 23, 23.603016, 60.3, 5.5, 198.91]])
```

```
print(result)
```

```
['pigeonpeas']
```

Create lambda function for calling SageMaker endpoint

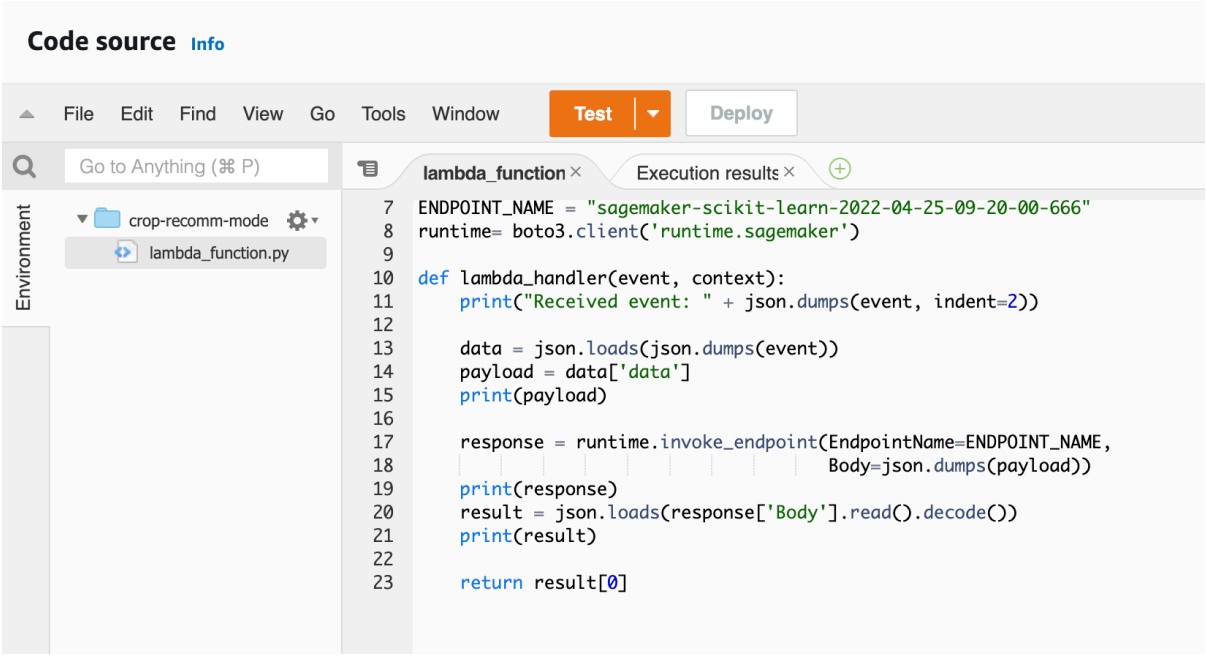


Figure 12: lambda function

4.1.1 API gateway

Create API Gateway to call lambda function

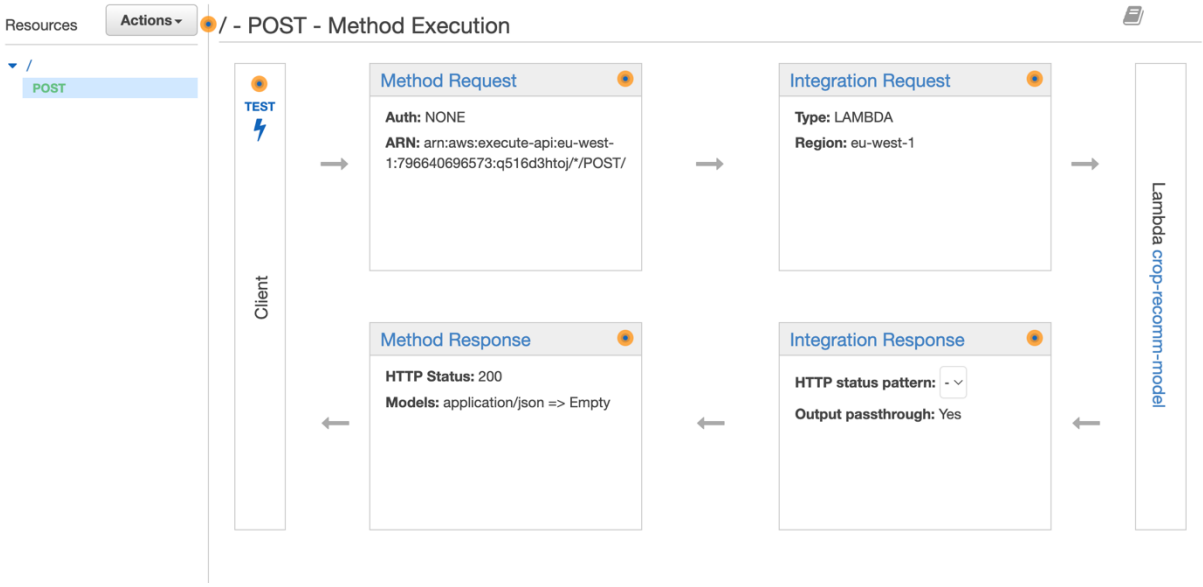


Figure 13: API Gateway

Output:

Using the postman call the endpoint check the output

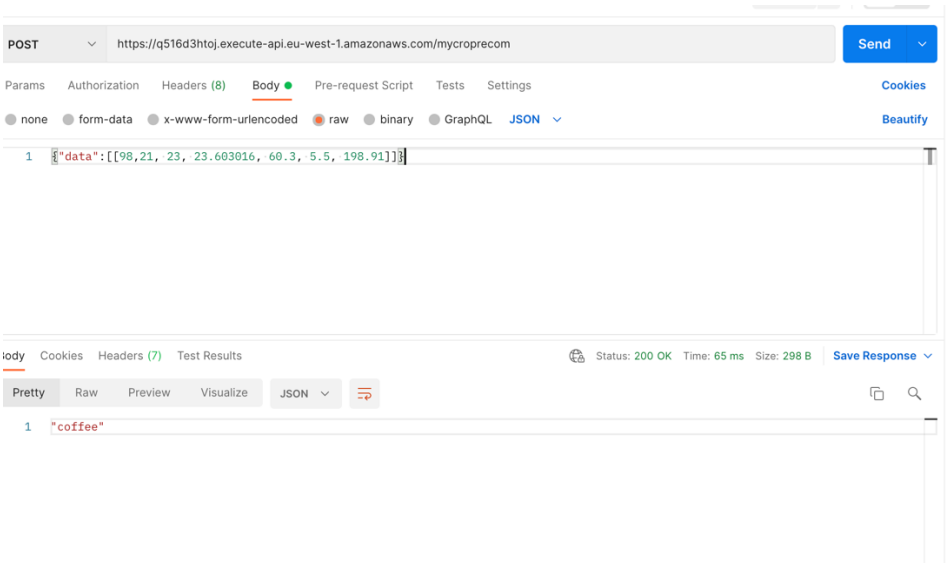


Figure 14: Output of lambda function

5 Performance testing

Install JMeter in Local machine

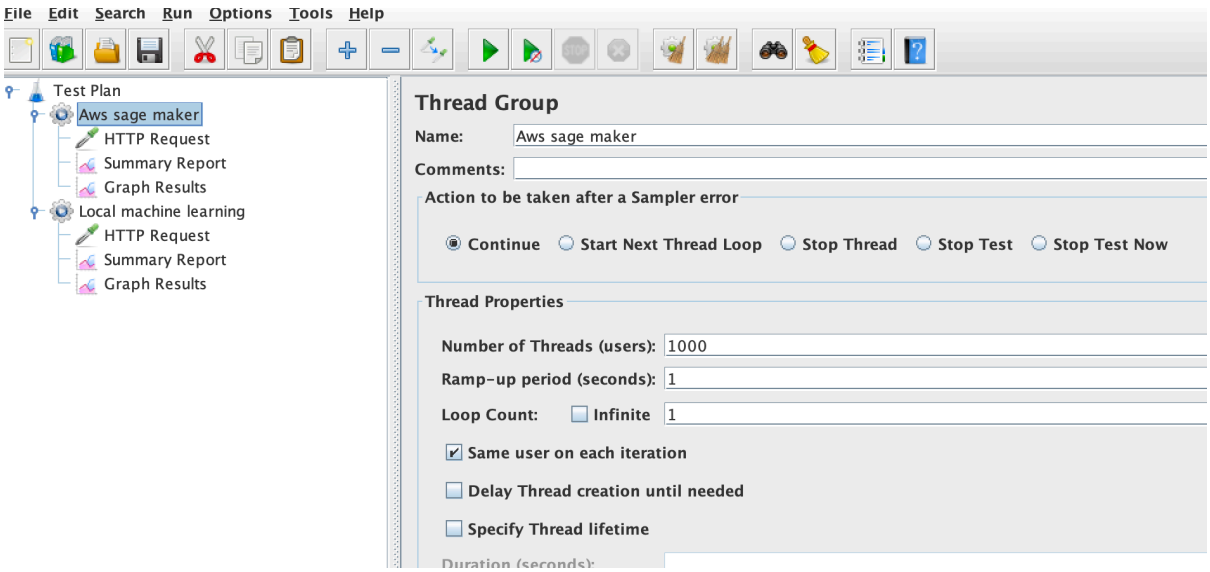


Figure 15: JMeter setup

Create two threads one fore AWS SageMaker endpoint and other is for web application

For each Thread add Http request, summary report and graphs.

One end point is

API Gateway enpoint: https://q516d3htoj.execute-api.eu-west-1.amazonaws.com/mycroprecom
Web application endpoint: http://croprecommyieldpred-env.eba-jvtxqipi.eu-west-1.elasticbeanstalk.com/crop-predict

For each experiment keep changing the no of threads

Sample summary report should look like below diagram

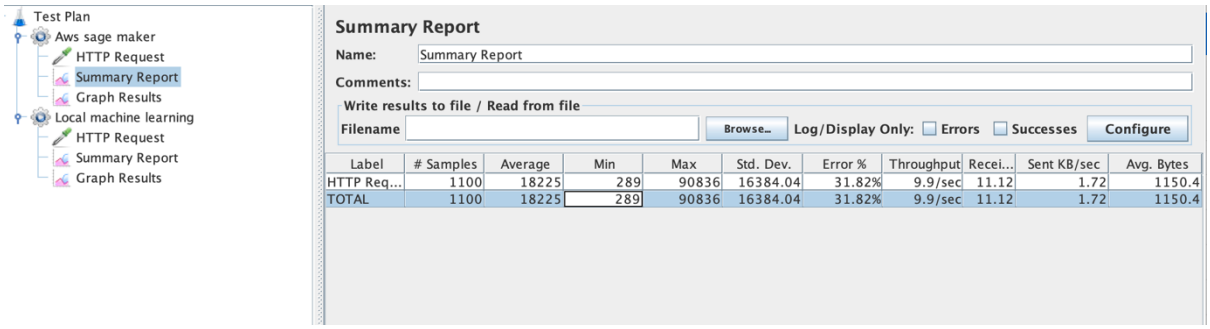


Figure 16: JMeter setup

References

Annaconda Jupyter (no date) *Anaconda*. Available at: https://www.anaconda.com/ (Accessed: April 28, 2022).
AWS (2022) *AWS Sage Maker*, *AWS*. Available at: https://aws.amazon.com/getting-started/hands-on/build-train-deploy-machine-learning-model-sagemaker/ (Accessed: April 28, 2022).
AWS (no date) *AWS code pipline*, *2022*. Available at: https://aws.amazon.com/codepipeline/ (Accessed: April 28, 2022).
GitHub (no date) *GiHUb*, *2022*. Available at: https://github.com/ (Accessed: April 28, 2022).