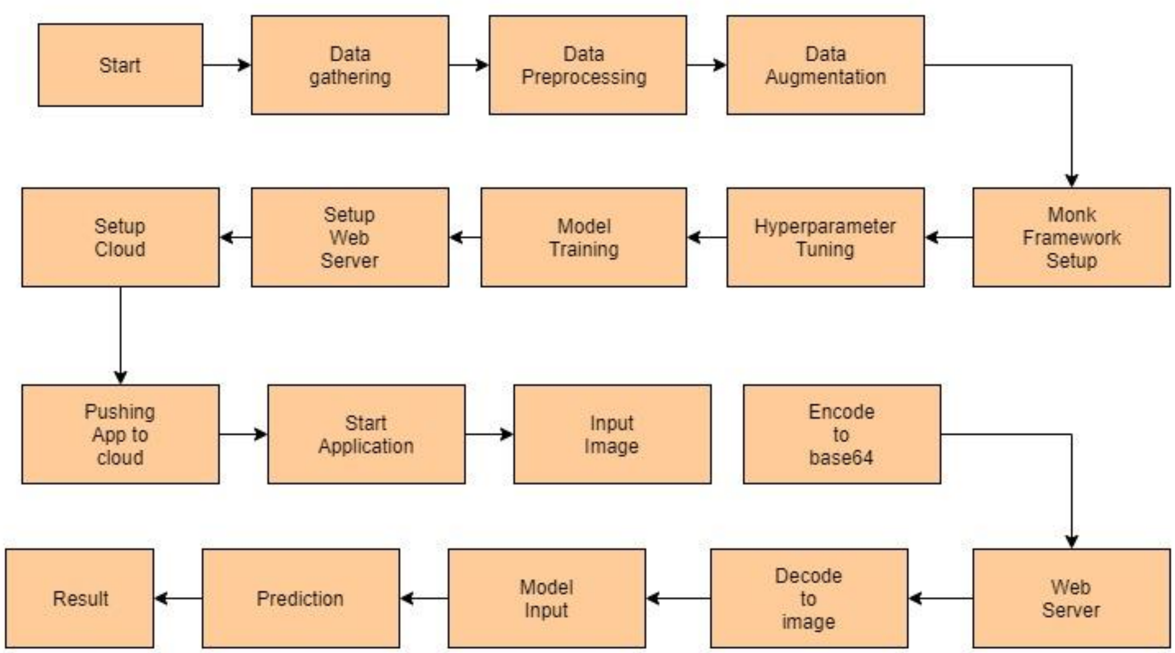
Plant Disease Classification

1. Description

In agriculture, leaf diseases cause a significant decrease in both quality and quantity of yields of crops. Automating the process of plant disease detection using Computer Vision could play a vital role in early detection and prevention of diseases.

Crop diseases are a significant threat to food security, but their rapid identification remains difficult in many parts of the world due to the lack of the necessary infrastructure. The combination of increasing edge and mobile devices penetration and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a public dataset of 54,306 images of diseased and healthy plant leaves collected under controlled conditions, we train a deep convolutional neural network to identify 14 crop species and 26 diseases.

2. Architecture



3. Data

We will be using the dataset gathered by PlantVillage (https://plantvillage.psu.edu/).

Dataset Link:-

https://www.dropbox.com/s/hgt9uystjlinzlp/plantVillage.zip

4. Data Description

We analyze 54,306 images of plant leaves, which have a spread of 38 class labels assigned to them. Each class label is a crop-disease pair, and we make an attempt to predict the crop-disease couple given just the image of the plant leaf. Figure 1 shows one example each from every crop-disease pair from the PlantVillage dataset. In all the approaches described in this paper, we resize the images to 256 × 256 pixels, and we perform both the model optimization and predictions on these downscaled images.

Dataset Size :-

* Number of train images: 44014

* Number of validation images: 11004

* Number of classes: 39

Name of different categories: -

id	labels
0	Strawberry___healthy
1	background
2	Grape___Black_rot
3	Potato___Early_blight
4	Blueberry___healthy
5	Corn_(maize)___healthy
6	Tomato___Target_Spot
7	Peach___healthy
8	Potato___Late_blight
9	Tomato___Late_blight
10	Tomato___Tomato_mosaic_virus
11	Pepper_bell___healthy

12	Orange___Haunglongbing_(Citrus_greening)
13	Tomato___Leaf_Mold
14	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)
15	Cherry_(including_sour)___Powdery_mildew
16	Apple___Cedar_apple_rust
17	Tomato___Bacterial_spot
18	Grape___healthy
19	Tomato___Early_blight
20	Corn_(maize)___Common_rust_
21	Grape___Esca_(Black_Measles)
22	Raspberry___healthy
23	Tomato___healthy
24	Cherry_(including_sour)___healthy
25	Tomato___Tomato_Yellow_Leaf_Curl_Virus
26	Apple___Apple_scab
27	Corn_(maize)___Northern_Leaf_Blight
28	Tomato___Spider_mites Two-spotted_spider_mite
29	Peach___Bacterial_spot
30	Pepper_bell___Bacterial_spot
31	Tomato___Septoria_leaf_spot
32	Squash___Powdery_mildew
33	Corn_(maize)___Cercospora_leaf_spot Gray_leaf_spot
34	Apple___Black_rot
35	Apple___healthy
36	Strawberry___Leaf_scorch
37	Potato___healthy
38	Soybean___healthy

Possible use cases in different domain

5. Data Augment

We can implement data augmentation by using the Augmentor Library. (https://github.com/mdbloice/Augmentor)

But we will not be implementing this right now.

Install the library by :- `pip install Augmentor`

There are multiple functions that you can implement some of them are applied here. For more check https://augmentor.readthedocs.io/en/master/

```
import Augmentor

# Initiating the Augmentor Pipeline
p = Augmentor.Pipeline("C:\\Users\soura\Desktop\Images")

# Applying various type of Transformations and augmentation strategies
p.rotate(probability=0.7, max_left_rotation=10, max_right_rotation=10)
p.rotate90(probability=0.5)
p.rotate270(probability=0.5)
p.flip_left_right(probability=0.75)
p.flip_top_bottom(probability=0.5)
p.crop_random(probability=1, percentage_area=0.5)
p.resize(probability=1.0, width=80, height=80)
p.random_brightness(probability = 0.5, min_factor=0.4, max_factor=0.9)
p.random_color(probability=0.5, min_factor=0.4, max_factor=0.9)
p.random_contrast(probability=0.5, min_factor=0.9, max_factor=1.4)
p.random_distortion(probability=0.5, grid_width=7, grid_height=8,
magnitude=9)
p.random_erasing(probability=0.5, rectangle_area=0.4)
p.zoom(probability=0.7, min_factor=1.1, max_factor=1.5)

#change the samples size according to requirements
p.sample(100)
```

6. Train test validation

7. Training

7.1 Installation and Setup

Here we will be using the monk framework (https://clever-noyce-f9d43f.netlify.com/#/) which is built on top of Pytorch to train and test our model.

Installation

1. Clone library from github

```
git clone https://github.com/Tessellate-Imaging/monk_v1
```

2. Setup virtual environment

```
virtualenv -p python3 monk
```

```
workon monk
```

3. Setup Dependencies

Install dependencies for Linux CPU-only

```
cd monk_v1/installation
```

```
pip install -r requirements-cpu.txt
```

Install dependencies for MacOS CPU-only

```
cd monk_v1/installation
```

```
pip install -r requirements-cpu_macos.txt
```

Install dependencies for systems with GPU

For CUDA == 9.0

```
cd monk_v1/installation
```

```
pip install -r requirements-cu9.txt
```

For CUDA == 10.0 (Colab/Kaggle)

```
cd monk_v1/installation
```

```
pip install -r requirements-cu10.txt
```

Dataset Download

```
wget https://www.dropbox.com/s/hgt9uystjlinzlp/plantVillage.zip
```

```
unzip plantVillage.zip
```

Import Monk library

Place monk inside your project folder

```
import os

import sys

sys.path.append("./monk/")

from pytorch_prototype import prototype
```

```
#import system packages
import sys
import os
sys.path.append("./monk_v1/monk")
```

```
from pytorch_prototype import prototype
```

Create Experiment Setup

Step 1. - Create experiment

```
experiment = prototype(verbose=1)
experiment.Prototype("plant_disease", "experiment1")
experiment.Default(dataset_path=["./dataset/train", "./dataset/val"], model_name="resnet18",
freeze_base_network=True, num_epochs=5);
experiment.train()
```

```
# Create experiment setup initializing the "experiment" object

experiment = prototype(verbose=1);
experiment.Prototype("plant_disease", "experiment1");
```

```
experiment.Default(dataset_path=[r"/home/paperspace/plantVillage/dataset/train",
                                 r"/home/paperspace/plantVillage/dataset/val"],
                   model_name="resnet18", freeze_base_network=True, num_epochs=5);
```

Step2. – Using the model finder to find the best parameters for model training.

model_fetch = "Model_Finder";

models = [["resnet34", True, True], ["resnet50", False, True], ["densenet121", False, True], ["densenet169", True, True], ["densenet201", True, True]];

- First element in the list — Model Name
- Second element in the list — Boolean value to freeze base network or not
- Third element in the list — Boolean value to use pretrained model as the starting point or not

Number of epochs for each experiment to run

epochs=5;

Percentage of original dataset to take in for experimentation

percent_data=10;

"keep_all" - Keep all the sub experiments created
"keep_non" - Delete all sub experiments created

experiment.Analyse_Models(model_fetch , models, percent_data, num_epochs=epochs, state="keep_none");

```
# Project Name: Model_Finder
model_fetch = "Model_Finder";

# Analyzing Model
# In the first element list- Model Names
# In the Second element list - Boolean value to freeze base network or not
# In the Third element list - Boolean value to use pretrained model as the starting point or not
models = [["resnet34", True, True], ["resnet50", False, True],
          ["densenet121", False, True], ["densenet169", True, True], ["densenet201", True, True]];

# Number of epochs for each experiment to run
epochs=5;

# Percentage of original dataset to take in for experimentation
percent_data=10;

# "keep_all" - Keep all the sub experiments created
# "keep_non" - Delete all sub experiments created
experiment.Analyse_Models(model_fetch, models, percent_data, num_epochs=epochs, state="keep_none");
```

```
Comparing Experiments
Comparison ID:      Comparison_Model_Finder
Generated statistics post all epochs
| Experiment Name                             |  Train Acc |  Val Acc |  Train Loss |  Val Loss |
|---------------------------------------------+------------+----------+-------------+-----------|
| Model_resnet34_freeze_base_pretrained       |   0.824629 | 0.8407   |    0.614053 |  0.468221 |
| Model_resnet50_unfreeze_base_pretrained     |   0.960775 | 0.973297 |    0.133728 |  0.112808 |
| Model_densenet121_unfreeze_base_pretrained  |   0.967617 | 0.979742 |    0.124    |  0.066871 |
| Model_densenet169_freeze_base_pretrained    |   0.880502 | 0.896869 |    0.466162 |  0.339534 |
| Model_densenet201_freeze_base_pretrained    |   0.873432 | 0.921731 |    0.486347 |  0.304517 |
```

Update the model

```
experiment.update_model_name("densenet121");
experiment.update_freeze_base_network(True);
experiment.update_use_pretrained(True);
experiment.Reload();
```

In [7]:
```
## Updating Model Architecture
experiment.update_model_name("densenet121");
experiment.update_freeze_base_network(True);
experiment.update_use_pretrained(True);
experiment.Reload();
```

Finding the best hyperparameters for the model

1. **Batch Size**

Finding the right batch size for training

Analysis Name :- batch_fetch

```
batch_fetch= "Batch_Size_Finder";
```

Best batch sizes to explore

```
batch_sizes = [4, 8, 16, 32];
```

Number of epochs for each experiment to run

```
epochs = 10;
```

Percentage of original dataset to take in for experimentation

percent_data = 10;

"keep_all" - Keep all the sub experiments created

"keep_non" - Delete all sub experiments created

experiment.Analyse_Batch_Sizes(batch_fetch, batch_sizes, percent_data, num_epochs=epochs, state="keep_none");

```
# Project Name: Batch_Size_Finder
batch_fetch = "Batch_Size_Finder";

# Batch sizes to explore
batch_sizes = [4, 8, 16, 32];

# Num epochs for each experiment to run
epochs = 10;

# Percentage of original dataset to take in for experimentation
percent_data = 10;

# "keep_all" - Keep all the sub experiments created
# "keep_non" - Delete all sub experiments created
experiment.Analyse_Batch_Sizes(batch_fetch, batch_sizes, percent_data, num_epochs=epochs, state="keep_none");
```

```
Comparing Experiments
Comparison ID:      Comparison_Batch_Size_Finder
Generated statistics post all epochs
| Experiment Name   |   Train Acc |   Val Acc |   Train Loss |   Val Loss |
|-------------------+-------------+-----------+--------------+------------|
| Batch_Size_4      |    0.896921 |  0.929098 |     0.368656 |   0.236665 |
| Batch_Size_8      |    0.934322 |  0.918048 |     0.274333 |   0.271655 |
| Batch_Size_16     |    0.94732  |  0.900552 |     0.286326 |   0.380388 |
| Batch_Size_32     |    0.936374 |  0.833333 |     0.390712 |   0.613298 |
```

Update batch size

Update Batch Size

experiment.update_batch_size(8);

experiment.Reload();

```
## Updating Batch Size
experiment.update_batch_size(8);
experiment.Reload();
```

2. Find the correct input size dimension

Analysis Project Name

inputsize_fetch = "Input_Size_Finder";

Input sizes to explore

input_sizes = [224, 256, 512];

Num epochs for each experiment to run

epochs=5;

Percentage of original dataset to take in for experimentation

percent_data=10;

"keep_all" - Keep all the sub experiments created

"keep_non" - Delete all sub experiments created

experiment.Analyse_Input_Sizes(inputsize_fetch , input_sizes, percent_data, num_epochs=epochs, state="keep_none");

```
# Project Name: Input_Size_Finder
input_fetch = "Input_Size_Finder";

# Input sizes to explore
input_sizes = [224, 256, 512];

# Num epochs for each experiment to run
epochs=5;

# Percentage of original dataset to take in for experimentation
percent_data=10;

# "keep_all" - Keep all the sub experiments created
# "keep_non" - Delete all sub experiments created
experiment.Analyse_Input_Sizes(input_fetch, input_sizes, percent_data, num_epochs=epochs, state="keep_none");
```

```
Comparing Experiments
Comparison ID:      Comparison_Input_Size_Finder
Generated statistics post all epochs
| Experiment Name    |  Train Acc |  Val Acc |  Train Loss |  Val Loss |
|--------------------+------------+----------+-------------+-----------|
| Input_Size_224     |    0.91106 | 0.881215 |     0.41042 |  0.405622 |
| Input_Size_256     |   0.904675 | 0.89779  |    0.429658 |  0.388663 |
| Input_Size_512     |   0.907412 | 0.922652 |    0.415748 |  0.331154 |
```

Update input size

experiment.update_input_size(224);

experiment.Reload();

```
## Update Input Size

experiment.update_input_size(224);
experiment.Reload();
```

3. **Finding the perfect Learning rate**

Analysis Project Name

lr_fetch = "Learning_Rate_Finder"

Learning rates to explore

lrs = [0.01, 0.005, 0.001, 0.0001];

Num epochs for each experiment to run

epochs=5

Percentage of original dataset to take in for experimentation

percent_data=10

"keep_all" - Keep all the sub experiments created

"keep_non" - Delete all sub experiments created

experiment.Analyse_Learning_Rates(lr_fetch, lrs, percent_data, num_epochs=epochs, state="keep_none");

```
# Project Name: Learning_Rate_Finder
lr_fetch = "Learning_Rate_Finder"

# Learning rates to explore
lrs = [0.01, 0.005, 0.001, 0.0001];

# Num epochs for each experiment to run
epochs=5

# Percentage of original dataset to take in for experimentation
percent_data=10

# "keep_all" - Keep all the sub experiments created
# "keep_non" - Delete all sub experiments created
experiment.Analyse_Learning_Rates(lr_fetch, lrs, percent_data, num_epochs=epochs, state="keep_none");
```

```
Comparing Experiments
Comparison ID:      Comparison_Learning_Rate_Finder
Generated statistics post all epochs
| Experiment Name       |   Train Acc |   Val Acc |   Train Loss |   Val Loss |
|-----------------------+-------------+-----------+--------------+------------|
| Learning_Rate_0.01    |    0.904219 |  0.879374 |      0.42099 |   0.431651 |
| Learning_Rate_0.005   |    0.878905 |  0.888582 |      0.620732 |   0.476572 |
| Learning_Rate_0.001   |    0.691448 |  0.765193 |      1.59023  |   1.33622  |
| Learning_Rate_0.0001  |    0.270924 |  0.276243 |      3.01024  |   2.93441  |
```

Update Learning Rate

Update Learning Rate

experiment.update_learning_rate(0.01);

experiment.Reload();

```
## Update Learning Rate
experiment.update_learning_rate(0.01);
experiment.Reload();
```

Finding the best Optimizer

Analysis Project Name

optimizer_fetch = "Optimiser_Finder";

Optimizers to explore

optimizers = ["sgd", "adam", "adamax", "rmsprop"];

Num epochs for each experiment to run

```
epochs = 5;
```

Percentage of original dataset to take in for experimentation

```
percent_data = 10;
```

"keep_all" - Keep all the sub experiments created

"keep_non" - Delete all sub experiments created

```
experiment.Analyse_Optimizers(optimizer_fetch, optimizers, percent_data,
num_epochs=epochs, state="keep_none");
```

```
# Project Name: Optimiser_Finder
optimizer_fetch = "Optimiser_Finder";

# Optimizers to explore
optimizers = ["sgd", "adam", "adamax", "rmsprop"];   #Model name, learning rate

# Num epochs for each experiment to run
epochs = 5;

# Percentage of original dataset to take in for experimentation
percent_data = 10;

# "keep_all" - Keep all the sub experiments created
# "keep_non" - Delete all sub experiments created
experiment.Analyse_Optimizers(optimizer_fetch, optimizers, percent_data, num_epochs=epochs, state="keep_none");
```

```
Comparing Experiments
Comparison ID:      Comparison_Optimiser_Finder
Generated statistics post all epochs
| Experiment Name   |  Train Acc |   Val Acc |   Train Loss |   Val Loss |
|-------------------+------------+-----------+--------------+------------|
| Optimizer_sgd     |   0.903307 |  0.868324 |     0.424622 |   0.43945  |
| Optimizer_adam    |   0.947548 |  0.935543 |     0.202524 |   0.340577 |
| Optimizer_adamax  |   0.931585 |  0.940147 |     0.229603 |   0.197292 |
| Optimizer_rmsprop |   0.86431  |  0.494475 |     1.10529  |   8.14648  |
```

Updating the optimizer

```
experiment.optimizer_adamax(0.001);
```

```
experiment.Reload();
```

```
## Update Optimiser

experiment.optimizer_adamax(0.001);
experiment.Reload();
```

Set intermediate state saving to True

experiment.update_save_intermediate_models(True);

```
experiment.update_save_intermediate_models(True);
```

```
#train model with 5 epochs
experiment.Train();
```

Here we training for only for 5 epochs

```
# Again we're Creating experiment setup initializing with "experiment2" object
experiment = prototype(verbose=1);
experiment.Prototype("plant_disease", "experiment2", copy_from=["plant_disease", "experiment1"]);
```

Again we are creating a new experiment and copy it from the previous one.

Update the number of epochs to 100

experiment.update_num_epochs(100)

experiment.Reload()

```
# update number of epochs
experiment.update_num_epochs(100)
experiment.Reload()
```

Train

experiment.Train();

```
#train model with 100 epochs
experiment.Train()
```

iNeuron

Now the model training will be finally completed after few hours based on the system you are training.

Now three models will be saved in the workspace folder of the following experiment.

Performance tuning

Possible tuning analytics

Comparison with benchmarks

	AlexNet		GoogleNet	
	Transfer learning	Training from scratch	Transfer learning	Training from scratch
TRAIN: 200%, TEST: 80%				
Color	0.9736 (0.9742, 0.9737, 0.9738)	0.9118 (0.9137, 0.9132, 0.9130)	**0.9820** (0.9824, 0.9821, 0.9821)	0.9430 (0.9440, 0.9431, 0.9429)
Grayscale	0.9361 (0.9368, 0.9369, 0.9371)	0.8524 (0.8539, 0.8555, 0.8553)	**0.9563** (0.9570, 0.9564, 0.9564)	0.8828 (0.8842, 0.6835, 0.8841)
Segmented	0.9724 (0.9727, 0.9727, 0.9726)	0.8945 (0.8956, 0.8963, 0.8969)	**0.9808** (0.9810, 0.9808, 0.9808)	0.9377 (0.9388, 0.9380, 0.9380)
TRAIN: 400%, TEST: 60%				
Color	0.9860 (0.9861, 0.9861, 0.9860)	0.9555 (0.9557, 0.9558, 0.9558)	**0.9914** (0.9914, 0.9914, 0.9914)	0.9729 (0.9731, 0.9729, 0.9729)
Grayscale	0.9584 (0.9588, 0.9589, 0.9588)	0.9088 (0.9090, 0.9101, 0.9100)	**0.9714** (0.9717, 0.9716, 0.9716)	0.9361 (0.9364, 0.9363, 0.9364)
Segmented	0.9812 (0.9814, 0.9813, 0.9813)	0.9404 (0.9409, 0.9408, 0.9408)	**0.9896** (0.9896, 0.9896, 0.9898)	0.9643 (0.9647, 0.9642, 0.9642)
TRAIN: 50%, TEST: 50%				
Color	0.9896 (0.9897, 0.9896, 0.9897)	0.9644 (0.9647, 0.9647, 0.9647)	**0.9916** (0.9916, 0.9916, 0.9916)	0.9772 (0.9774, 0.9773, 0.9773)
Grayscale	0.9661 (0.9663, 0.9663, 0.9663)	0.9312 (0.9315, 0.9318, 0.9319)	**0.9788** (0.9789, 0.9788, 0.9788)	0.9507 (0.9510, 0.9507, 0.9509)
Segmented	0.9867 (0.9868, 0.9868, 0.9869)	0.9551 (0.9552, 0.9555, 0.9556)	**0.9909** (0.9910, 0.9910, 0.9910)	0.9720 (0.9721, 0.9721, 0.9722)
TRAIN: 600%, TEST: 40%				
Color	0.9907 (0.9908, 0.9908, 0.9907)	0.9724 (0.9725, 0.9725, 0.9725)	**0.9924** (0.9924, 0.9924, 0.9924)	0.9824 (0.9825, 0.9824, 0.9824)
Grayscale	0.9686 (0.9689, 0.9688, 0.9688)	0.9388 (0.9396, 0.9395, 0.9391)	**0.9785** (0.9789, 0.9786, 0.9787)	0.9547 (0.9554, 0.9548, 0.9551)
Segmented	0.9855 (0.9856, 0.9856, 0.9856)	0.9595 (0.9597, 0.9597, 0.9596)	**0.9905** (0.9906, 0.9906, 0.9906)	0.9740 (0.9743, 0.9740, 0.9745)
TRAIN: 80%, TEST: 20%				
Color	**0.9927** (0.9928, 0.9927, 0.9928)	**0.9782** (0.9786, 0.9782, 0.9782)	**0.9934** (0.9935, 0.9935, 0.9935)	**0.9836** (0.9839, 0.9837, 0.9837)
Grayscale	**0.9726** (0.9728.0.9727, 0.9725)	**0.9449** (0.9451, 0.9454, 0.9452)	**0.9800** (0.9804, 0.9801, 0.9798)	**0.9621** (0.9624, 0.9621, 0.9621)
Segmented	**0.9891** (0.9893, 0.9891, 0.9892)	**0.9722** (0.9725, 0.9724, 0.9723)	**0.9925** (0.9925, 0.9925, 0.9924)	**0.9824** (0.9827, 0.9824, 0.9822)

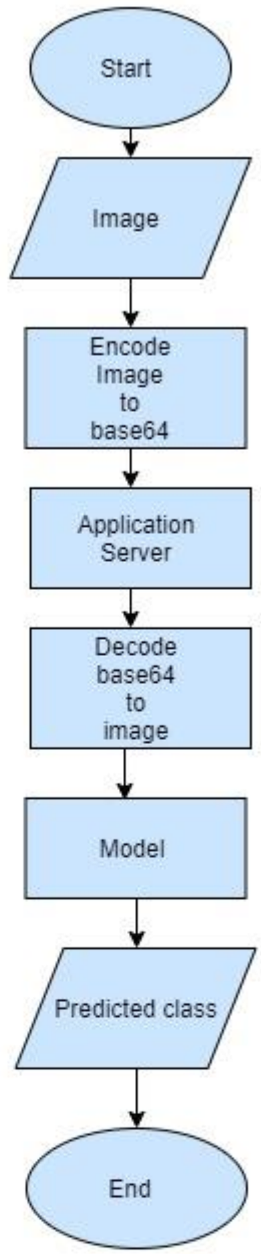
Each cell in the table represents the mean F_1 score$_{(mean\ precision,\ mean\ recall,\ overall\ accuracy)}$ for the corresponding experimental configuration.
The bold values are the F_1 scores of the best performing models in the respective row/column.

These are the various benchmarks score when using different CNN architectures like AlexNet, GoogleNet with variety of transfer learning or scratch learning and different data size.

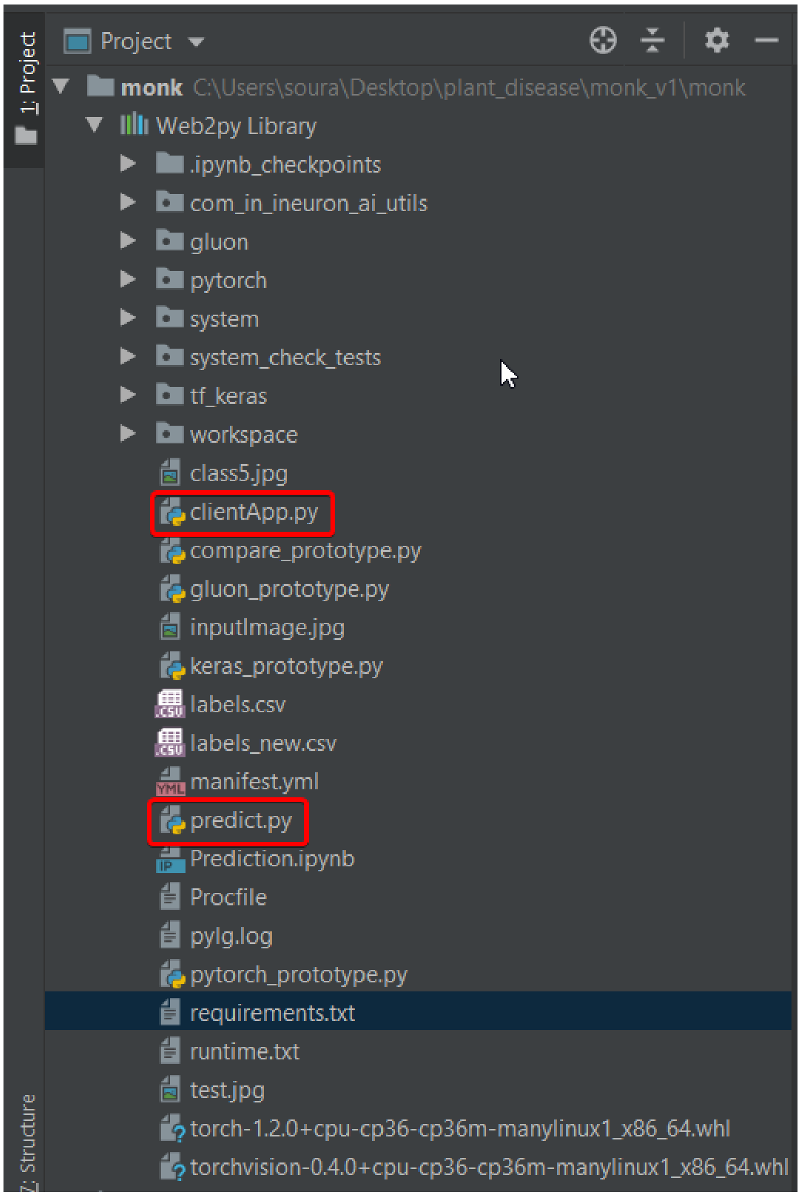
Deployment

We will be deploying the model to the Pivotal Cloud Foundry platform.

This is workflow diagram for prediction of diseases using the trained model.



Now let’s see the Plant Disease Classification project folder structure.



requirements.txt file consists of all the packages that you need to deploy the app in the cloud.

clientApp.py | results.html | index.html | labels_new.csv | predict.py | manifest

```python

app = Flask(__name__)
CORS(app)
class ClientApp:
    def __init__(self):
        self.filename = "inputImage.jpg"
        self.objectDetection = plant_prediction(img_name=self.filename)

@app.route("/", methods=['GET'])
def home():
    return render_template("index.html")

@app.route("/predict", methods=['POST'])
@cross_origin()
def predictRoute():
    #image = request.json['image']
    image = request.form['content']
    decodeImage(image, clApp.filename)
    result = clApp.objectDetection.predict_label()
    #return jsonify(result)
    return render_template("results.html",result=result)

port = int(os.getenv("PORT"))
if __name__ == "__main__":
    clApp = ClientApp()
    app.run(host='0.0.0.0', port=port)
```

ClientApp.py is the entry point of our application, where the flask server starts. Here we will be decoding a base64 to an image, and then we will be doing predictions.

clientApp.py predict.py requirements.txt manifest.yml Procfile runtime.txt

```python
import csv
from pytorch_prototype import prototype

class plant_prediction:
    def __init__(self, img_name):
        self.img_name = img_name

    def read_labels(self):
        mydict = {}
        with open('labels.csv', mode='r') as infile:
            reader = csv.reader(infile)
            with open('labels_new.csv', mode='w') as outfile:
                writer = csv.writer(outfile)
                mydict = {rows[0]: rows[1] for rows in reader}
        return mydict

    def predict_label(self):
        experiment = prototype(verbose=1)
        experiment.Prototype("plant_disease", "exp3", eval_infer=True)
        predictions = experiment.Infer(img_name=self.img_name, return_raw=True)
        pred_class = predictions['predicted_class']
        label_dict = self.read_labels()
        out_label = label_dict[pred_class]
        return out_label
```

This is the **predict.py** file where the predictions take place based on the image we are giving input to the model.

```yaml

---
applications:
- name: agriculture_plant_disease_classification
  memory: 1024MB
  disk_quota: 2GB
  random-route: true
  parameters:
    memory: 1024M
    buildpack: 'python_buildpack'
```

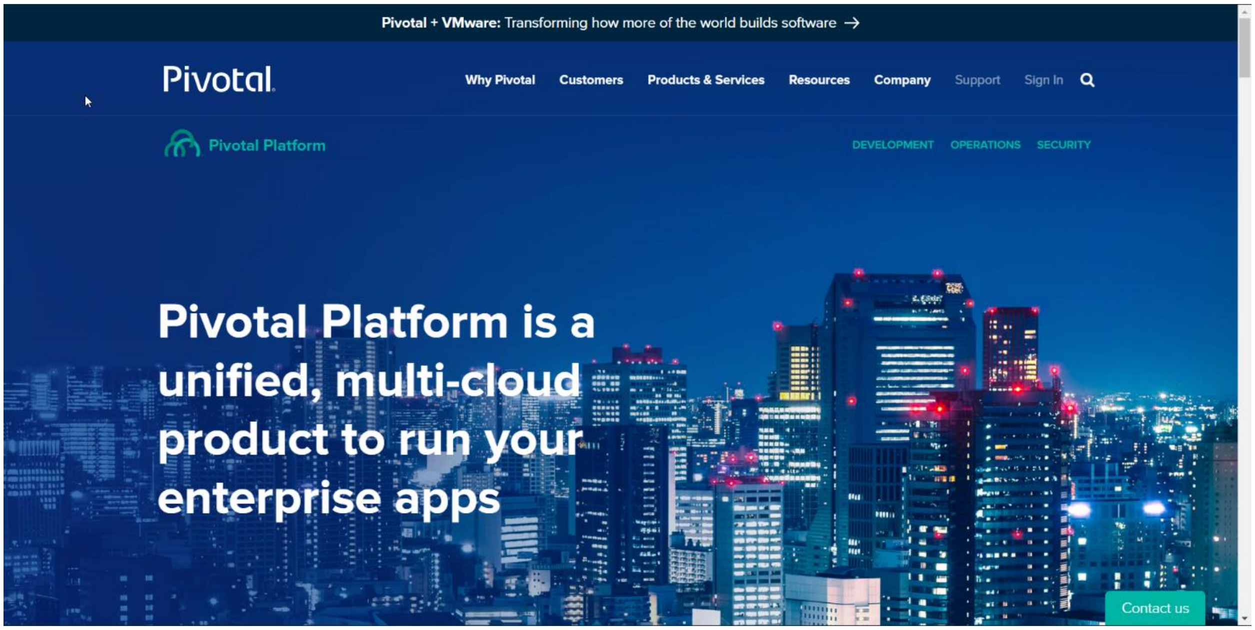
manifest.yml:- This file contains the instance configuration, app name and buildpack language.

```
web: python clientApp.py   --master --processes 4 --threads 2
```

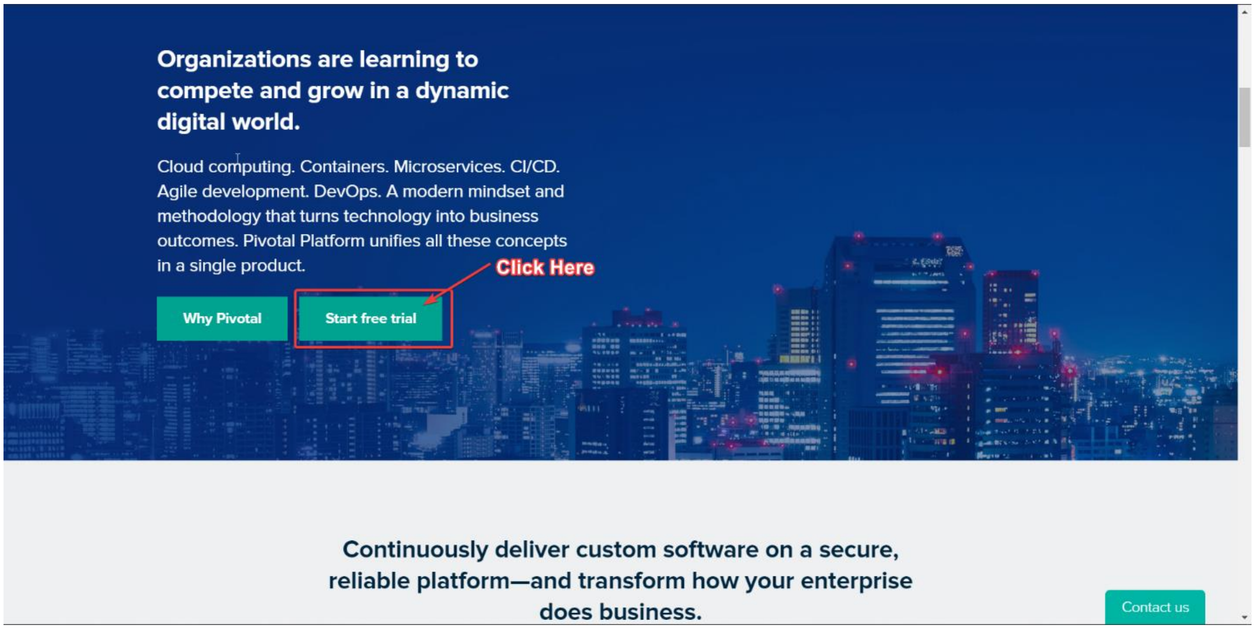
Procfile :- It contains the entry point of the app.

```
python-3.6.8
```

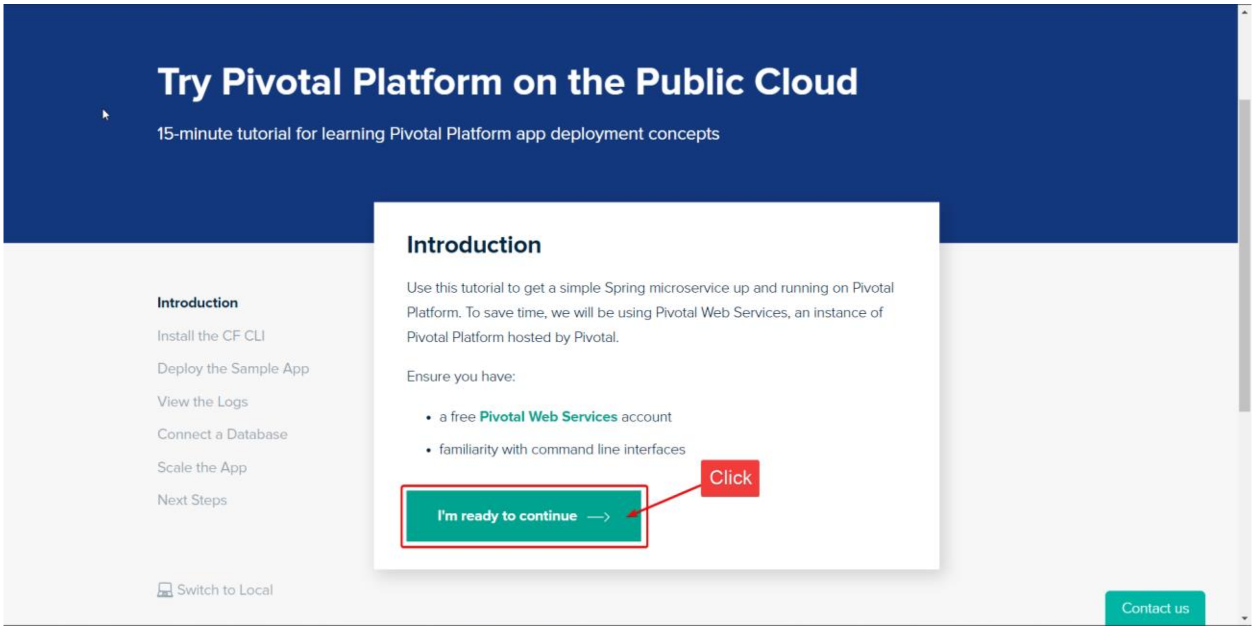
runtime.txt:- It contains the Python version number.



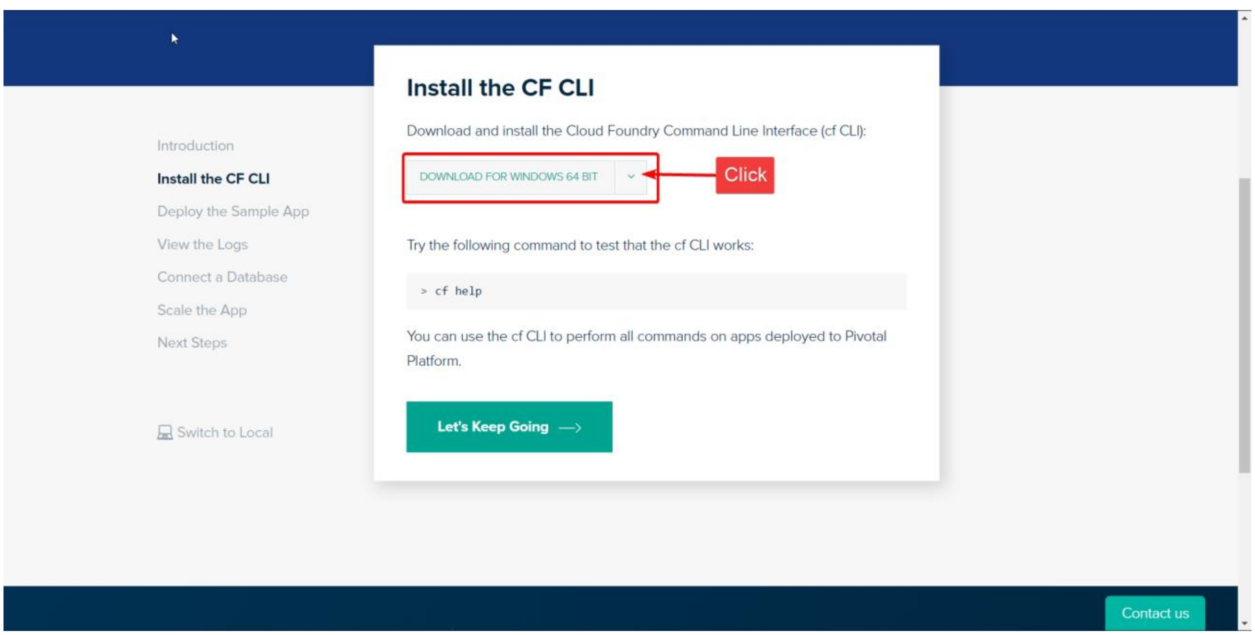
Visit the official website **https://pivotal.io/platform.**



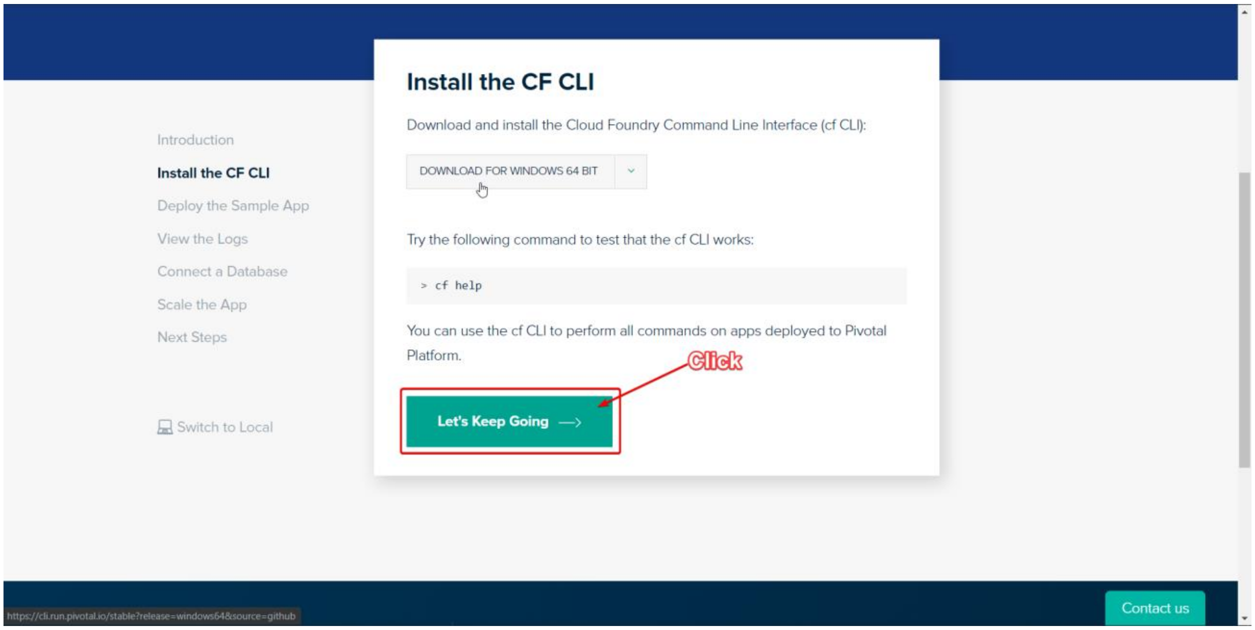
Scroll Down to see the **Start Trial Button**



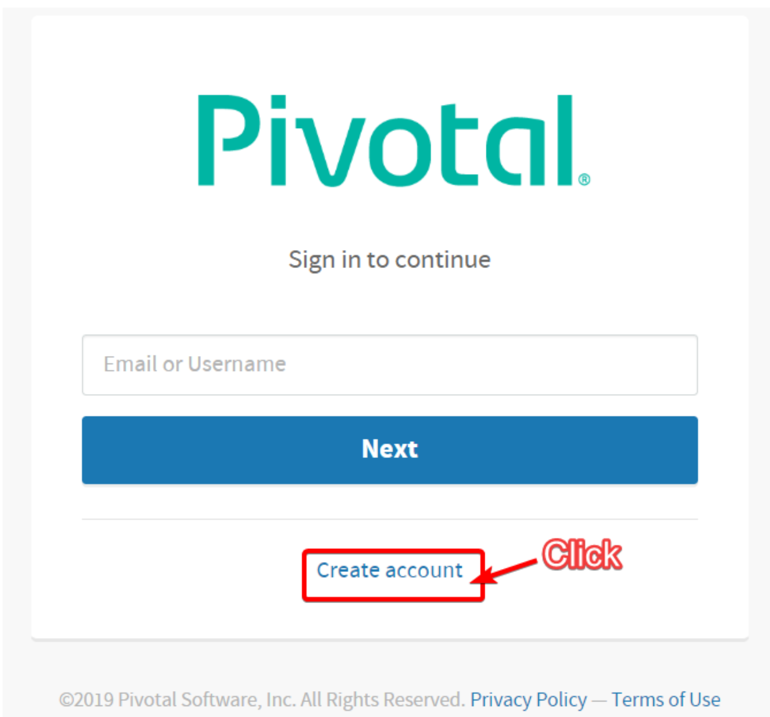
Click on the start trial button and next interface will open. Then I will click on **I'm ready to continue**



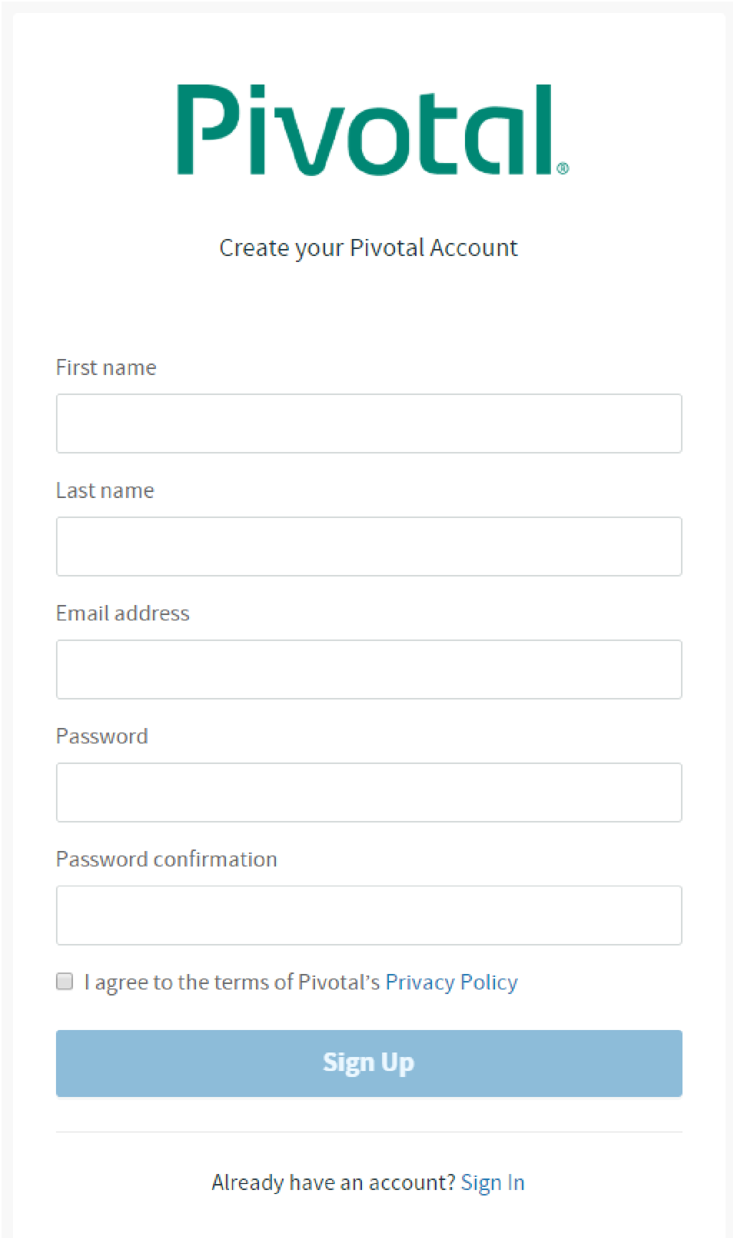
Click on Download for **Windows 64 bit** then zip file will be downloaded. Keep it for future uses.



Now click on **Let's Keep Going**



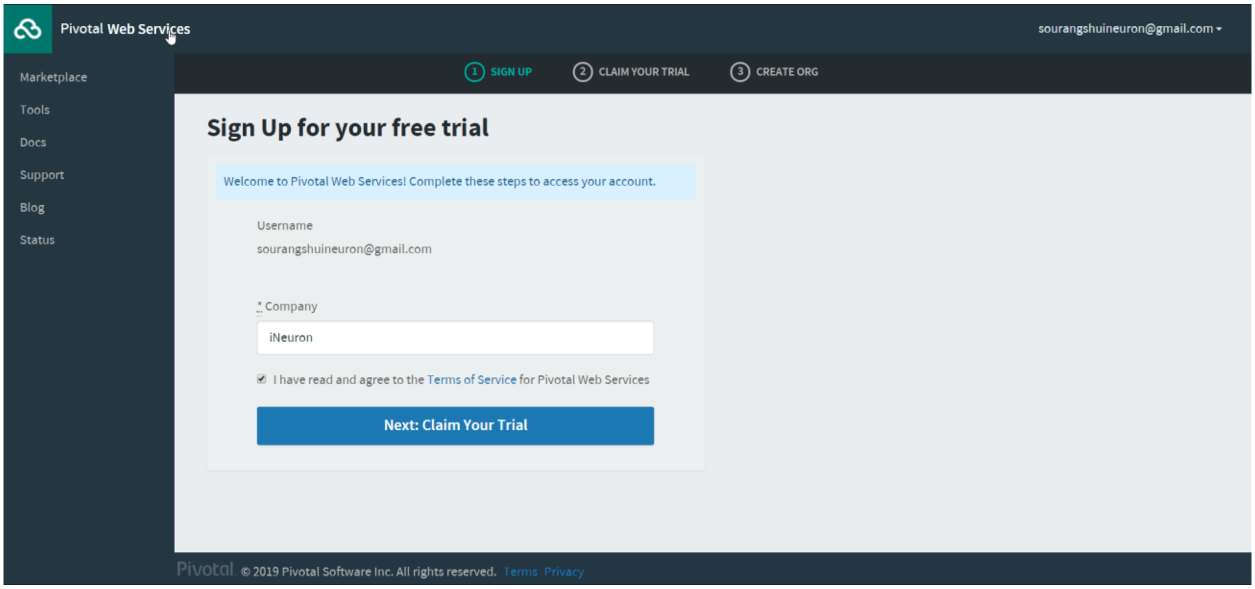
Click on **Create Your Account**



Fill Up your Details For registration

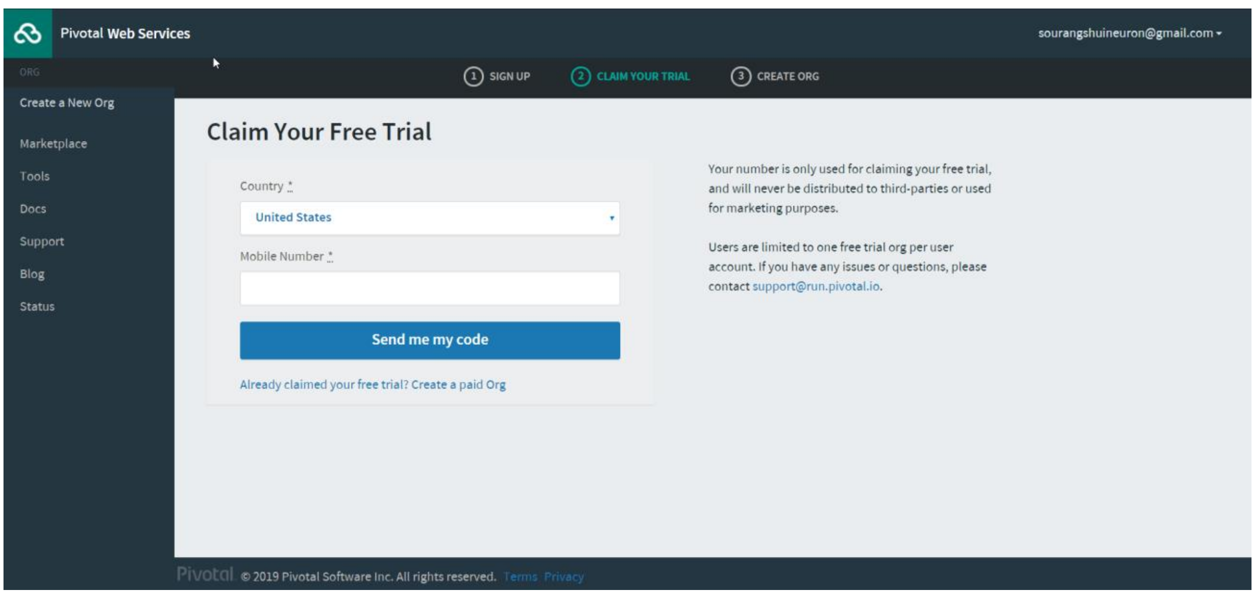
Do the email verification

Then login in again

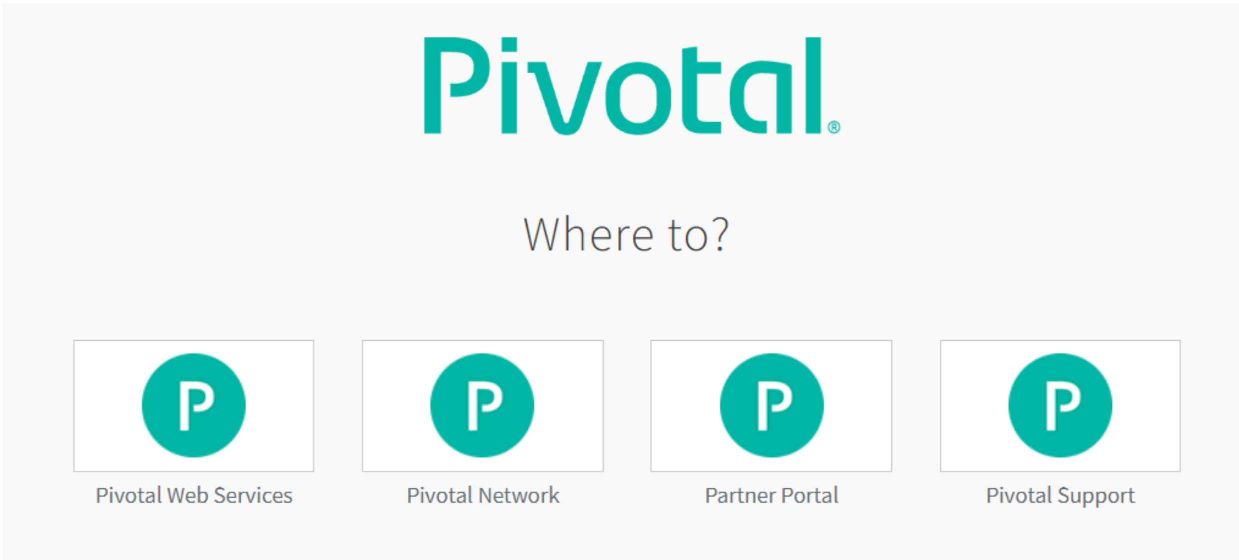


After logging you will see this screen below and start your free trial.

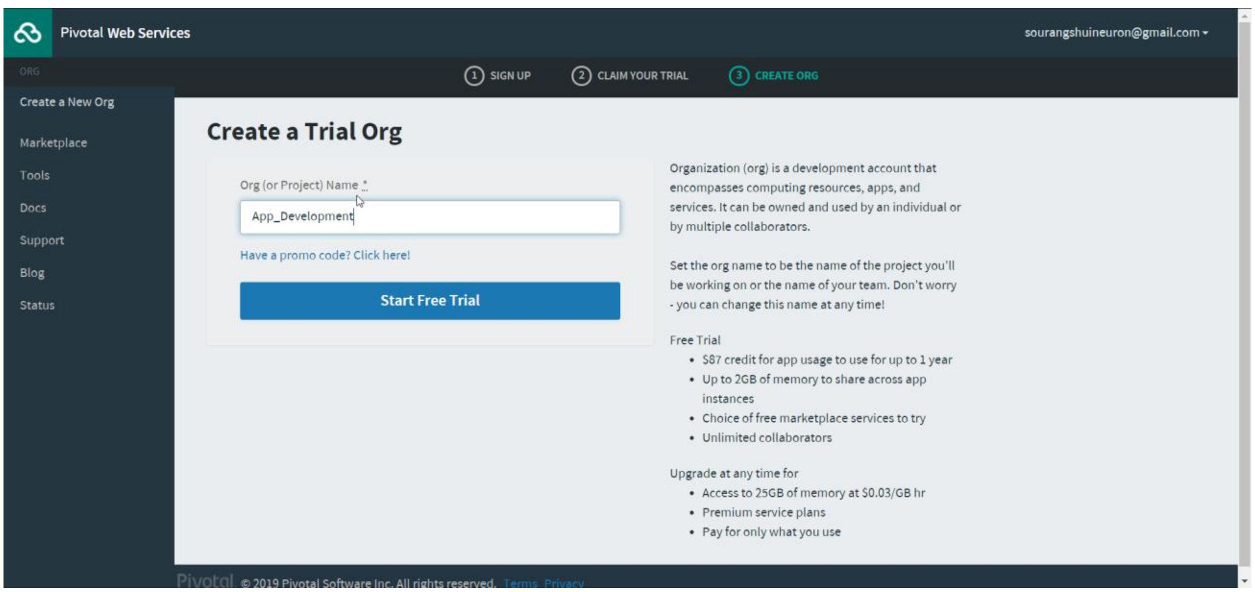
Write any Company or which one you prefer



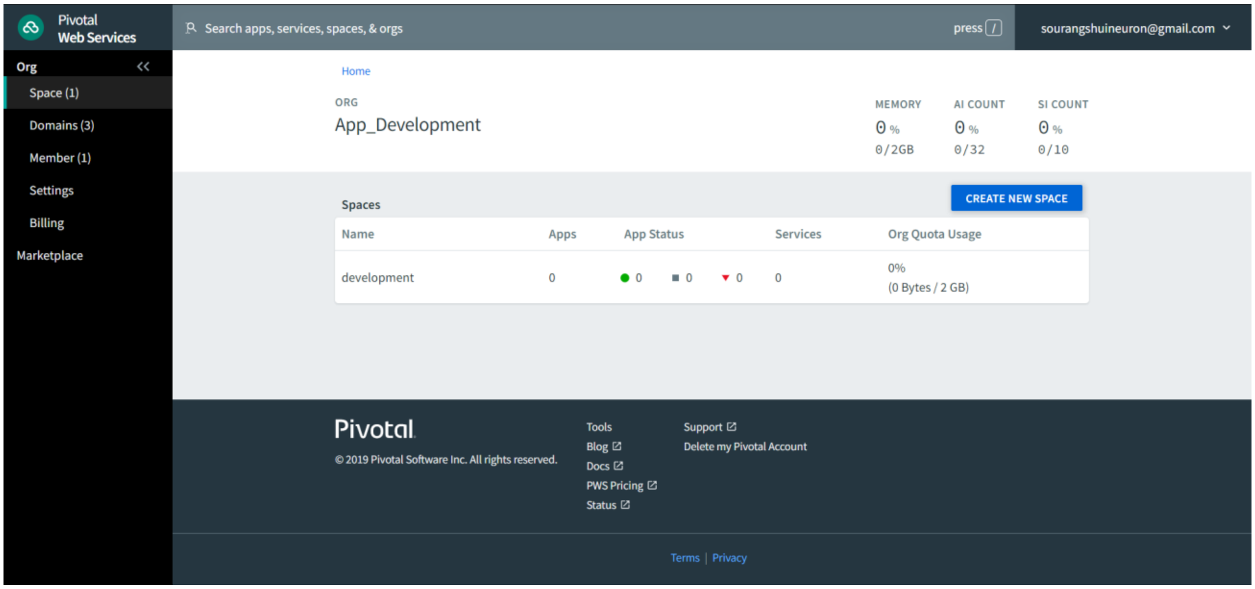
Enter your **Mobile Number** for Verification



Click on **Pivotal Web Services**



Give any **Org** name



Now you are inside your Org and by default development space is created in your org. You can push your apps here.

The cloud signup process is done and setup is ready for us to push the app.

Previously you have downloaded the **CLI.zip** file. Unzip the file and install the .exe file with admin rights.

After successful installation, you can verify by opening your CMD and type **cf**.

Then you will get a screen which is shown below

```
Microsoft Windows [Version 10.0.18362.418]
(c) 2019 Microsoft Corporation. All rights reserved.

C:\Users\soura>cf
cf version 6.46.1+4934877ec.2019-08-23, Cloud Foundry command line tool
Usage: cf [global options] command [arguments...] [command options]

Before getting started:
  config    login,l      target,t
  help,h    logout,lo

Application lifecycle:
  apps,a        run-task,rt    events
  push,p        logs           set-env,se
  start,st      ssh            create-app-manifest
  stop,sp       app            delete,d
  restart,rs    env,e
  restage,rg    scale

Services integration:
  marketplace,m        create-user-provided-service,cups
  services,s           update-user-provided-service,uups
  create-service,cs    create-service-key,csk
  update-service       delete-service-key,dsk
  delete-service,ds    service-keys,sk
  service              service-key
  bind-service,bs      bind-route-service,brs
  unbind-service,us    unbind-route-service,urs

Route and domain management:
  routes,r        delete-route    create-domain
  domains         map-route
  create-route    unmap-route

Space management:
  spaces         create-space    set-space-role
  space-users    delete-space    unset-space-role

Org management:
  orgs,o       set-org-role
  org-users    unset-org-role

CLI plugin management:
  plugins           add-plugin-repo      repo-plugins
  install-plugin    list-plugin-repos

Commands offered by installed plugins:

Global options:
```

If you see this screen in your CMD the installation is successful.

Now type the command to login via cf-cli

cf login -a https://api.run.pivotal.io

Next enter your email and password. Now you are ready to push your app.

Now let’s go to the app which we have built.

```
Microsoft Windows [Version 10.0.18363.535]
(c) 2019 Microsoft Corporation. All rights reserved.

C:\Users\soura>cf login
API endpoint: https://api.run.pivotal.io

Email> sourangshuineuron@gmail.com

Password>
Authenticating...
OK

Targeted org App_Development

Targeted space development



API endpoint:   https://api.run.pivotal.io (API version: 2.144.0)
User:           sourangshuineuron@gmail.com
Org:            App_Development
Space:          development
```

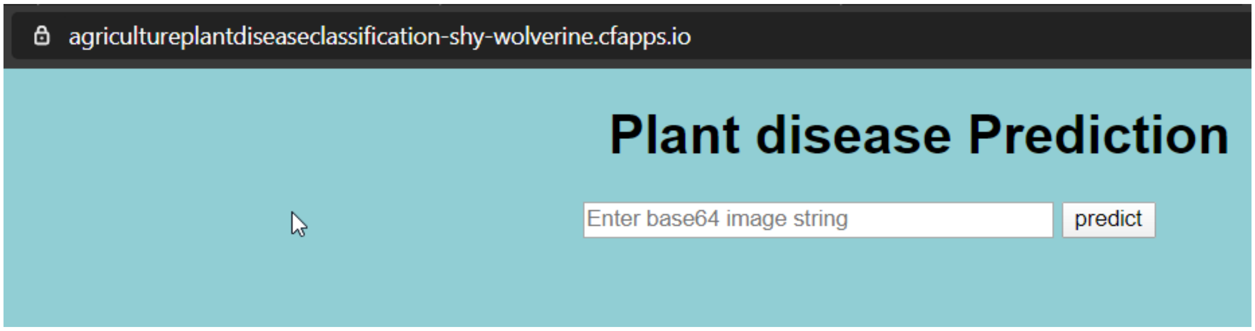
Navigate to the project folder after downloading from the given below link :-

```
C:\Users\soura\Desktop\plant_disease\monk_v1\monk>cf push
```

After the app is successfully deployed in cloud you will be seeing the below screen with the route.

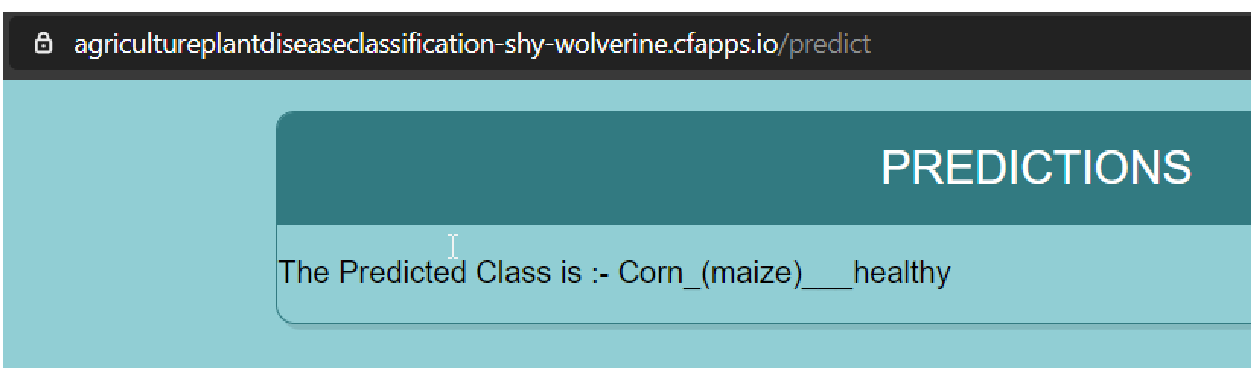
```
name:              agriculture_plant_disease_classification
requested state:   started
routes:            agricultureplantdiseaseclassification-shy-wolverine.cfapps.io
last uploaded:     Sat 28 Dec 18:55:45 IST 2019
stack:             cflinuxfs3
buildpacks:        python
                                                          Route
type:            web
instances:       1/1
memory usage:    1024M
start command:   python clientApp.py   --master --processes 4 --threads 2
     state     since                  cpu     memory        disk          details
#0   running   2019-12-28T13:27:26Z   99.6%   86.5M of 1G   1.3G of 2G
```

Lets visit the route in your browser



Visit this website to encode the predicted image to base64 encoding.

https://base64.guru/converter/encode/image



Finally we get the predicted class.

Conclusion

Hence we have successfully deployed the plant prediction model in cloud and we are able to do predictions.