



Data Science Intern at Data Glacier

Week 5: Cloud API Development

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Date: 21 OCT 2022

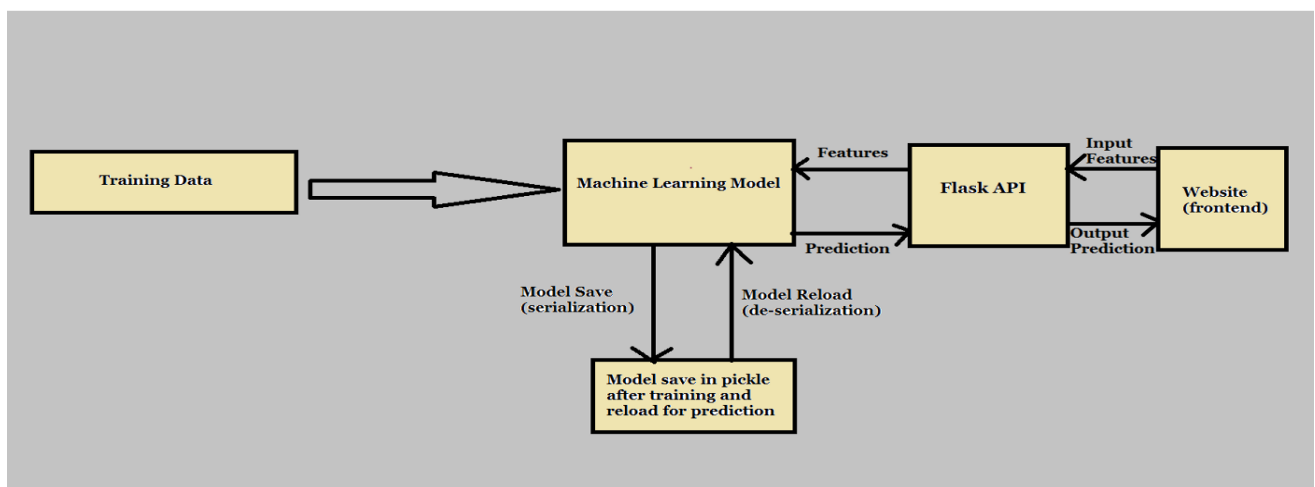
Submitted to: Data Glacier

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1. Introduction

In this project, we are going to deploying machine learning model using the Flask Framework. As a demonstration, our model helps to predict the values based on the input given in Iris Dataset.

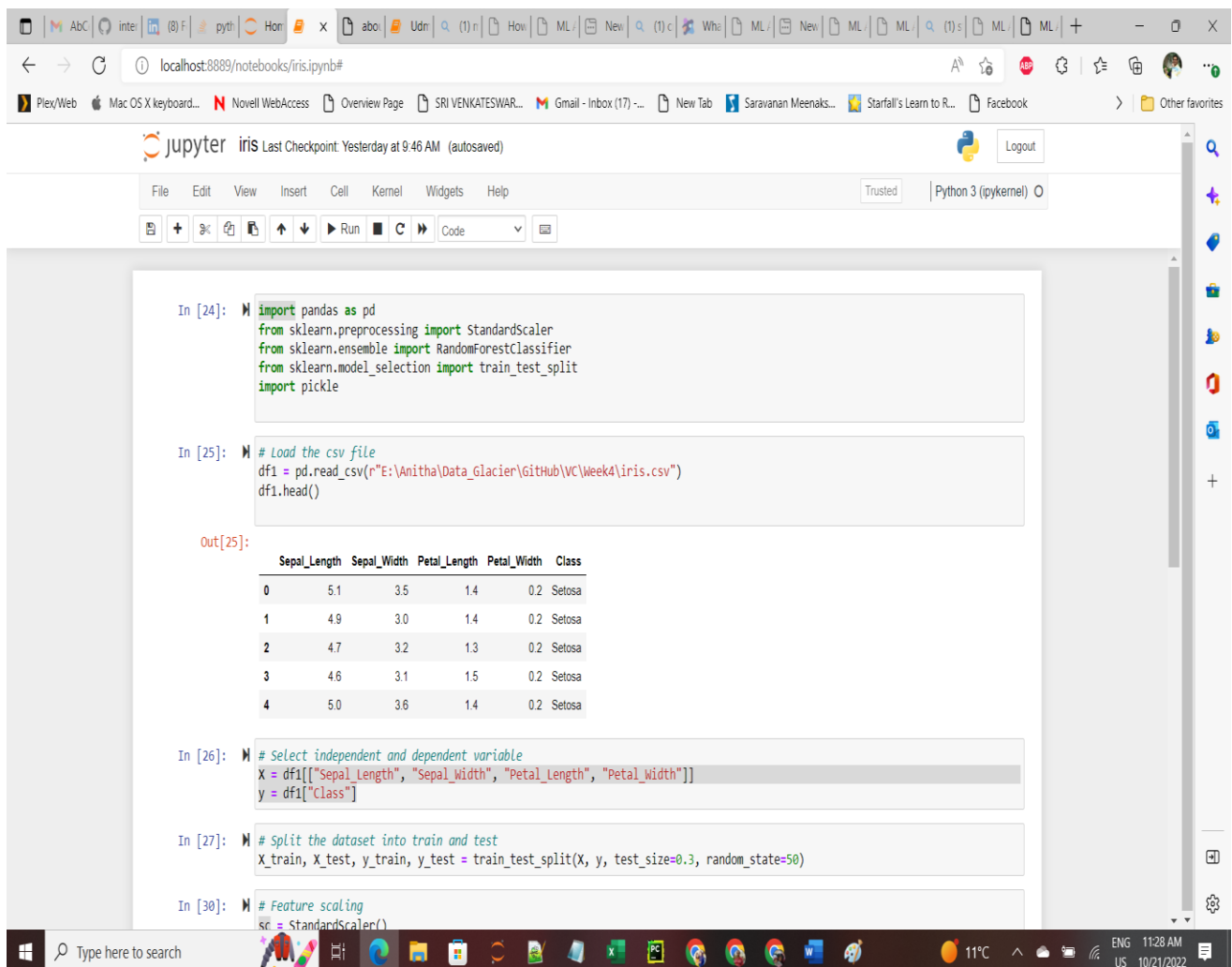


we will focus on both: building a machine learning model for Iris Dataset, then create an API for the model, using Flask, the Python micro-framework for building web applications. This API allows us to utilize predictive capabilities through HTTP requests.

2. Building a Model

2.1.1 Import Required Libraries and Dataset

In this part, we import libraires and dataset which contain the information of Iris dataset.



The screenshot shows a Jupyter Notebook running in a web browser. The notebook is titled 'iris' and shows the following code cells:

```
In [24]: import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
import pickle
```

```
In [25]: # Load the csv file
df1 = pd.read_csv(r"E:\Anitha\Data_Glacier\GitHub\VC\Week4\iris.csv")
df1.head()
```

The output of the second cell is a table showing the first five rows of the dataset:

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Class
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

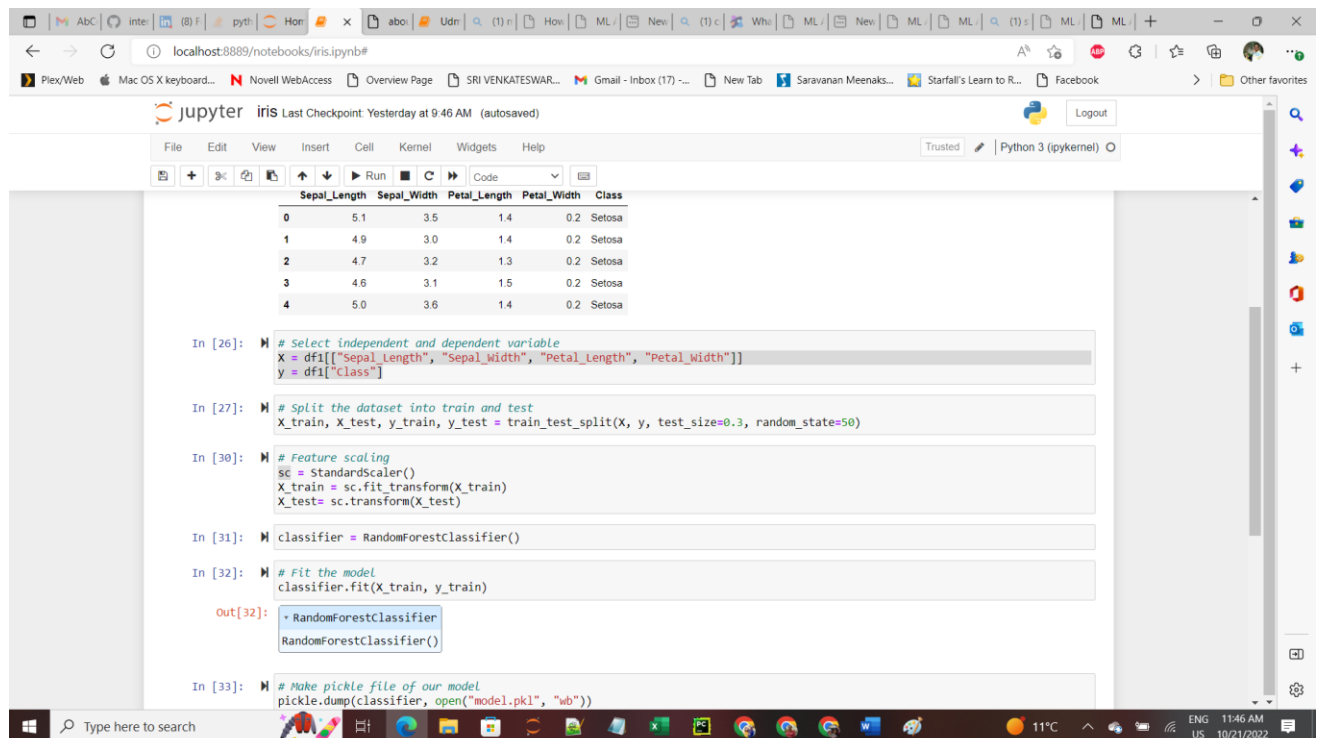
```
In [26]: # Select independent and dependent variable
X = df1[["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"]]
y = df1["Class"]
```

```
In [27]: # Split the dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=50)
```

```
In [30]: # Feature scaling
sc = StandardScaler()
```

3.1.1 Build Model

After data preprocessing, we implement machine learning model to predict the iris value in the dataset. For this purpose, we implement Standard scalar using sklearn. After importing and initialize Standard scalar model we fit into training dataset.



The screenshot shows a Jupyter Notebook running on a local host. The notebook displays the first five rows of the Iris dataset, which include Sepal Length, Sepal Width, Petal Length, Petal Width, and Class. Below the data, the code implements a machine learning pipeline: selecting independent and dependent variables, splitting the dataset into training and testing sets, applying feature scaling using StandardScaler, initializing a RandomForestClassifier, fitting the model to the training data, and finally saving the trained model as a pickle file.

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Class
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

```
In [26]: # Select independent and dependent variable
X = df[["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"]]
y = df["Class"]

In [27]: # Split the dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=50)

In [30]: # Feature scaling
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

In [31]: classifier = RandomForestClassifier()

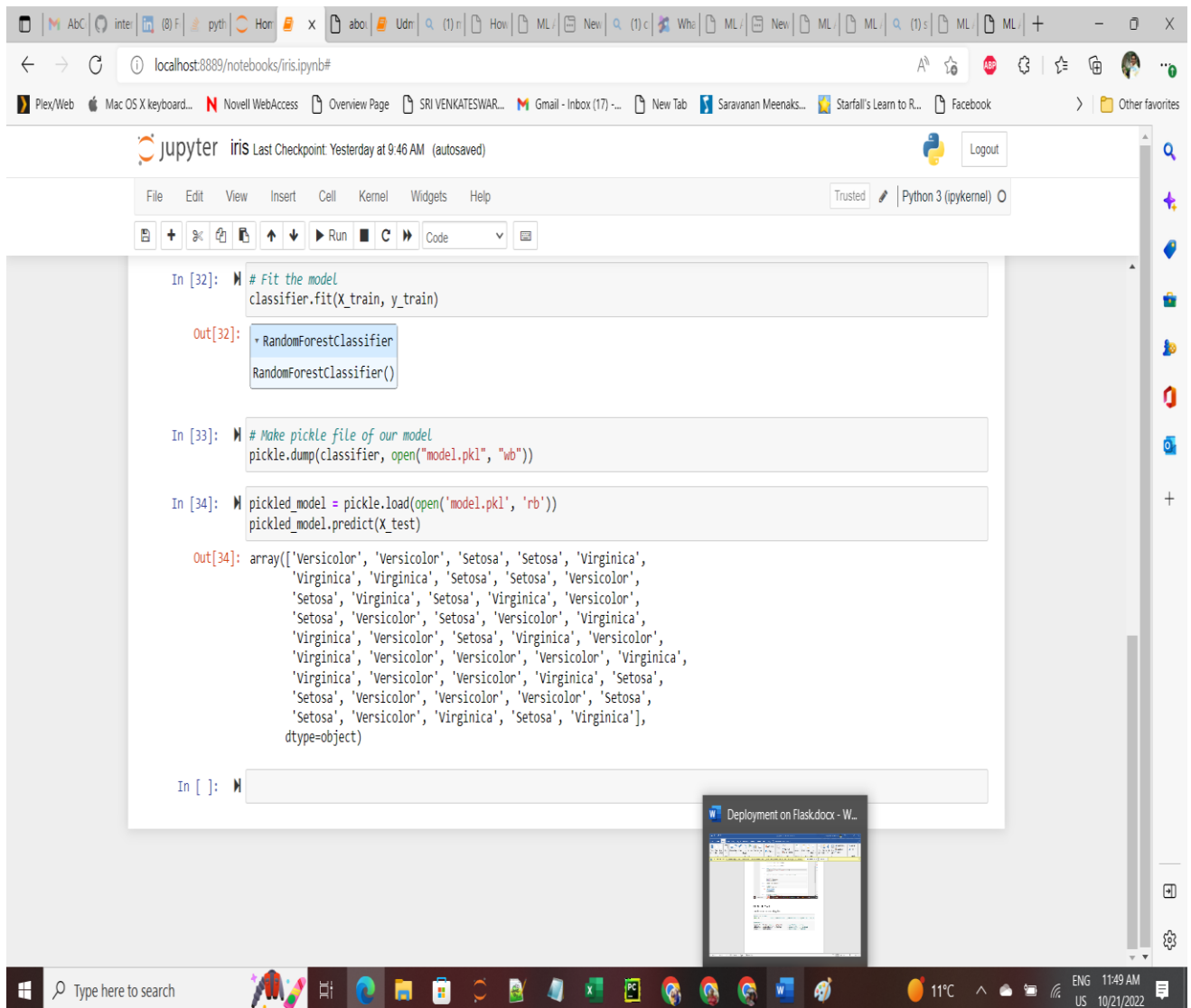
In [32]: # Fit the model
classifier.fit(X_train, y_train)

Out[32]: RandomForestClassifier
RandomForestClassifier()

In [33]: # Make pickle file of our model
pickle.dump(classifier, open("model.pkl", "wb"))
```

3.1.3 Save the Model

After that we save our model using pickle



4. Turning Model into Web Application

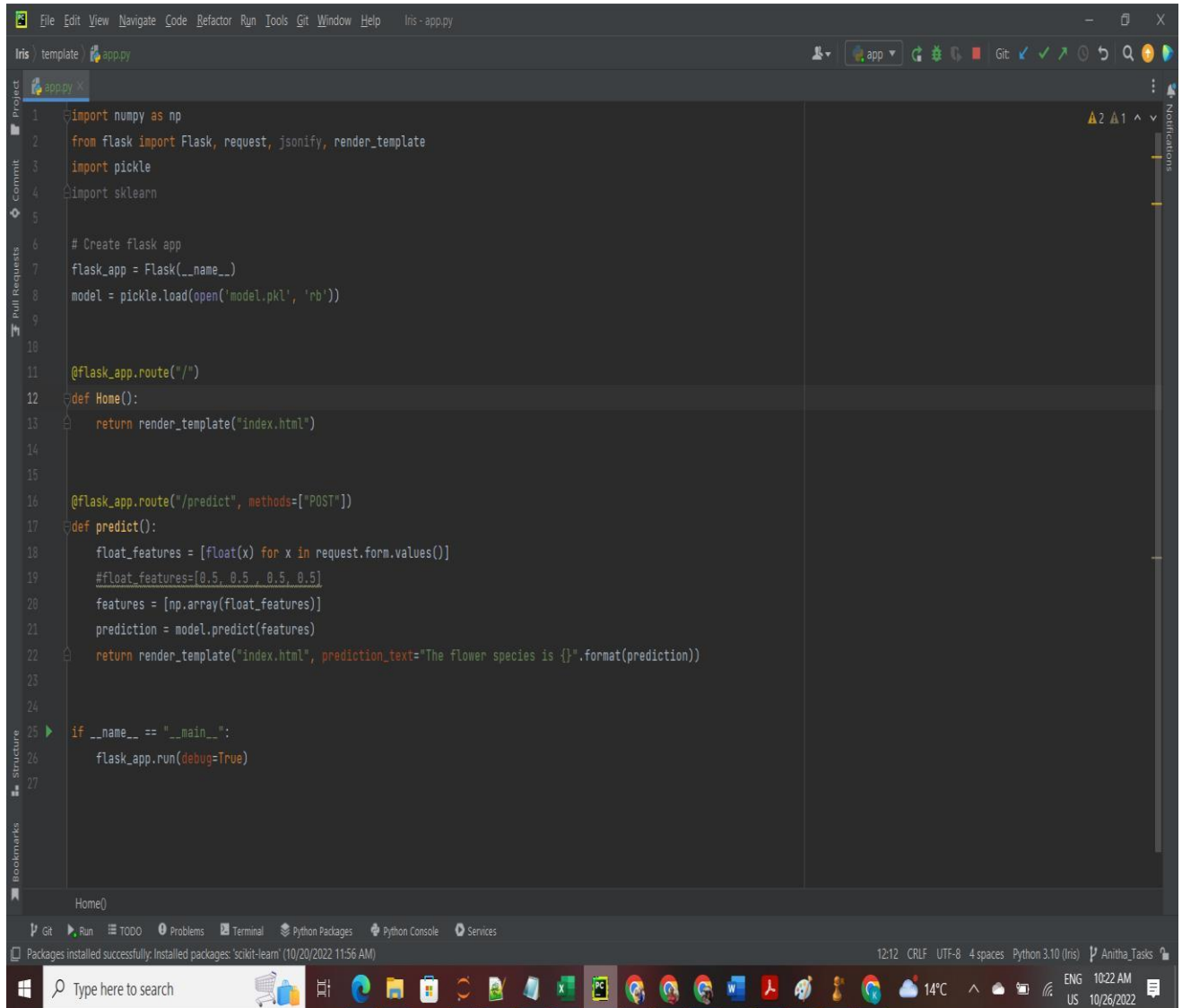
We develop a web application that consists of a simple web page with a form field with entering the values and predict. After submitting the message to the web application, it will render it on a new page which gives us a result of Versicolor, Virginica. First, we create a folder for this project called Iris, this is the directory tree inside the folder. We will explain each file.

Table 3.1: Application Folder File Directory

app.py	
Templates	Index.html
Model	model.pkl
Dataset/	Iris.csv

3.1 App.py

The *app.py* file contains the main code that will be executed by the Python interpreter to run the Flask web application, it included the ML code for classifying SD.



```
1 import numpy as np
2 from flask import Flask, request, jsonify, render_template
3 import pickle
4 import sklearn
5
6 # Create flask app
7 flask_app = Flask(__name__)
8 model = pickle.load(open('model.pkl', 'rb'))
9
10
11 @flask_app.route("/")
12 def Home():
13     return render_template("index.html")
14
15
16 @flask_app.route("/predict", methods=["POST"])
17 def predict():
18     float_features = [float(x) for x in request.form.values()]
19     #float_features=[0.5, 0.5, 0.5, 0.5]
20     features = [np.array(float_features)]
21     prediction = model.predict(features)
22     return render_template("index.html", prediction_text="The flower species is {}".format(prediction))
23
24
25 if __name__ == "__main__":
26     flask_app.run(debug=True)
27
```

Figure 3.1: App.py

- We ran our application as a single module; thus, we initialized a new Flask instance with the argument *_name* to let Flask know that it can find the HTML template folder (*templates*) in the same directory where it is located.
- Our *home* function simply rendered the *Index.html* HTML file, which is located in the *templates* folder.

- Inside the *predict* function, we access the Iris data set, pre-process the values, and make predictions, then store the model. We access the new message entered by the user and use our model to make a prediction for its label.
- we used the *POST* method to transport the form data to the server in the message body. Finally, by setting the *debug=True* argument inside the *app.run* method, we further activated Flask's debugger.
- Lastly, we used the *run* function to only run the application on the server when this script is directly executed by the Python interpreter, which we ensured using the *if* statement with `__name__ == '__main__'`.

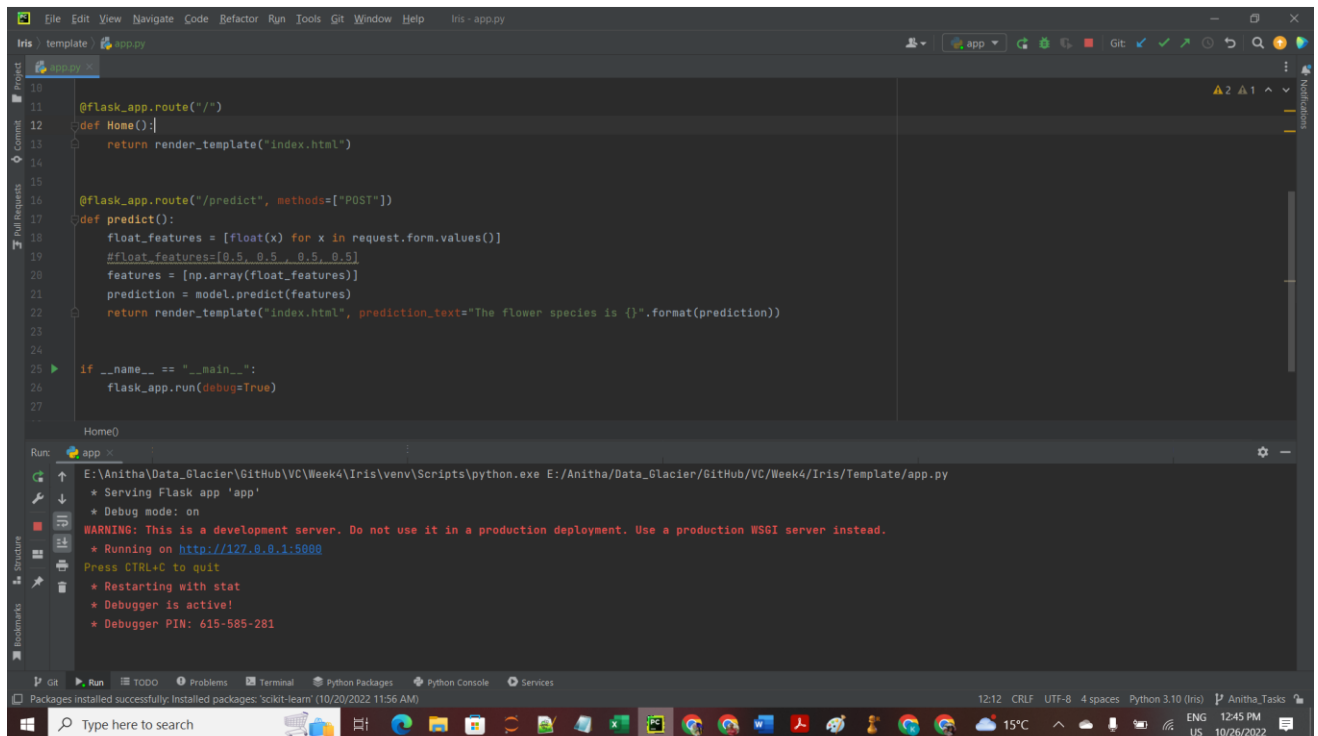
• **3.2 Index.html**

The following are the contents of the *Index.html* file that will enter the values to predict the flowers.


```
1 <!DOCTYPE html>
2 <html>
3 <!--From https://codepen.io/frtytyler/pen/EGdtq-->
4 <head>
5   <meta charset="UTF-8">
6   <title>ML API</title>
7   <link href="https://fonts.googleapis.com/css?family=Pacifico" rel="stylesheet" type="text/css">
8   <link href="https://fonts.googleapis.com/css?family=Arimo" rel="stylesheet" type="text/css">
9   <link href="https://fonts.googleapis.com/css?family=Hind:300" rel="stylesheet" type="text/css">
10  <link href="https://fonts.googleapis.com/css?family=Open+Sans+Condensed:300" rel="stylesheet" type="text/css">
11 </head>
12
13 <body>
14   <div class="login">
15     <h1>Flower Class Prediction</h1>
16
17     <!-- Main Input For Receiving Query to our ML -->
18     <form action="{{ url_for('predict')}}" method="post">
19       <input type="text" name="Sepal_Length" placeholder="Sepal_Length" required="required" />
20       <input type="text" name="Sepal_Width" placeholder="Sepal_Width" required="required" />
21       <input type="text" name="Petal_Length" placeholder="Petal_Length" required="required" />
22       <input type="text" name="Petal_Width" placeholder="Petal_Width" required="required" />
23
24       <button type="submit" class="btn btn-primary btn-block btn-large">Predict</button>
25     </form>
26
27     <br>
28     <br>
29     {{ prediction_text }}
30   </div>
31
32 </body>
33 </html>
```

- **4.1.2 Running Procedure**

Once we have done all of the above, we can start running the API by clicking run button in *app.py* screen:



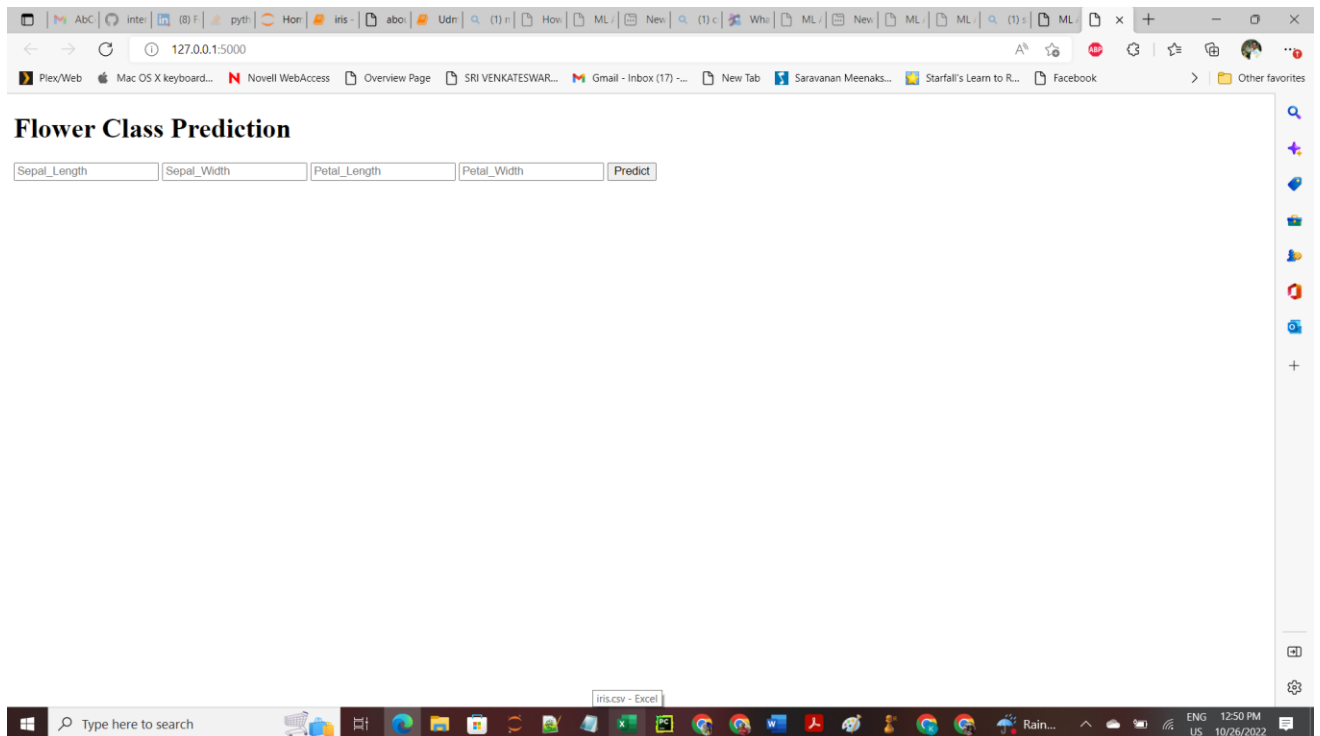
```
10
11 @flask_app.route("/")
12 def Home():
13     return render_template("index.html")
14
15
16 @flask_app.route("/predict", methods=["POST"])
17 def predict():
18     float_features = [float(x) for x in request.form.values()]
19     #float_features=[0.5, 0.5, 0.5, 0.5]
20     features = np.array(float_features)
21     prediction = model.predict(features)
22     return render_template("index.html", prediction_text="The flower species is {}".format(prediction))
23
24
25 if __name__ == "__main__":
26     flask_app.run(debug=True)
27
```

Run: app

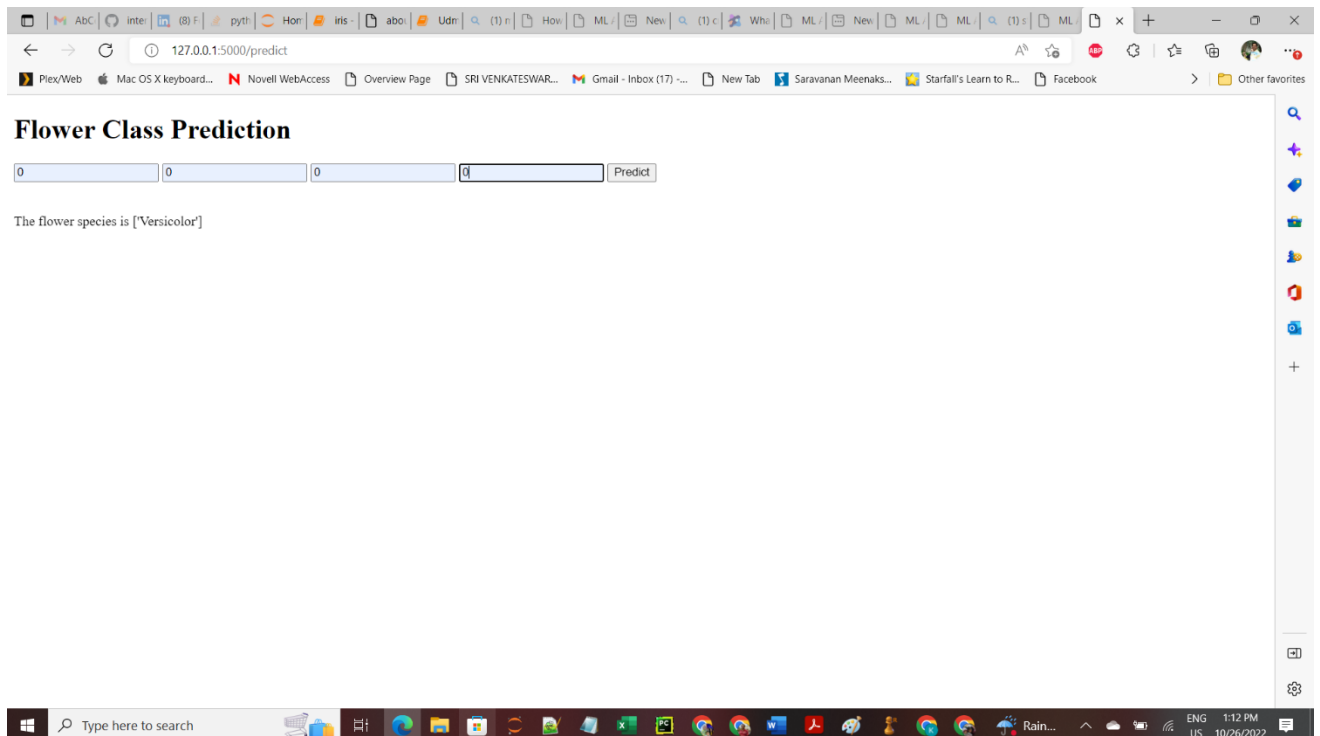
E:\Anitha\Data_Glacier\GitHub\VC\Week4\Iris\venv\Scripts\python.exe E:/Anitha/Data_Glacier/GitHub/VC/Week4/Iris/Template/app.py

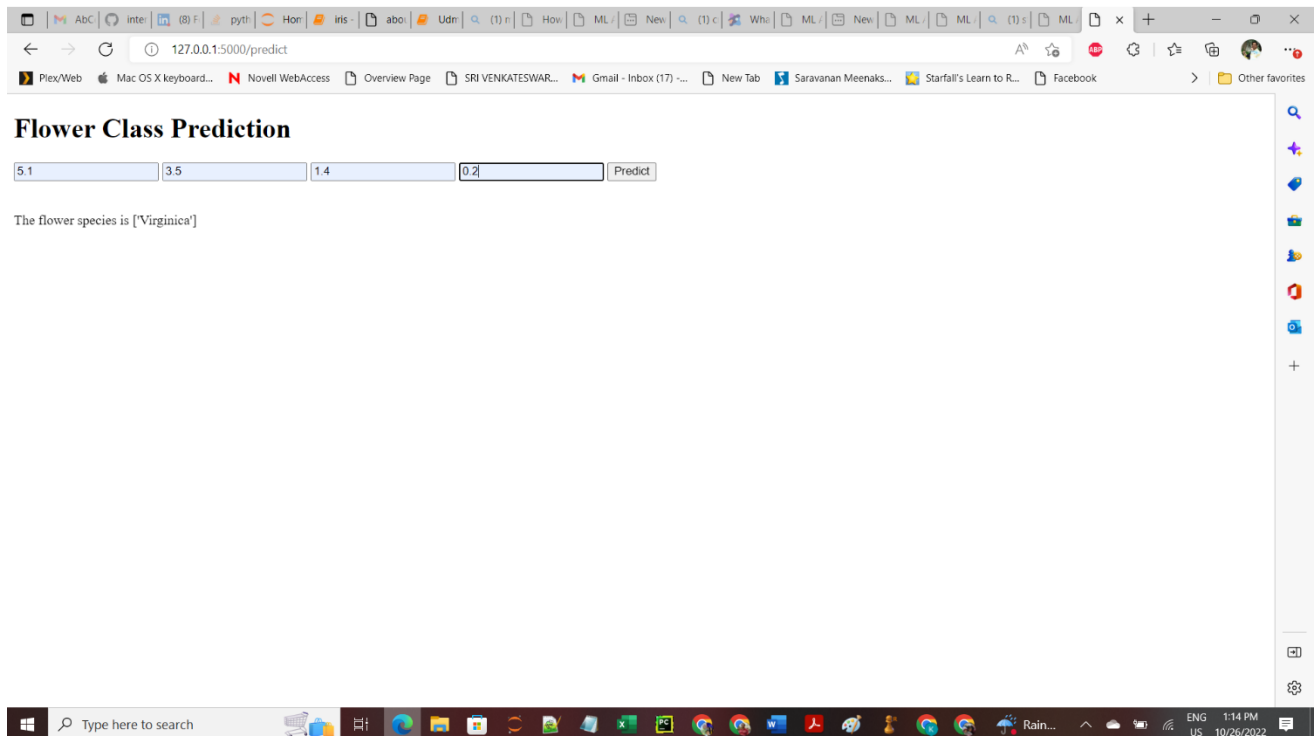
- * Serving Flask app 'app'
- * Debug mode: on
- WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
- * Running on <http://127.0.0.1:5000>
- Press CTRL+C to quit
- * Restarting with stat
- * Debugger is active!
- * Debugger PIN: 615-585-281

Now we could open a web browser and navigate to <http://127.0.0.1:5000/>, we should see a simple website with the content like so



Now we enter input in the values in textbox and the value is predicted.





5. Model deployment using Heroku

We're ready to start our Heroku deployment now that our model has been trained, the machine learning pipeline has been set up, and the application has been tested locally. There are a few ways to upload the application source code onto Heroku. The easiest way is to link a GitHub repository to your Heroku account.

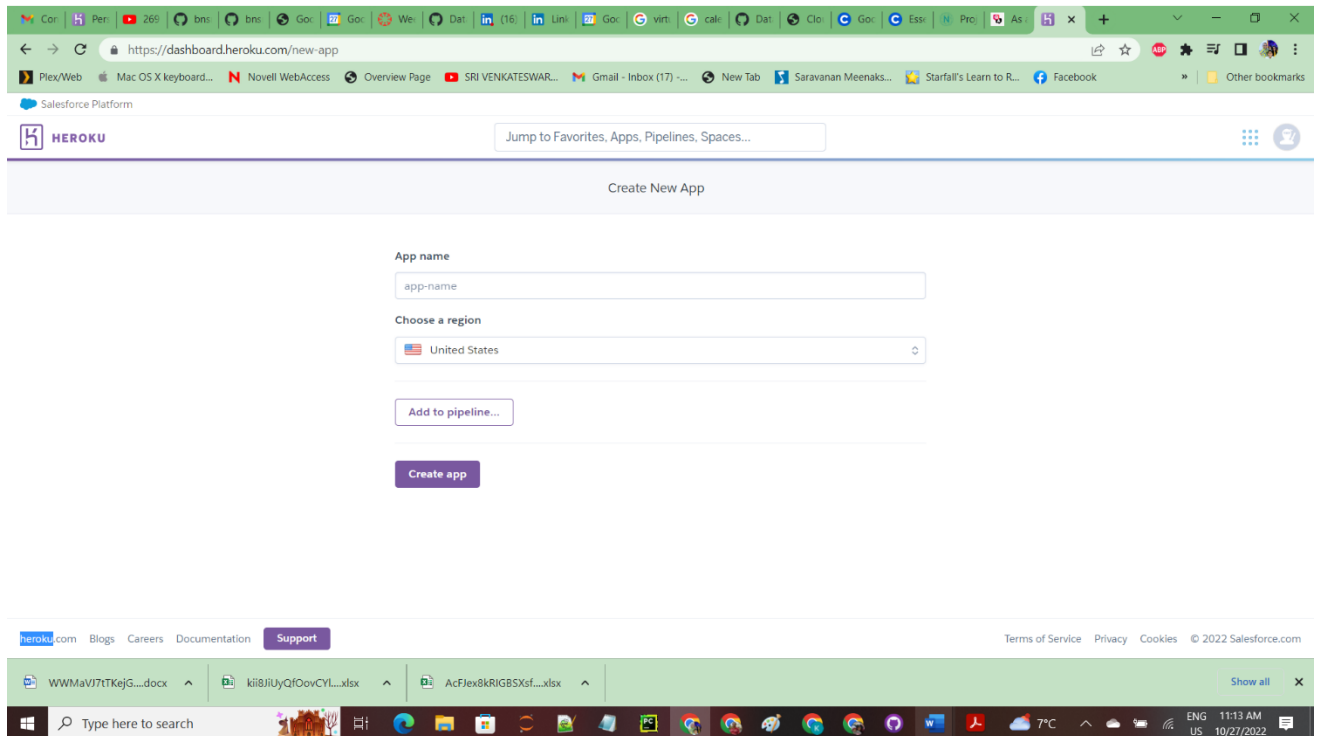
Requirement.txt

It is a text file containing the python packages required to execute the application.

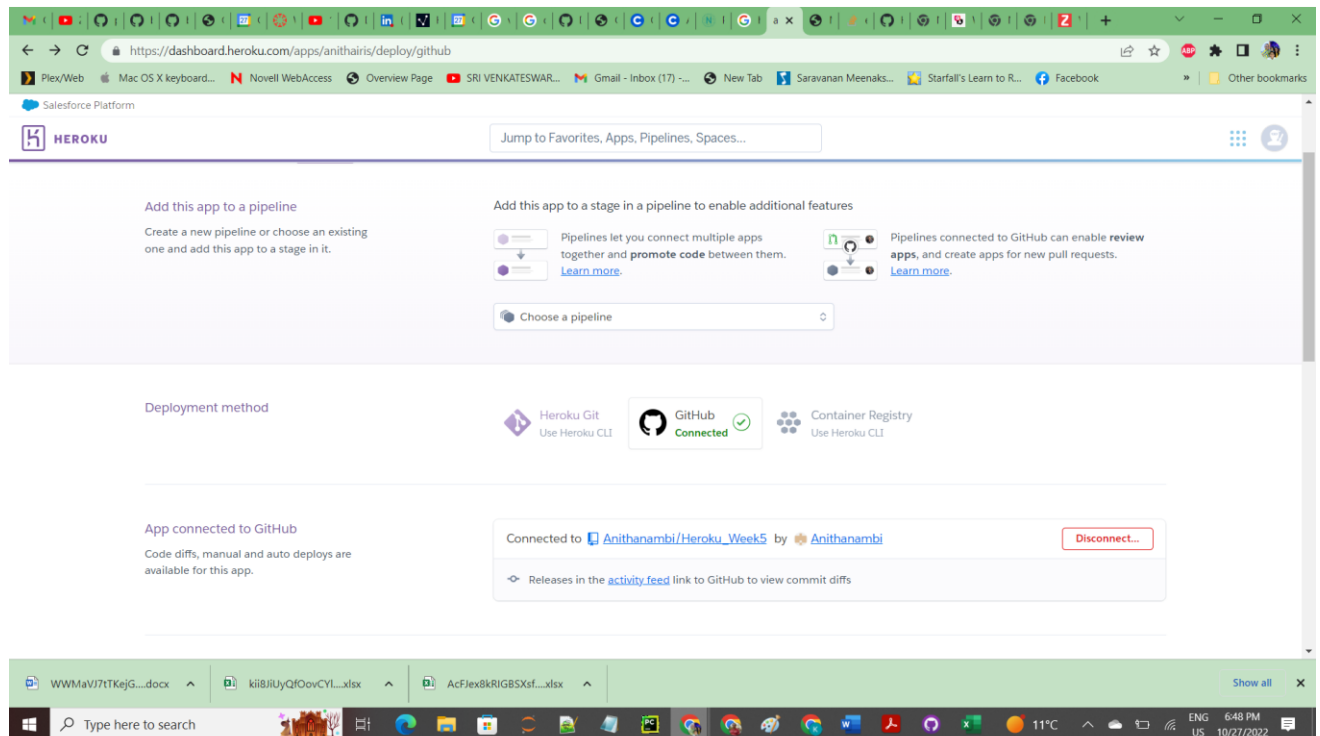
5.1 Steps for Model Deployment Using Heroku

Once we uploaded files to the GitHub repository, we are now ready to start deployment on Heroku. Follow the steps below:

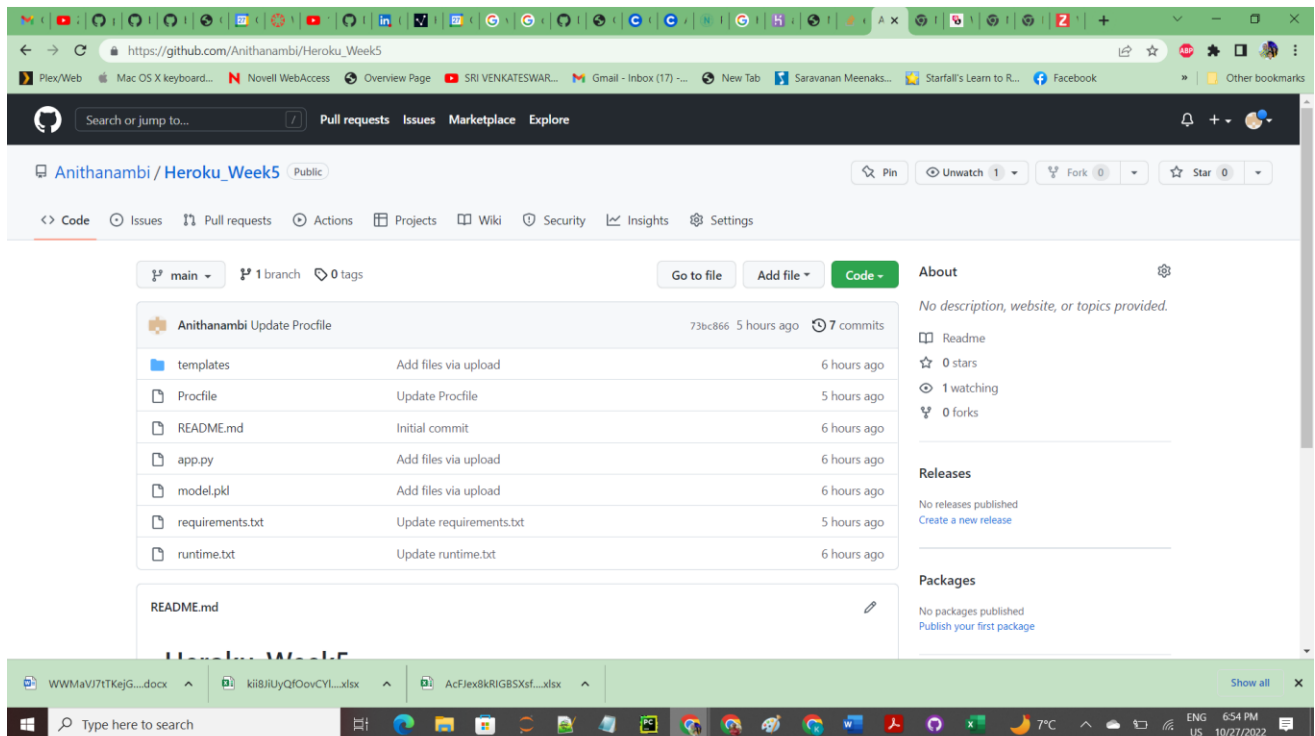
After sign up on **heroku.com** then click on **Create new app**



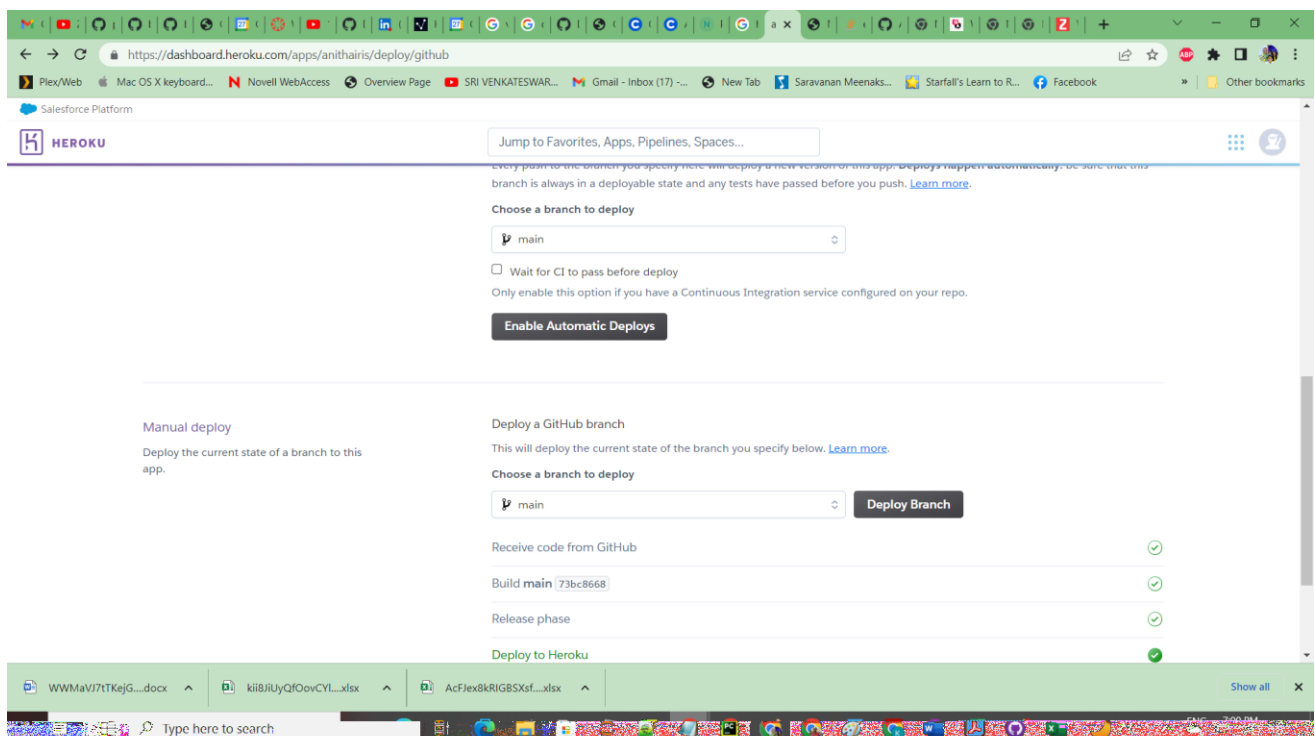
3. Connect to GitHub repository where code is I uploaded.



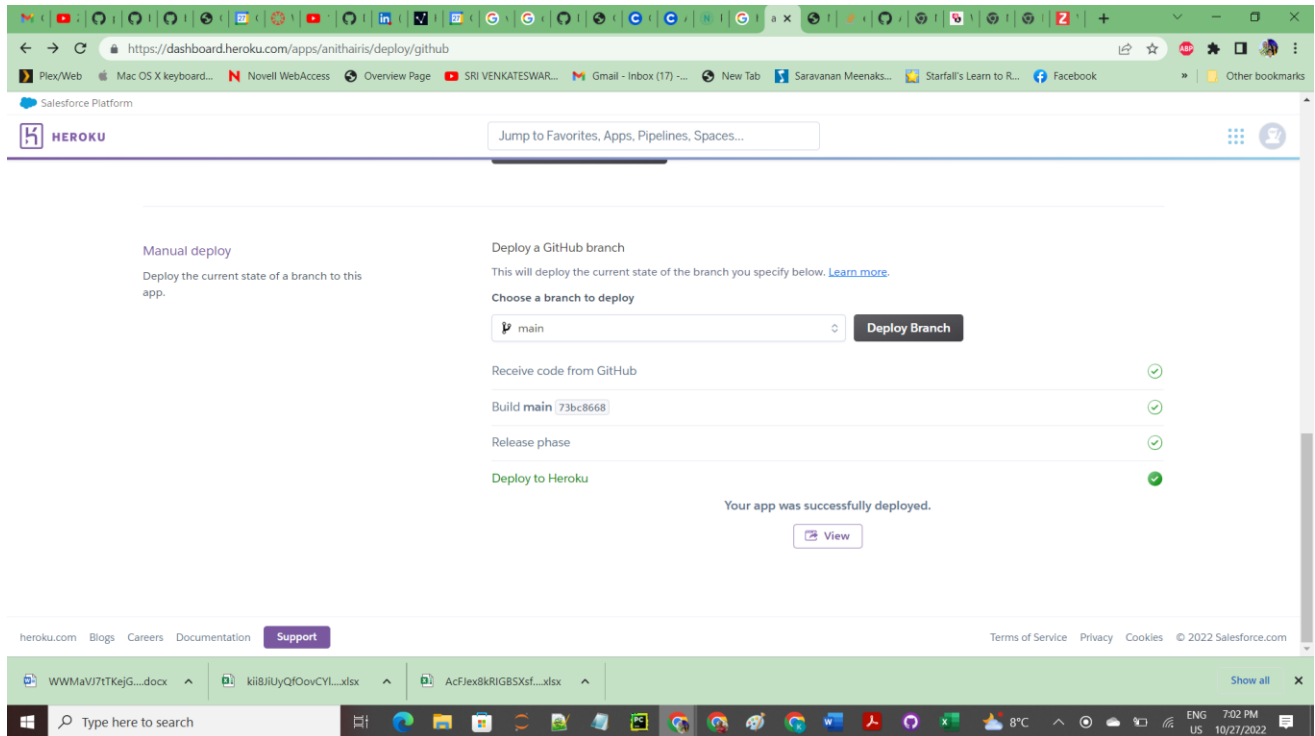
After that I choose the repository where I upload the code.



4. Deploy branch



After 5 minutes our application is Ready



The app is Successfully Published at

<https://anithairis.herokuapp.com/>