Cloud Web App & API Deployment - Iris Data Model

Week 5 Assignment

Name: Nazri

Batch code: LISUM34

Submission date: 04/07/2024

Submitted to: Data Glacier

Table of Contents

Flask Deployment of Iris Data Model

Steps Followed:

1. Pick Iris Toy Data Set

	A	B	C	D	E
1	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width	Class
2	5.1	3.5	1.4	0.2	Setosa
3	4.9	3	1.4	0.2	Setosa
4	4.7	3.2	1.3	0.2	Setosa
5	4.6	3.1	1.5	0.2	Setosa
6	5	3.6	1.4	0.2	Setosa
7	5.4	3.9	1.7	0.4	Setosa
8	4.6	3.4	1.4	0.3	Setosa
9	5	3.4	1.5	0.2	Setosa
10	4.4	2.9	1.4	0.2	Setosa
11	4.9	3.1	1.5	0.1	Setosa
12	5.4	3.7	1.5	0.2	Setosa
13	4.8	3.4	1.6	0.2	Setosa
14	4.8	3	1.4	0.1	Setosa
15	4.3	3	1.1	0.1	Setosa
16	5.8	4	1.2	0.2	Setosa
17	5.7	4.4	1.5	0.4	Setosa
18	5.4	3.9	1.3	0.4	Setosa
19	5.1	3.5	1.4	0.3	Setosa
20	5.7	3.8	1.7	0.3	Setosa
21	5.1	3.8	1.5	0.3	Setosa

2. Import necessary libraries:

Prepare the environment by installing necessary libraries like Scikit-learn and importing them. Also ensure the compatibility of Scikit-learn version with the IDE PyCharm

```
[23] !pip install scikit-learn==1.5.1
```

```
Requirement already satisfied: scikit-learn==1.5.1 in /usr/local/lib/python3.10/dist-packages (1.5.1)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.10/dist-packages (from scikit-learn==1.5.1) (1.26.4)
Requirement already satisfied: scipy>=1.6.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn==1.5.1) (1.13.1)
Requirement already satisfied: joblib>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn==1.5.1) (1.4.2)
Requirement already satisfied: threadpoolctl>=3.1.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn==1.5.1) (3.5.0)
```

```
[2] # Import Libraries
import pandas as pd
import sklearn
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import pickle
import gdown
```

```
print(sklearn.__version__)
```

```
1.5.1
```

3. Downloading the Dataset:

Using ‘gdown’ download the Iris dataset from Google Drive.

4. Loading the Iris Dataset into a Dataframe:

The dataset is read from the CSV file using pandas from the contents folder.

```
[4] #importing the dataset from drive
    gdown.download_folder('https://drive.google.com/drive/folders/1Akoln8Xc14yMx01AXQw88YddMFyrfEft?', quiet=True)
```

```
['/content/Iris-Dataset/iris.csv']
```

```
[5] #Load the dataset
    iris_data = pd.read_csv('/content/Iris-Dataset/iris.csv')
```

5. Exploratory Data Analysis:

The head, shape, info, and isnull methods are used to inspect the dataset's structure, datatypes, and check for missing values.

```
iris_data.head()
```

	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

```
[7] iris_data.shape
```

```
(150, 5)
```

```
iris_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   Sepal_Length  150 non-null    float64
 1   Sepal_Width   150 non-null    float64
 2   Petal_Length  150 non-null    float64
 3   Petal_Width   150 non-null    float64
 4   Class         150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
[9] # check fo null vallues
    iris_data.isnull().sum()
```

	0
Sepal_Length	0
Sepal_Width	0
Petal_Length	0
Petal_Width	0
Class	0

dtype: int64

Check the summary statistics

```
[13] iris_data.describe()
```

	Sepal_Length	Sepal_Width	Petal_Length	Petal_Width
count	149.000000	149.000000	149.000000	149.000000
mean	5.843624	3.059732	3.748993	1.194631
std	0.830851	0.436342	1.767791	0.762622
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.300000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

Check for Duplicates

```
[10] # Check for duplicates
     num_duplicates = iris_data.duplicated().sum()
     print(f"Number of duplicate rows: {num_duplicates}")
```

```
Number of duplicate rows: 1
```

```
[11] # Identify duplicate records
     duplicates = iris_data[iris_data.duplicated()]

     # Print duplicate records
     print("Duplicate records:")
     print(duplicates)
```

```
Duplicate records:
     Sepal_Length  Sepal_Width  Petal_Length  Petal_Width      Class
142           5.8          2.7           5.1          1.9  Virginica
```

Note: In the excel sheet, the duplicated data is aligned in the 103 and 144 row.

101	5.7	2.8	4.1	1.3	Versicolor
102	6.3	3.3	6	2.5	Virginica
103	5.8	2.7	5.1	1.9	Virginica
104	7.1	3	5.9	2.1	Virginica
105	6.3	2.9	5.6	1.8	Virginica

142	6.7	3.1	5.6	2.4	Virginica
143	6.9	3.1	5.1	2.3	Virginica
144	5.8	2.7	5.1	1.9	Virginica
145	6.8	3.2	5.9	2.3	Virginica
146	6.7	3.3	5.7	2.5	Virginica

6. Data Preprocessing:

Remove the duplicate rows identified during EDA process.

```
[12] # Remove duplicate rows
     iris_data = iris_data.drop_duplicates()

     # Verify that duplicates are removed
     num_duplicates_after = iris_data.duplicated().sum()
     print(f"Number of duplicate rows after cleaning: {num_duplicates_after}")
```

```
Number of duplicate rows after cleaning: 0
```

7. Splitting the Dataset

Select the features and target variables from the dataset and split the dataset into training and testing sets.

```
[14] # Select independent and dependent variable
     # Split the data into features and target
     X = iris_data[["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"]]
     y = iris_data["Class"]
```

```
[15] # Split the dataset into train and test
     X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

8. Model Selection and Training the model:

Train the machine learning model on the pre-processed data with machine learning algorithms such as random forest classifier and logistic regression. Fit the model on the training data.

9. Model Evaluation:

Evaluate the model using the test set. And check its accuracy, precision, recall, and F1-score.

```
[16] # Train the model with Randon forest classifier
     rfc = RandomForestClassifier()

     # Fit the model
     rfc.fit(X_train, y_train)
```

```
RandomForestClassifier
RandomForestClassifier()
```

```
[17] #Evaluate the model
     y_pred = rfc.predict(X_test)
     accuracy = accuracy_score(y_test, y_pred)
     print('Randon Forest Model Accuracy:', accuracy)
```

```
Randon Forest Model Accuracy: 1.0
```

```
[18] # Train the model with logistic regression
lg= LogisticRegression(max_iter=200)

# Fit the model
lg.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=200)
```

```
# Evaluate the model
y_pred = lg.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print('Logistic Regression Model Accuracy:', accuracy)
```

```
Logistic Regression Model Accuracy: 1.0
```

```
from sklearn.metrics import classification_report

# Evaluate Random Forest
y_pred_rf = rfc.predict(X_test)
print('Random Forest Classification Report:\n', classification_report(y_test, y_pred_rf))

# Evaluate Logistic Regression
y_pred_lg = lg.predict(X_test)
print('Logistic Regression Classification Report:\n', classification_report(y_test, y_pred_lg))
```

```
Random Forest Classification Report:
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        10
  Versicolor       1.00      1.00      1.00         9
   Virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30

Logistic Regression Classification Report:
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        10
  Versicolor       1.00      1.00      1.00         9
   Virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

Summary:

When both models achieve an accuracy of 1 on the test data, it might indicate that the models are overfitting, especially if the dataset is small or lacks complexity. Overfitting occurs when a model learns the training data too well, including noise and outliers, leading to poor generalization on unseen data.

10. Perform Cross-Validation on the models

To ensure that the models are truly generalizing well, we should use cross-validation. This involves splitting the dataset into multiple folds and training/evaluating the model on different folds. This process helps in assessing how the model performs across different subsets of the data.

```
[21] from sklearn.model_selection import cross_val_score

     # Cross-validation for Random Forest
     rf_cv_scores = cross_val_score(rfc, X_train, y_train, cv=5)
     print('Random Forest Cross-Validation Scores:', rf_cv_scores)
     print('Random Forest Mean CV Score:', rf_cv_scores.mean())

     # Cross-validation for Logistic Regression
     lg_cv_scores = cross_val_score(lg, X_train, y_train, cv=5)
     print('Logistic Regression Cross-Validation Scores:', lg_cv_scores)
     print('Logistic Regression Mean CV Score:', lg_cv_scores.mean())
```

```
Random Forest Cross-Validation Scores: [1.         0.91666667 0.875      1.         0.95652174]
Random Forest Mean CV Score: 0.9496376811594203
Logistic Regression Cross-Validation Scores: [1.         0.91666667 0.875      1.         0.95652174]
Logistic Regression Mean CV Score: 0.9496376811594203
```

11. Choosing the Best Model Random Forest:

Choose the model Random Forest Classifier considering the following features

- Handle Non-linearity
- Robustness to Outliers
- Handle large datasets and Complex Patterns

12. Save the trained model using pickle

```
[22] # Choosing the model
     # Make pickle file of our model
     pickle.dump(rfc, open("model.pkl", "wb"))
```

13. Setting up Flask Application

Create a Flask application (app.py).

- Load the saved model in the Flask app.
- Define routes for prediction, such as /predict.
- Use request to get input from the user and return predictions.

Create a HTML Template (index.html)

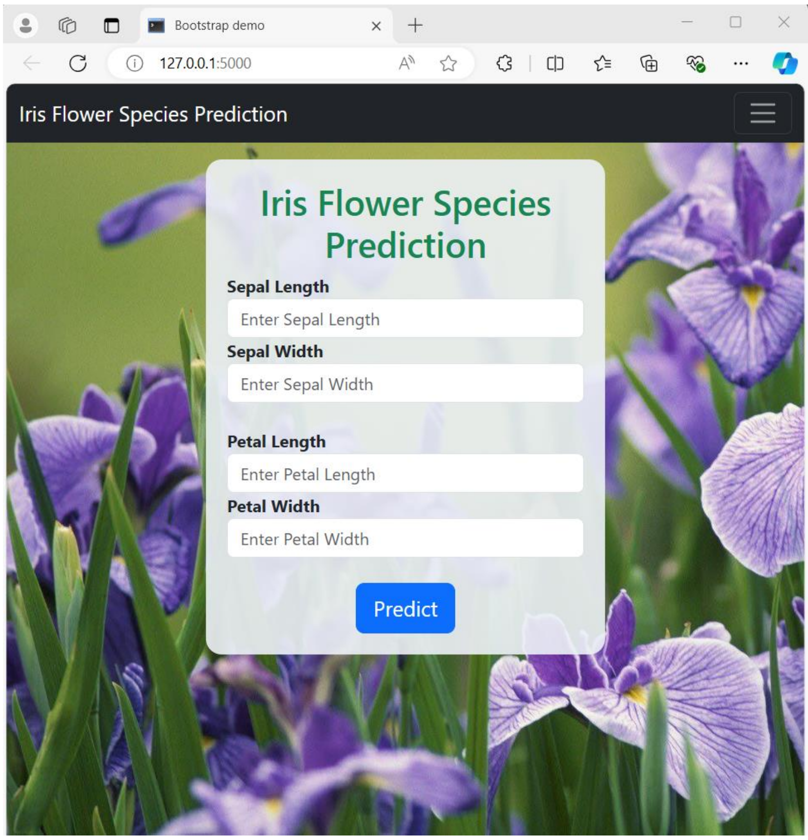
- In a templates directory, create index.html for user input

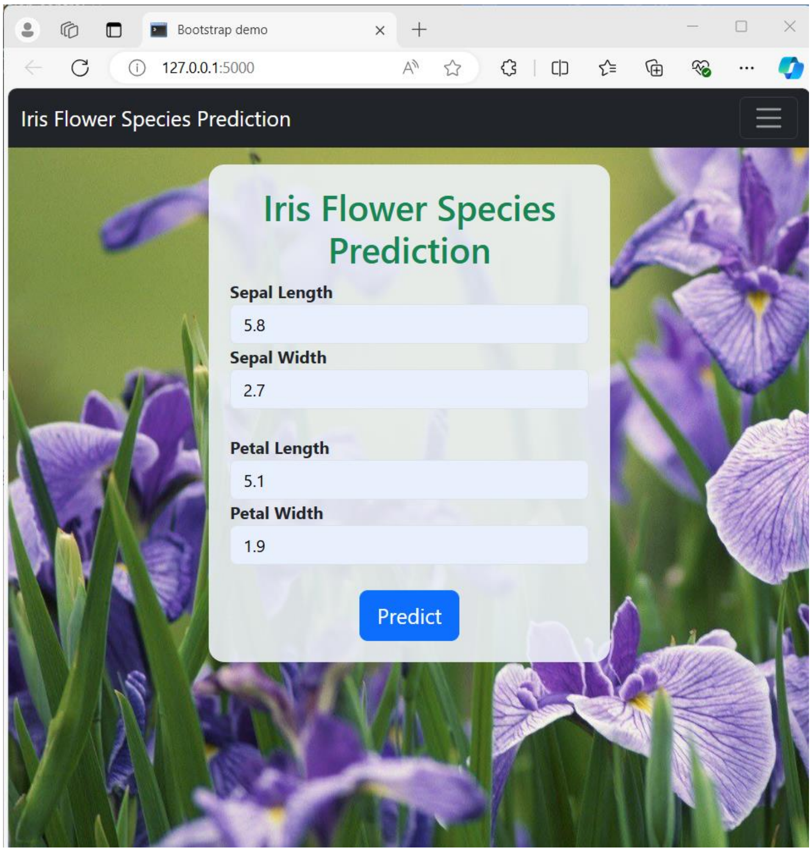
14. Running the Flask App:

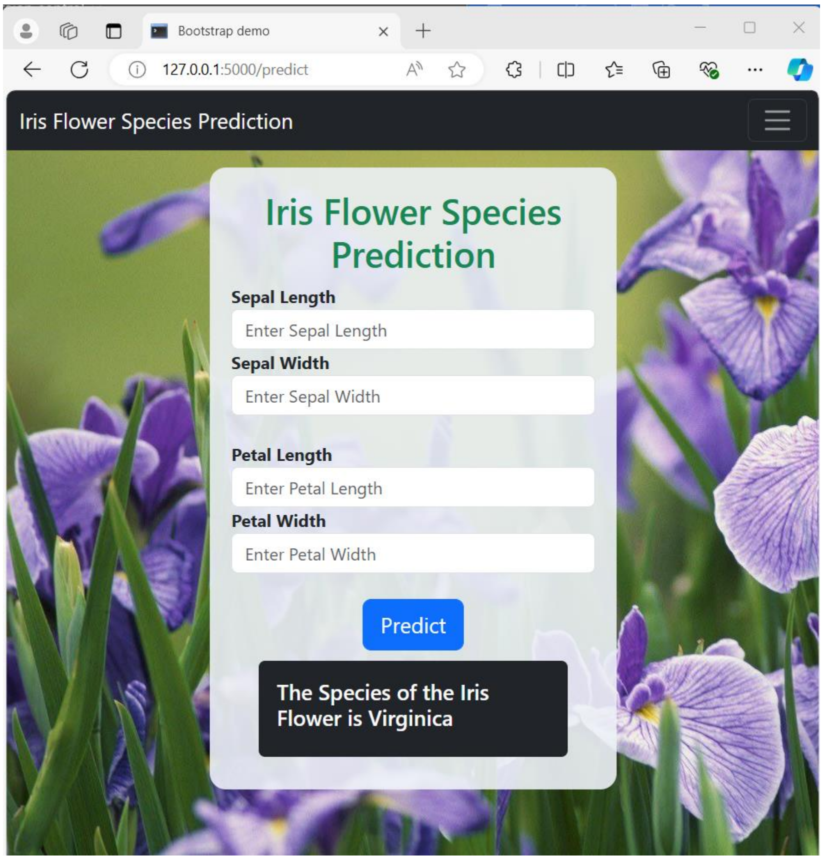
- Run the Flask app locally.

```
"C:\Users\nazri_c98ckep\PycharmProject\Flask Deployment-Iris Data\venv\Scripts\python.exe" "C:\Users\nazri_c98ckep\PycharmProject\Flask Deployment-Iris Data\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: 420-096-619
```

Output







app.py

```
from flask import Flask, request, render_template
import numpy as np
import pickle
import sklearn
import pandas as pd

# importing model
model = pickle.load(open('model.pkl', 'rb'))

# creating flask app
app = Flask(__name__)

@app.route('/')
def index():
    return render_template("index.html")

@app.route("/predict", methods=['POST'])
def predict():
    # Collecting input features from the form
    float_features = [float(x) for x in request.form.values()]
    # print("Received input features:", float_features)  # Debugging

    # Defining the feature names as used during the model training
    feature_names = ['Sepal_Length', 'Sepal_Width', 'Petal_Length', 'Petal_Width']

    # Creating a DataFrame with the feature names
```

```
    features = pd.DataFrame([float_features], columns=feature_names)
    # print("DataFrame created:", features)  # Debugging

    # Making predictions
    prediction = model.predict(features)
    # print("Prediction:", prediction)  # Debugging

    # Rendering the template with the prediction result
    return render_template("index.html", prediction_text="The Species of the Iris Flower is
{}".format(prediction[0]))

# Main function to run the Flask app
if __name__ == "__main__":
    app.run(debug=True)
```

index.html

```
<!doctype html>
<html lang="en">
  <head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <title>Bootstrap demo</title>
    <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0-alpha3/dist/css/bootstrap.min.css"
rel="stylesheet" integrity="sha384-
KK94CHFLLe+nY2dmCWGMq91rCGa5gtU4mk92HdvYe+M/SXH301p5ILy+dN9+nJOZ"
crossorigin="anonymous">
  </head>
  <style>
    body {
      background-image: url('{{ url_for('static', filename='img.jpeg') }}');
      background-size: cover;
      background-repeat: no-repeat;
      background-attachment: fixed;
    }
    h1 {
      color: #BE2ED6;
      text-align: center;
    }
    .warning {
      color: red;
      font-weight: bold;
      text-align: center;
    }
    .card {
      margin: 10px auto;
      color: white;
    }
    .container {
      background: rgba(237, 242, 247, 0.9); /* Semi-transparent background */
      font-weight: bold;
```

```
      padding: 20px; /* Increased padding for better spacing */
      border-radius: 15px;
      width: 50%; /* Set width to 50% of the viewport */
      max-width: 600px; /* Maximum width */
      margin: 0 auto; /* Center the container horizontally */
    }
  </style>

  <body>
    <!--
===========================navbar=========================================================
====-->
    <nav class="navbar navbar-expand-lg navbar-dark bg-dark">
      <div class="container-fluid">
        <a class="navbar-brand" href="/">Iris Flower Species Prediction</a>
        <button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-
target="#navbarSupportedContent" aria-controls="navbarSupportedContent" aria-expanded="false" aria-
label="Toggle navigation">
          <span class="navbar-toggler-icon"></span>
        </button>
        <div class="collapse navbar-collapse" id="navbarSupportedContent">
          <ul class="navbar-nav me-auto mb-2 mb-lg-0">
            <li class="nav-item">
              <a class="nav-link active" aria-current="page" href="#">Home</a>
            </li>
            <li class="nav-item">
              <a class="nav-link" href="#">Contact</a>
            </li>
            <li class="nav-item">
              <a class="nav-link" href="#">About</a>
            </li>
          </ul>
          <form class="d-flex" role="search">
            <input class="form-control me-2" type="search" placeholder="Search" aria-label="Search">
            <button class="btn btn-outline-success" type="submit">Search</button>
          </form>
        </div>
      </div>
    </nav>

    <!--
==========================================================================================
=============-->
    <div class="container my-3 mt-3">
      <h1 class="text-success">Iris Flower Species Prediction<span class="text-success"></span></h1>

      <!-- adding form -->
      <form action="/predict" method="POST">
        <div class="row">
          <div class="col-md-6">
            <label for="Sepal Length">Sepal Length</label>
```

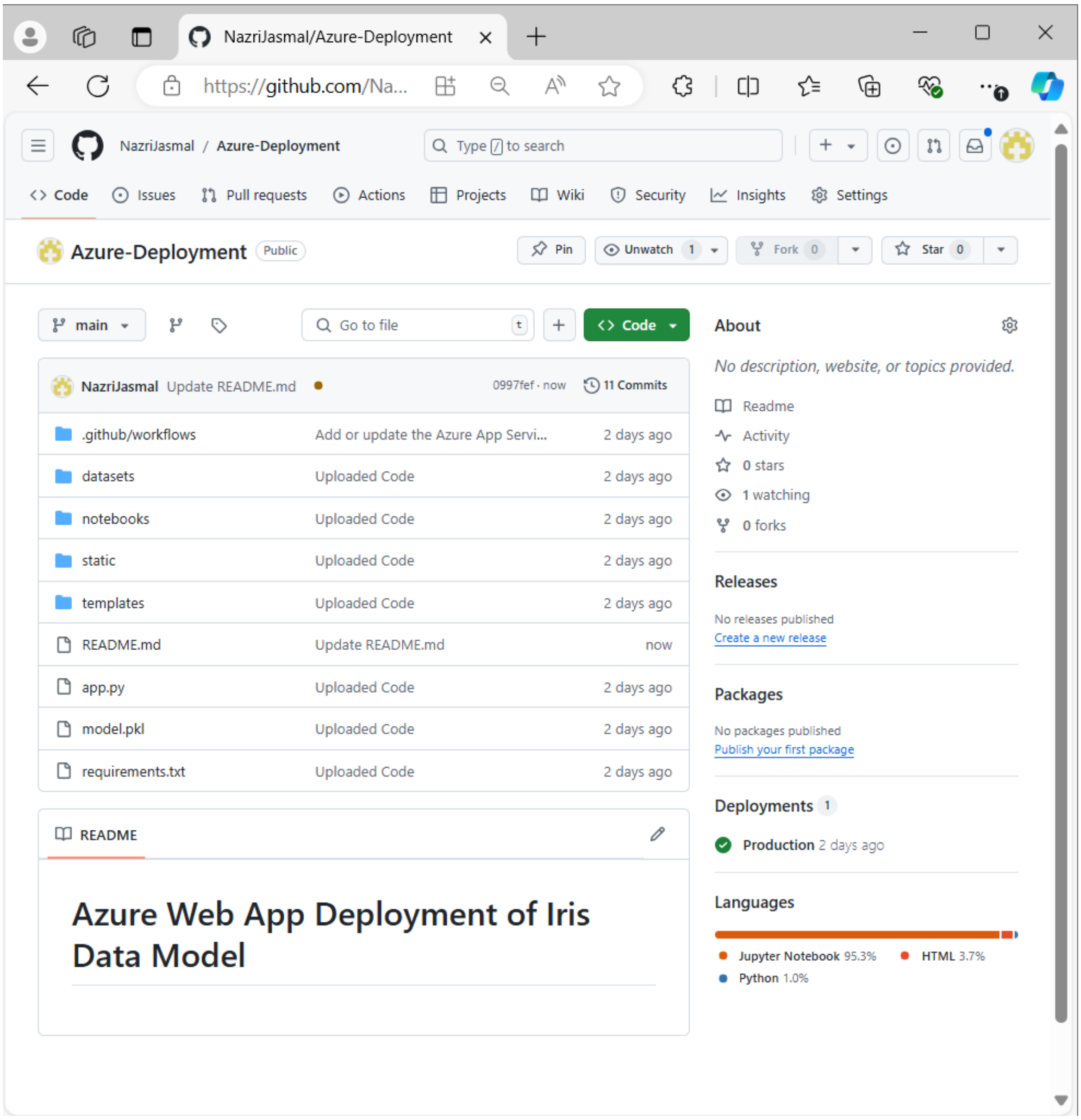
```html
          <input type="text" id="Sepal_Length" name="Sepal Length" placeholder="Enter Sepal Length"
class="form-control" required="required">
        </div>
        <div class="col-md-6">
          <label for="Sepal Width">Sepal Width</label>
          <input type="text" id="Sepal_Width" name="Sepal Width" placeholder="Enter Sepal Width"
class="form-control" required="required">
        </div>
      </div>

      <div class="row mt-4">
        <div class="col-md-6">
          <label for="Petal Length">Petal Length</label>
          <input type="text" id="Petal_Length" name="Petal Length" placeholder="Enter Petal Length"
class="form-control" required="required">
        </div>
        <div class="col-md-6">
          <label for="Petal Width">Petal Width</label>
          <input type="text" id="Petal_Width" name="Petal Width" placeholder="Enter Petal Width"
class="form-control" required="required">
        </div>
      </div>

      <div class="row mt-4">
        <div class="col-md-12 text-center">
          <button type="submit" class="btn btn-primary btn-lg">Predict</button>
        </div>
      </div>
    </form>

    {% if prediction_text %}
    <div class="card bg-dark" style="width: 18rem;">
      <div class="card-body">
        <h5 class="card-title">{{ prediction_text }}</h5>
      </div>
    </div>
    {% endif %}
  </div>

  <script src="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0-alpha3/dist/js/bootstrap.bundle.min.js"
integrity="sha384-ENjdO4Dr2bkBIFxQpeoTz1HIcje39Wm4jDKdf19U8gI4ddQ3GYNS7NTKfAdVQSZe"
crossorigin="anonymous"></script>
 </body>
</html>
```

Web App Deployment of Iris data Model in Azure Cloud

Web App Deployment: This means the model should also be accessible via a web interface where users can input data directly on a webpage and see the predictions. This could be a simple web page (built with HTML/CSS and perhaps some JavaScript) with a form where users can enter data, click a button, and see the results. This web app will also be hosted on Azure, so anyone with the URL can access it via their web browser.

GitHub Repository of the Source Code

Link: https://github.com/NazriJasmal/Azure-Deployment.git



Deploy the Flask application to Azure App Service: This involves creating an Azure Web App, configuring the deployment settings, and deploying the application code.

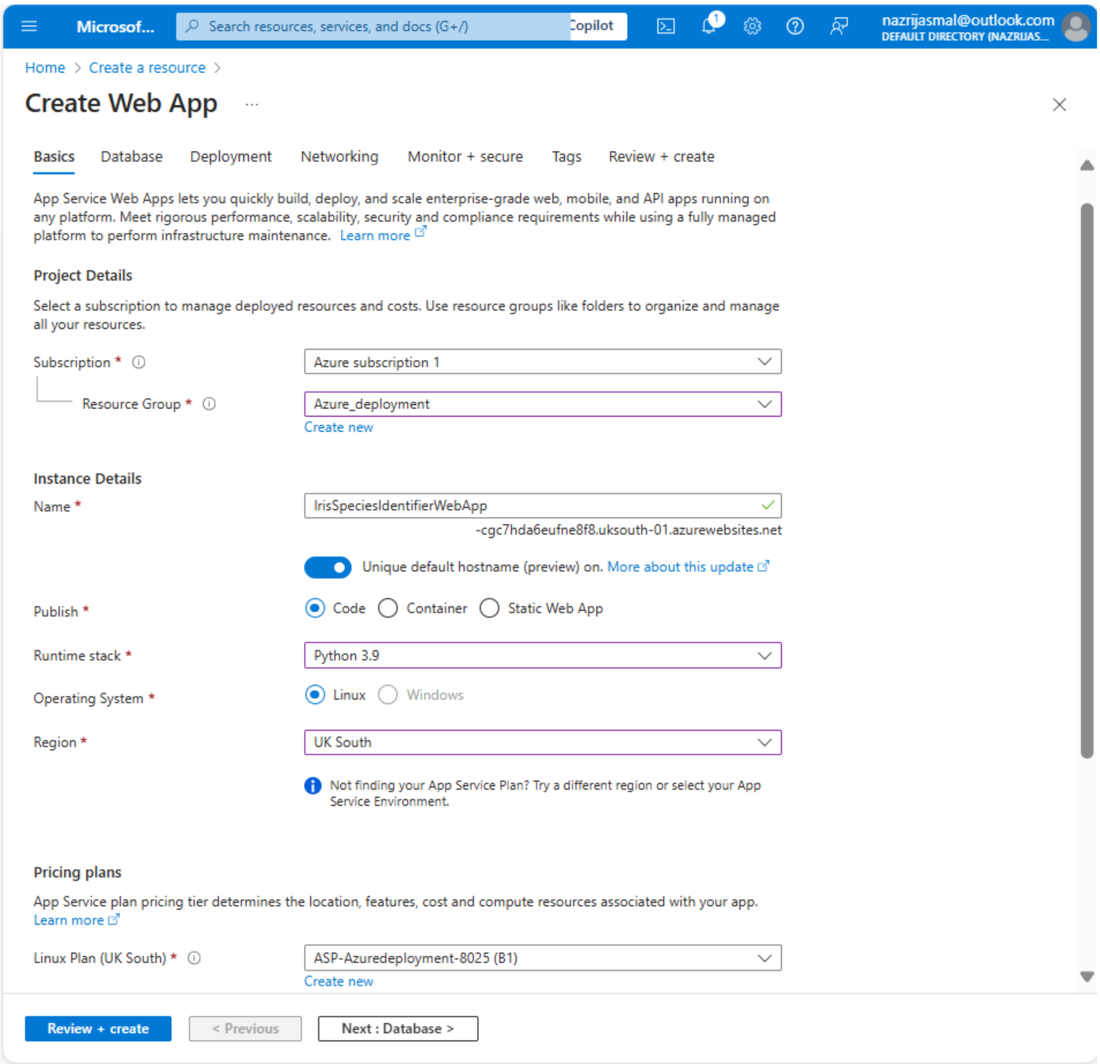
Steps Followed:

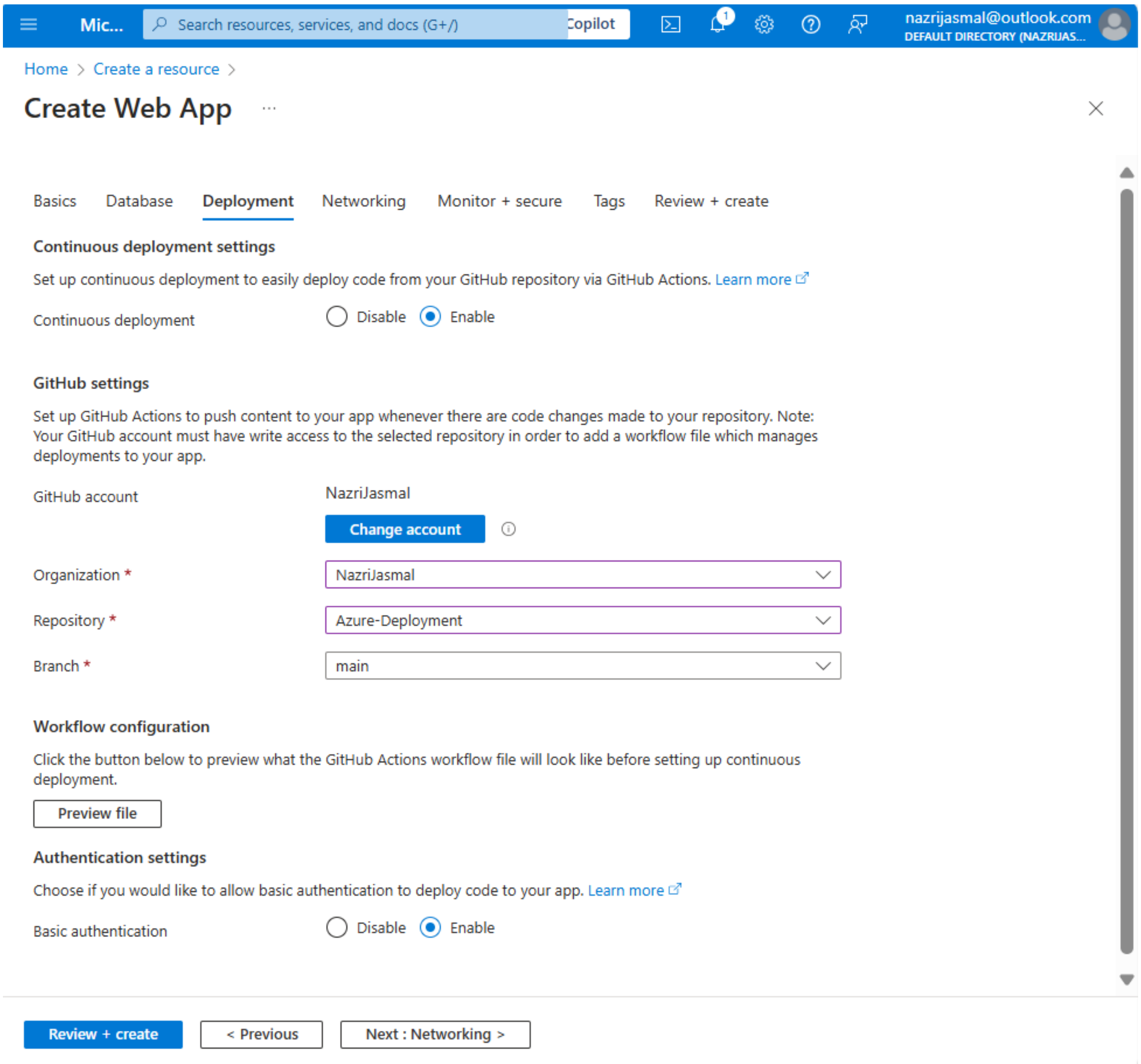
1) Prepare the Flask Application

- Make sure the Flask app (app.py) is working locally.
- Create requirements.txt: To generate a requirements.txt file listing all the project's dependencies, run the command pip freeze > requirements.txt in the terminal of IDE Pycharm.

2) Log in to the Azure Portal with the Microsoft account
3) Create a new Web App
   Navigate to **Create a Resource > Web > Web App > Click Create**
4) Configure the Web App

   - Subscription: Select the Azure subscription.
   - Resource Group: Create a new resource group or select an existing one.
   - Name: Enter a name for the Web App. This will be part of your web app's URL.
   - Publish: Select Code.
   - Runtime Stack: Choose the version of Python that matches with the local environment, which is Python 3.9. (To get this, Run the command 'python --version' in the terminal of IDE Pycharm.)
   - Region: Select the Azure region where we want to deploy the app.
   - Go to Deployment tab and enable continuous deployment and basic authentication.
   - Connect to GitHub account: Select the repository and branch that contains the source code of the Flask app.
   - Click Review + Create, then Create.





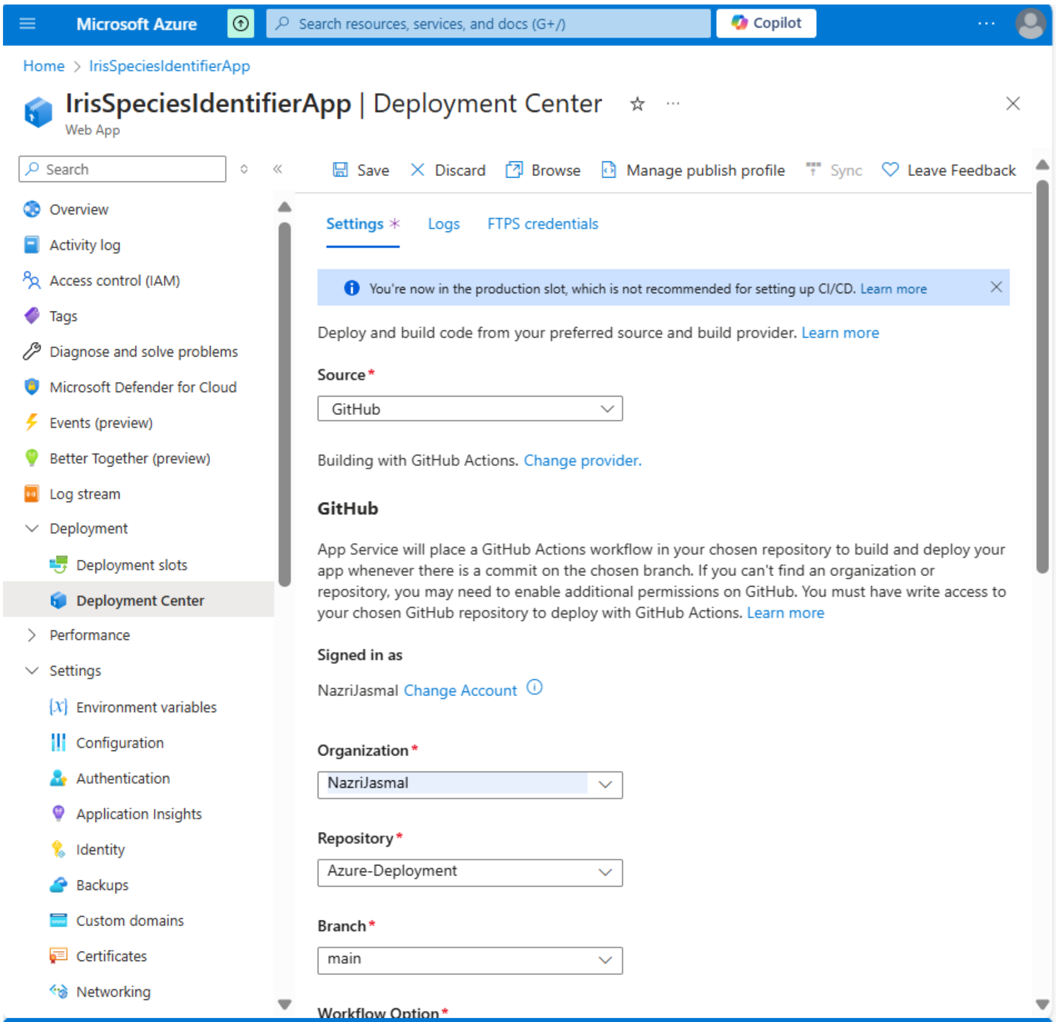
5) Access the Web App
   After creation, go to the Resource page of the new Web App.

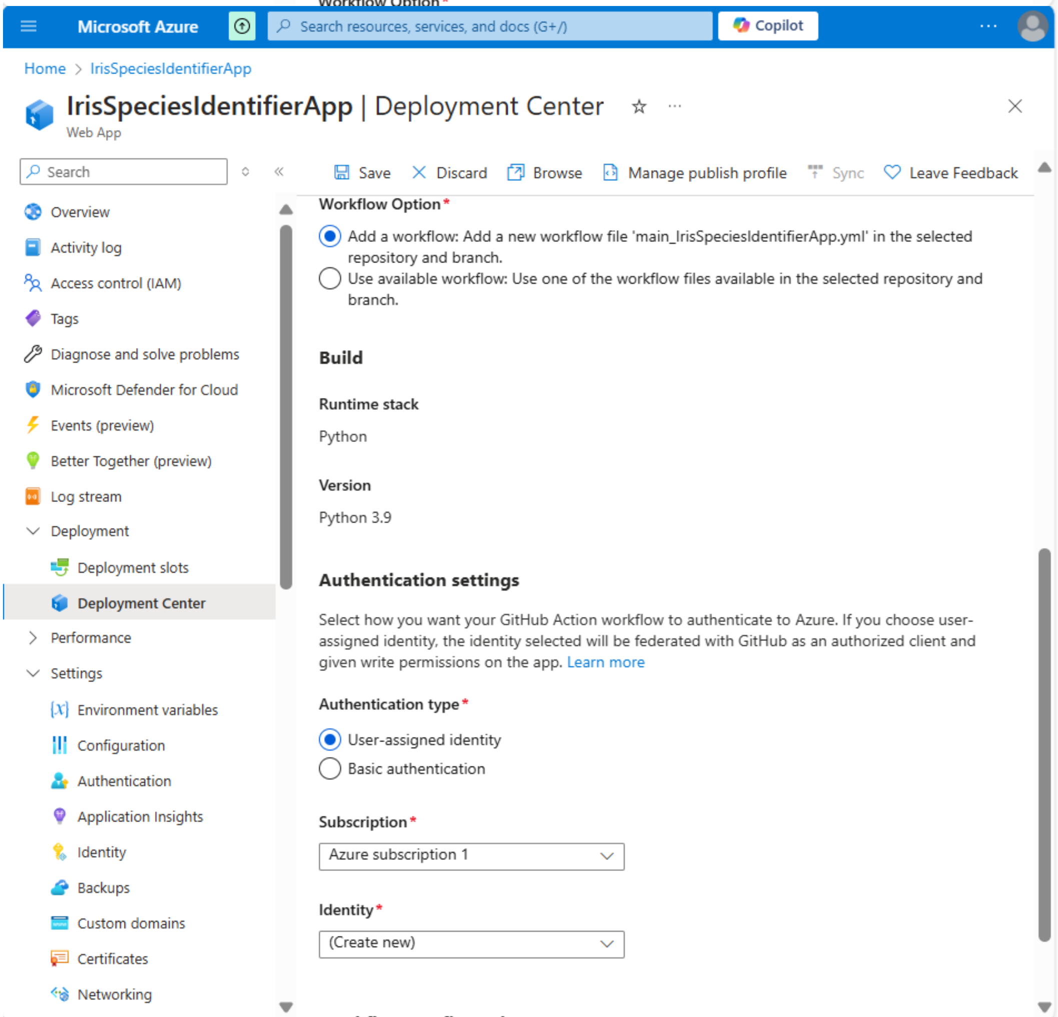
6) Deployment will be in progress as we have already enabled continuous deployment.

Enabling continuous deployment in Azure allows your code changes to be automatically updated and deployed to your app or service, without needing manual intervention.

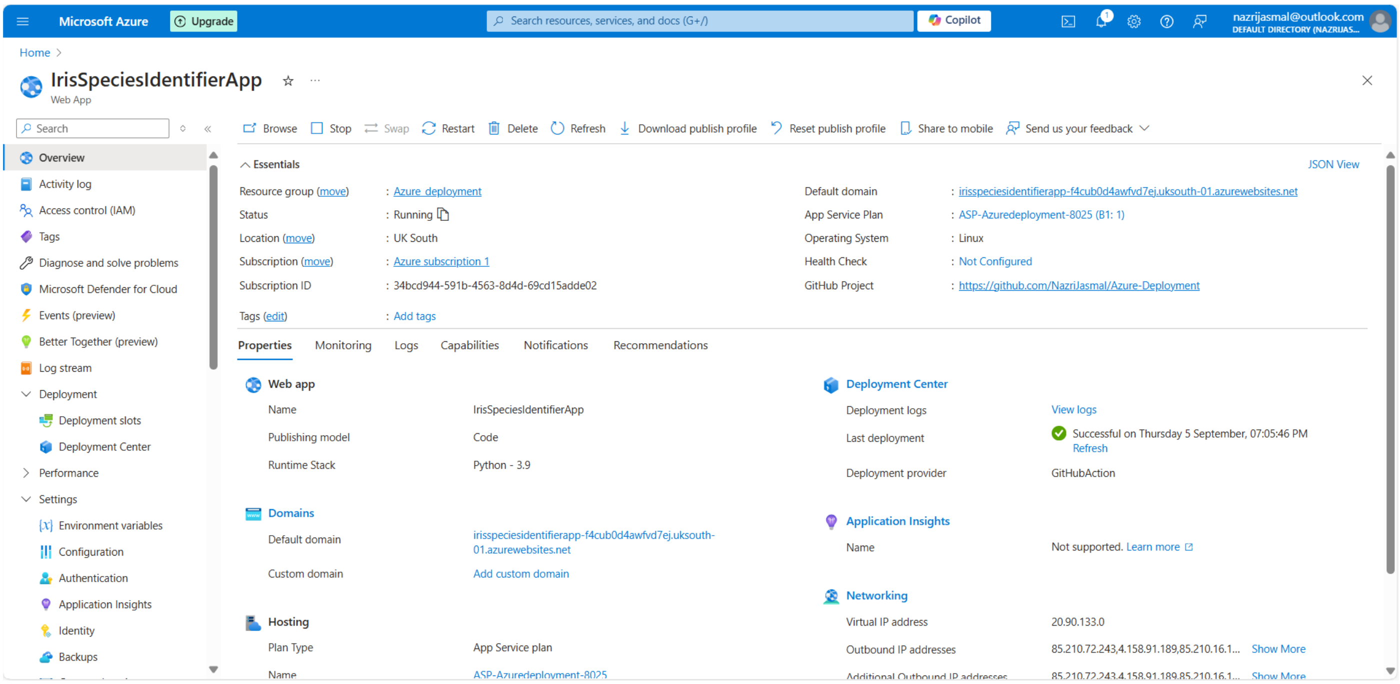
7) If Continuous Deployment is not enabled

- Go to the Resource page of the Web App. Then select Deployment > Deployment Centre, in the left-hand menu.
- Then Select Settings and enter the details of the GitHub Repo and branch that contains the source code of the Flask app. Then Click Save


Microsoft Azure
Search resources, services, and docs (G+/)
Copilot
Home > IrisSpeciesIdentifierApp
IrisSpeciesIdentifierApp | Deployment Center
Web App
Search
Overview
Activity log
Access control (IAM)
Tags
Diagnose and solve problems
Microsoft Defender for Cloud
Events (preview)
Better Together (preview)
Log stream
Deployment
Deployment slots
Deployment Center
Performance
Settings
Environment variables
Configuration
Authentication
Application Insights
Identity
Backups
Custom domains
Certificates
Networking
Save
Discard
Browse
Manage publish profile
Sync
Leave Feedback
Settings
Logs
FTPS credentials
You're now in the production slot, which is not recommended for setting up CI/CD. Learn more
Deploy and build code from your preferred source and build provider. Learn more
Source *
GitHub
Building with GitHub Actions. Change provider.
GitHub
App Service will place a GitHub Actions workflow in your chosen repository to build and deploy your app whenever there is a commit on the chosen branch. If you can't find an organization or repository, you may need to enable additional permissions on GitHub. You must have write access to your chosen GitHub repository to deploy with GitHub Actions. Learn more
Signed in as
NazriJasmal Change Account
Organization *
NazriJasmal
Repository *
Azure-Deployment
Branch *
main
Workflow Option *

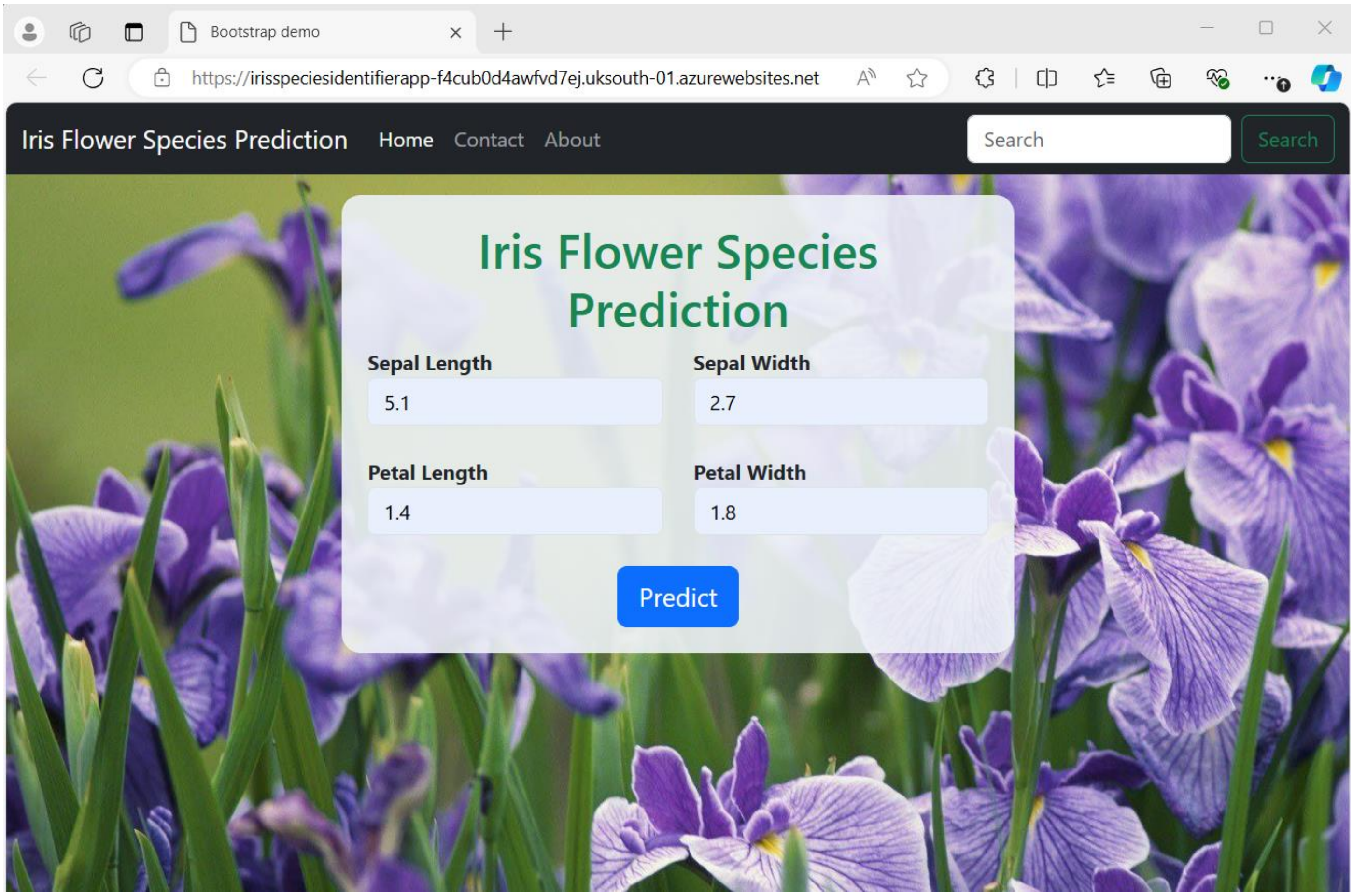

Microsoft Azure
Search resources, services, and docs (G+/)
Copilot
Home > IrisSpeciesIdentifierApp
IrisSpeciesIdentifierApp | Deployment Center
Web App
Search
Overview
Activity log
Access control (IAM)
Tags
Diagnose and solve problems
Microsoft Defender for Cloud
Events (preview)
Better Together (preview)
Log stream
Deployment
Deployment slots
Deployment Center
Performance
Settings
Environment variables
Configuration
Authentication
Application Insights
Identity
Backups
Custom domains
Certificates
Networking
Save
Discard
Browse
Manage publish profile
Sync
Leave Feedback
Workflow Option *
Add a workflow: Add a new workflow file 'main_IrisSpeciesIdentifierApp.yml' in the selected repository and branch.
Use available workflow: Use one of the workflow files available in the selected repository and branch.
Build
Runtime stack
Python
Version
Python 3.9
Authentication settings
Select how you want your GitHub Action workflow to authenticate to Azure. If you choose user-assigned identity, the identity selected will be federated with GitHub as an authorized client and given write permissions on the app. Learn more
Authentication type *
User-assigned identity
Basic authentication
Subscription *
Azure subscription 1
Identity *
(Create new)

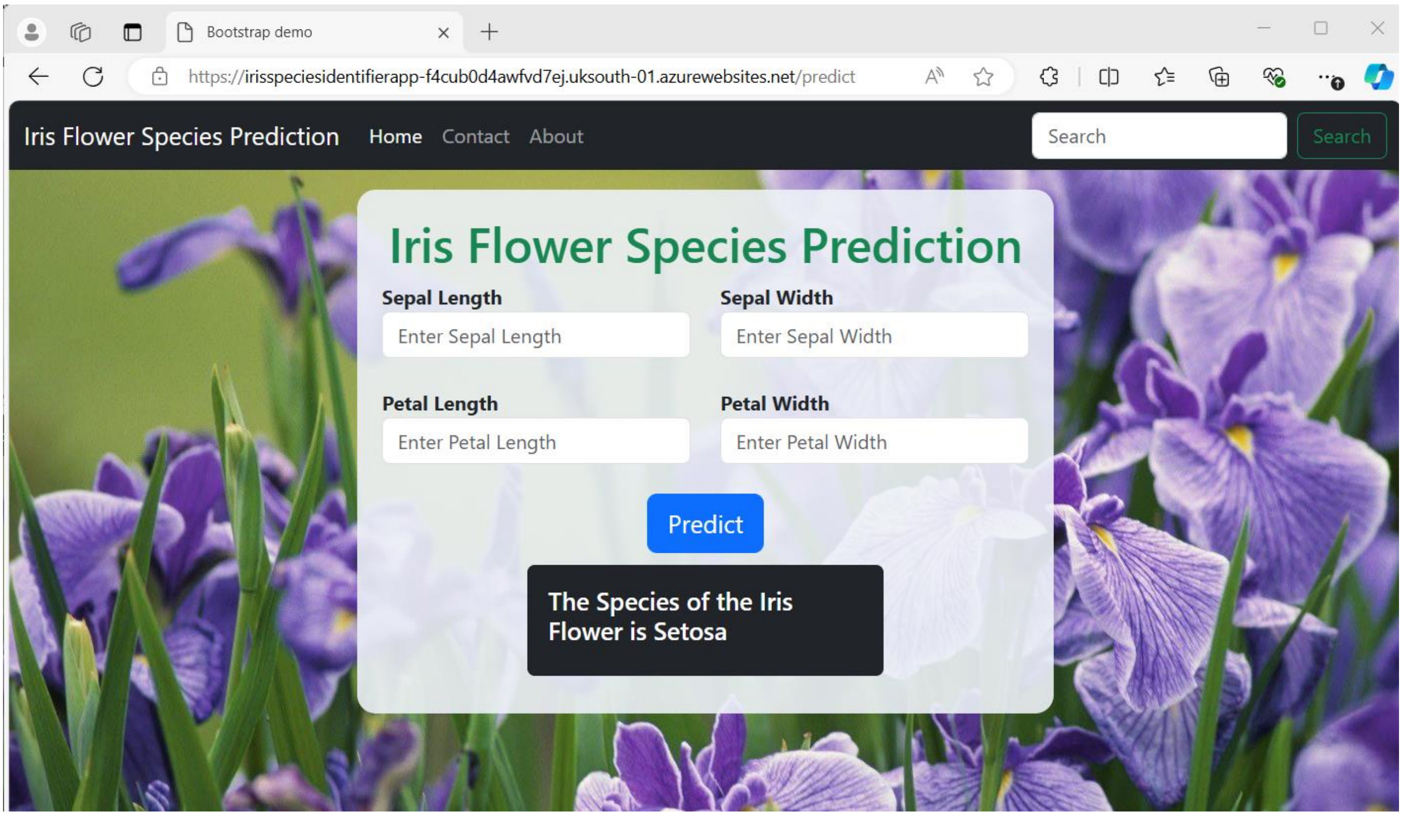
8) Go to the Overview tab and we can see Deployment is successful and the Web App is Created Successfully.



Output

Azure Web App Link: https://irisspeciesidentifierapp-f4cub0d4awfvd7ej.uksouth-01.azurewebsites.net/




Bootstrap demo
https://irisspeciesidentifierapp-f4cub0d4awfvd7ej.uksouth-01.azurewebsites.net/predict
Iris Flower Species Prediction
Home
Contact
About
Search
Search
Iris Flower Species Prediction
Sepal Length
Enter Sepal Length
Sepal Width
Enter Sepal Width
Petal Length
Enter Petal Length
Petal Width
Enter Petal Width
Predict
The Species of the Iris Flower is Setosa

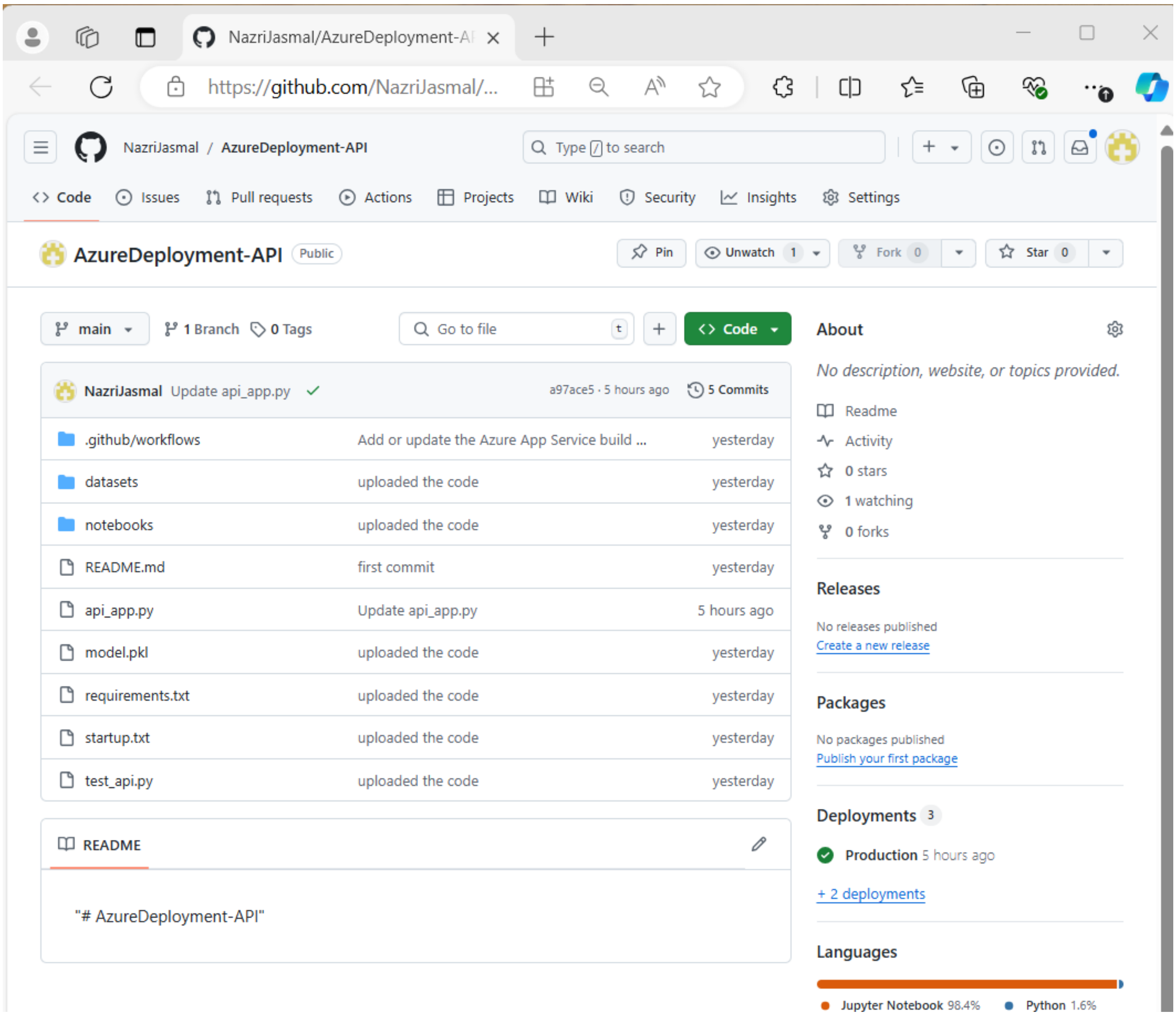
API Deployment of Iris data Model in Azure Cloud

API Deployment: This means the model should be accessible through an HTTP endpoint where we can send data and receive predictions. The model is deployed in such a way that it runs in the background, waiting for incoming HTTP requests.

We can use Azure Machine Learning or Azure Web App Services that supports RESTful APIs to expose the model as an API. When we deploy the model as an API, other developers or applications can send data to the API endpoint, and the model will return predictions.

GitHub Repository of the Source Code

Link: https://github.com/NazriJasmal/AzureDeployment-API.git



Steps Followed:

1. Create an API Application

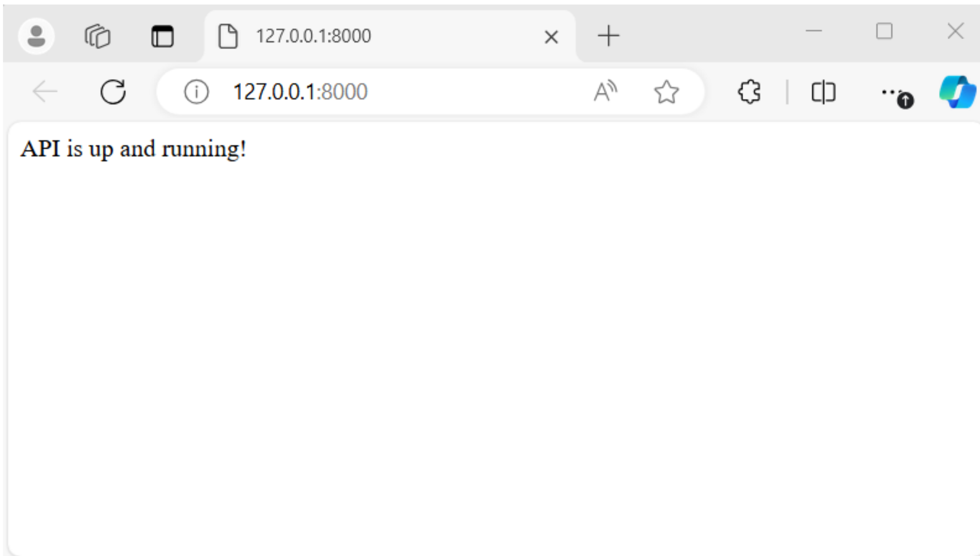
- Create dedicated Flask app for the API. This app will only serve the API endpoint and will be deployed separately from the web app.
- Create a new Python file, api_app.py, that contain the API code

api_app.py

```
from flask import Flask, request, jsonify
import numpy as np
import pickle
import pandas as pd

# Import the trained model
model = pickle.load(open('model.pkl', 'rb'))

# Create the Flask app for the API
app = Flask(__name__)

@app.route("/")
def home():
    # Root route for testing
    return "API is up and running!"

@app.route("/api/predict", methods=['POST'])
def api_predict():
    # Expecting a JSON payload
    data = request.get_json(force=True)

    # Extract features from JSON (assuming data['data'] is a list of values)
    features = pd.DataFrame([data['data']], columns=data['columns'])

    # Make predictions
    prediction = model.predict(features)

    # Return the prediction in JSON format
    return jsonify({'prediction': prediction[0]})

# Main function to run the API Flask app
if __name__ == "__main__":
    app.run(host='127.0.0.1', port=8000)
```

2. Make sure the Flask app (api_app.py) is working locally.

```
Run   api_app ×

"C:\Users\nazri_c98ckep\PycharmProject\Flask Deployment-Iris Data\venv\Scripts\python.exe" "C:\Users\nazri_c98ckep\PycharmProject\API Deployment-Iris Data\api_app.py"
 * Serving Flask app 'api_app'
 * Debug mode: off
WARNING: This is a development server. Do not use it in a production deployment. Use a production WSGI server instead.
 * Running on http://127.0.0.1:8000
Press CTRL+C to quit
```



Testing the API Endpoint

- **By Creating a test_api.py: Test Success**

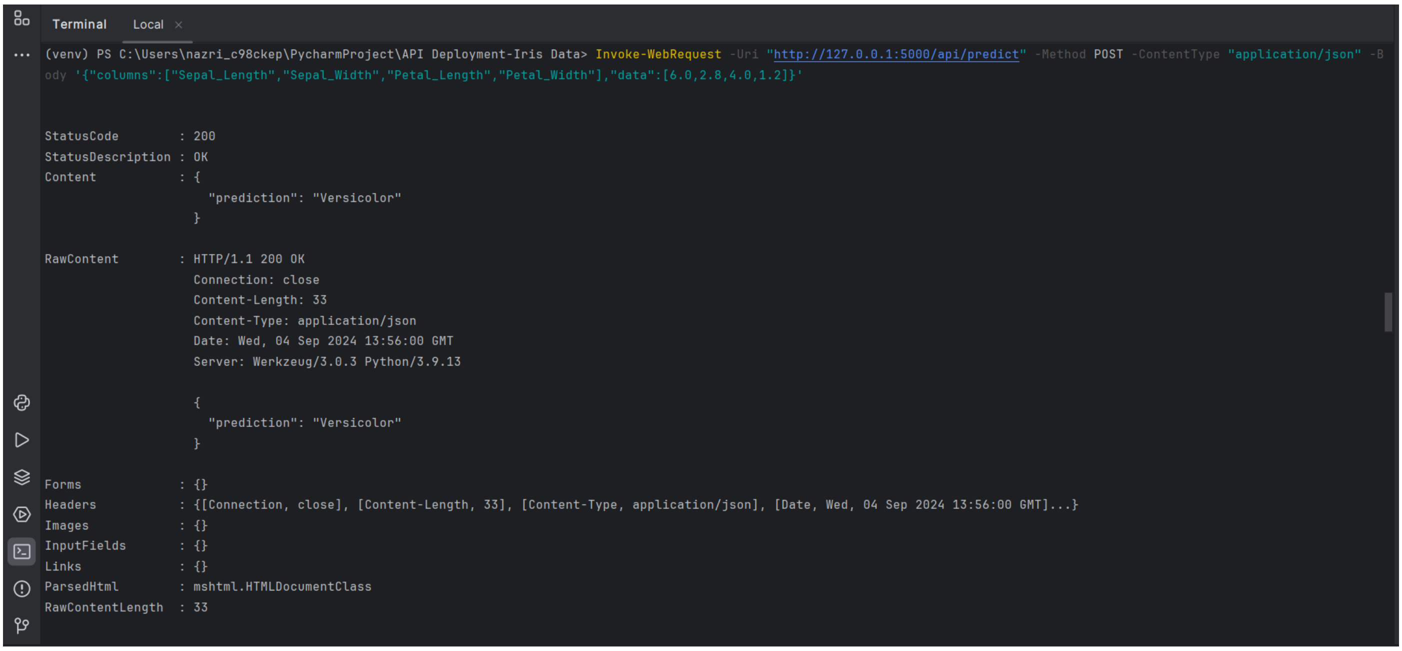
```python
# test_api.py
import requests
import json

# API URL
url = 'http://127.0.0.1:5000/api/predict'

# Data to be sent
data = {
    "columns": ["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"],
    "data": [5.1, 3.5, 1.4, 0.2]
}

# Send POST request
response = requests.post(url, json=data)

# Print response
print("Status Code:", response.status_code)
print("Response JSON:", response.json())
```

```
Run   test_api ×

"C:\Users\nazri_c98ckep\PycharmProject\Flask Deployment-Iris Data\venv\Scripts\python.exe" "C:\Users\nazri_c98ckep\PycharmProject\API Deployment-Iris Data\test_api.py"
Status Code: 200
Response JSON: {'prediction': 'Setosa'}

Process finished with exit code 0
```

- **By Invoking Web Request: Test Success**

Test Case 1:

Invoke-WebRequest -Uri "http://127.0.0.1:5000/api/predict" -Method POST -ContentType "application/json" -Body '{"columns":["Sepal_Length","Sepal_Width","Petal_Length","Petal_Width"],"data":[6.0,2.8,4.0,1.2]}'



```
Terminal   Local
(venv) PS C:\Users\nazri_c98ckep\PycharmProject\API Deployment-Iris Data> Invoke-WebRequest -Uri "http://127.0.0.1:5000/api/predict" -Method POST -ContentType "application/json" -B
ody '{"columns":["Sepal_Length","Sepal_Width","Petal_Length","Petal_Width"],"data":[6.0,2.8,4.0,1.2]}'


StatusCode        : 200
StatusDescription : OK
Content           : {
                      "prediction": "Versicolor"
                    }

RawContent        : HTTP/1.1 200 OK
                    Connection: close
                    Content-Length: 33
                    Content-Type: application/json
                    Date: Wed, 04 Sep 2024 13:56:00 GMT
                    Server: Werkzeug/3.0.3 Python/3.9.13

                    {
                      "prediction": "Versicolor"
                    }

Forms             : {}
Headers           : {[Connection, close], [Content-Length, 33], [Content-Type, application/json], [Date, Wed, 04 Sep 2024 13:56:00 GMT]...}
Images            : {}
InputFields       : {}
Links             : {}
ParsedHtml        : mshtml.HTMLDocumentClass
RawContentLength  : 33
```

Test Case 2:

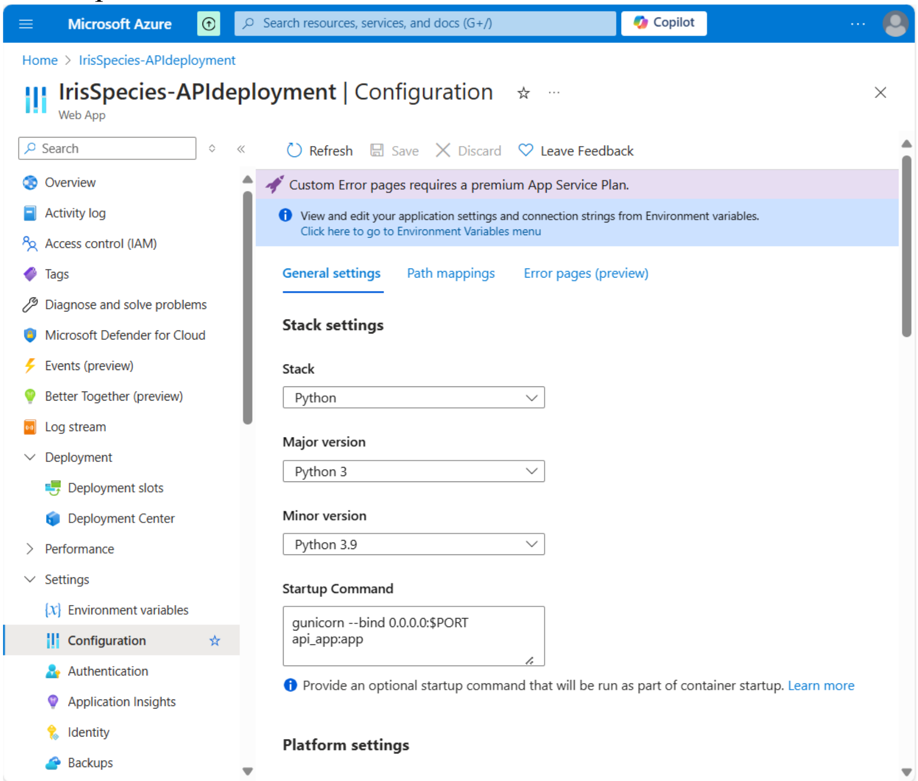
Invoke-WebRequest -Uri "http://127.0.0.1:5000/api/predict" -Method POST -ContentType "application/json" -Body '{"columns":["Sepal_Length","Sepal_Width","Petal_Length","Petal_Width"],"data":[6.5,3.0,5.5,2.0]}'

```
Terminal   Local
(venv) PS C:\Users\nazri_c98ckep\PycharmProject\API Deployment-Iris Data> Invoke-WebRequest -Uri "http://127.0.0.1:5000/api/predict" -Method POST -ContentType "application/json" -B
ody '{"columns":["Sepal_Length","Sepal_Width","Petal_Length","Petal_Width"],"data":[6.5,3.0,5.5,2.0]}'


StatusCode        : 200
StatusDescription : OK
Content           : {
                      "prediction": "Virginica"
                    }

RawContent        : HTTP/1.1 200 OK
                    Connection: close
                    Content-Length: 32
                    Content-Type: application/json
                    Date: Wed, 04 Sep 2024 13:56:25 GMT
                    Server: Werkzeug/3.0.3 Python/3.9.13

                    {
                      "prediction": "Virginica"
                    }

Forms             : {}
Headers           : {[Connection, close], [Content-Length, 32], [Content-Type, application/json], [Date, Wed, 04 Sep 2024 13:56:25 GMT]...}
Images            : {}
InputFields       : {}
Links             : {}
ParsedHtml        : mshtml.HTMLDocumentClass
RawContentLength  : 32
```

3. Prepare the Flask Application

- Create requirements.txt: To generate a requirements.txt file listing all the project's dependencies, run the command pip freeze > requirements.txt in the terminal of IDE Pycharm

- Configure Startup Command: Go to Settings > Configuration > General settings > Startup Command
Enter the command to start the Flask app as gunicorn --bind 0.0.0.0:$PORT api_app:app
This tells Azure to use gunicorn to serve the Flask app where $PORT is a placeholder that Azure uses for the port.



- Update app.run()
Update `app.run` method from `app.run(host='127.0.0.1', port=8000)` to `app.run(host='0.0.0.0', port=8000)` was made, to ensure that the Flask application is accessible externally when deployed on Azure.
    - `127.0.0.1` binds the app to the local loopback interface, making it accessible only from the local machine (localhost).
    - `0.0.0.0` binds the app to all available network interfaces, allowing it to be accessed externally over the network, which is required when deploying to a cloud platform like Azure.

4. Log in to the Azure Portal with the Microsoft account

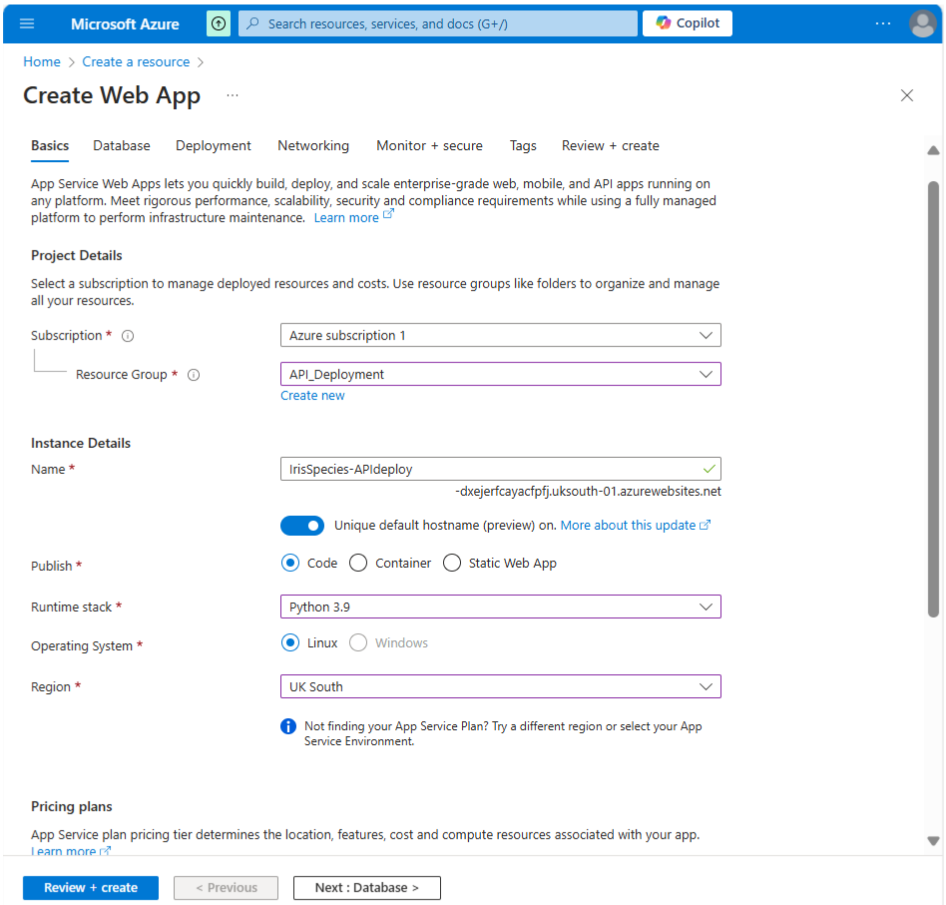
5. Create a new Web App

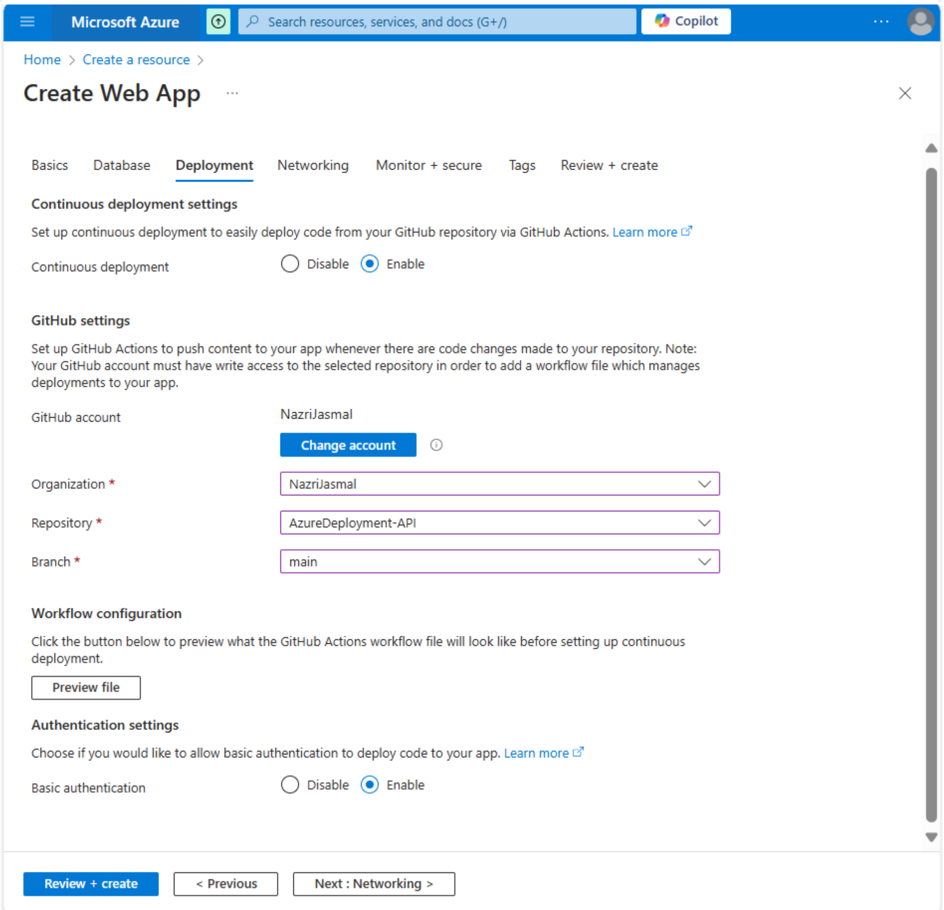
6. Navigate to Create a Resource > Web > Web App > Click Create

7. Configure the Web App

    - Subscription: Select the Azure subscription.
    - Resource Group: Create a new resource group or select an existing one.
    - Name: Enter a name for the Web App. This will be part of your web app's URL.
    - Publish: Select Code.
    - Runtime Stack: Choose the version of Python that matches with the local environment, which is Python 3.9. (To get this, Run the command 'python --version' in the terminal of IDE Pycharm.)

- Region: Select the Azure region where we want to deploy the app.
- Go to Deployment tab and enable continuous deployment and basic authentication.
- Connect to GitHub account: Select the repository and branch that contains the source code of the Flask app.
- Click Review + Create, then Create.

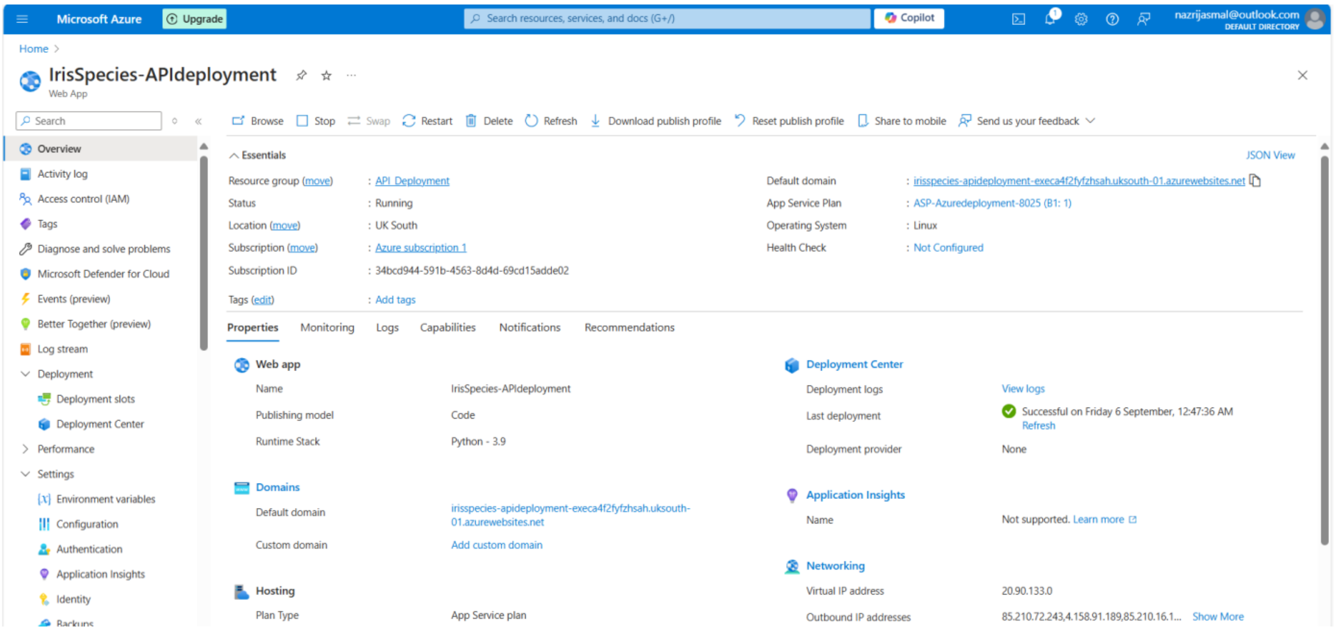




8. Access the Web App
   After creation, go to the Resource page of the new Web App.

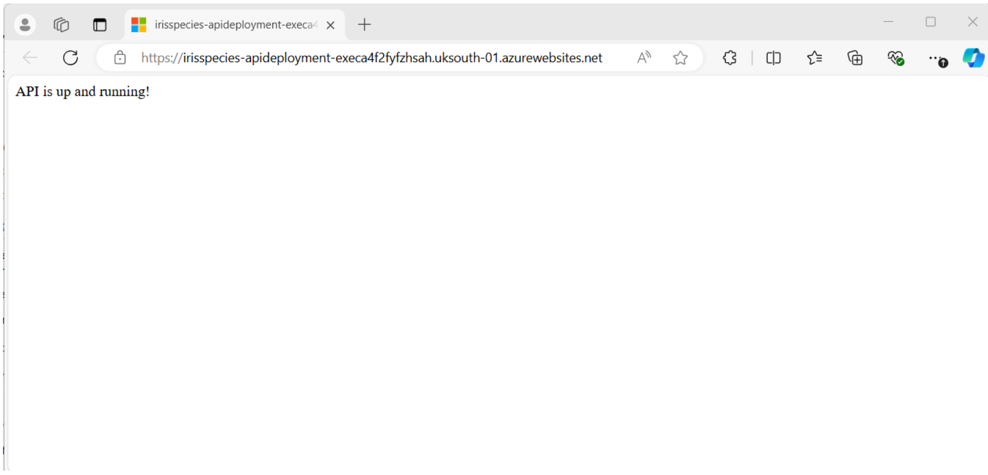
9. Deployment will be in progress as we have already enabled continuous deployment.

10. Go to the Overview tab and we can see API Deployment is Created Successful.



Output

API Domain Link: https://irisspecies-apideployment-execa4f2fyfzhsah.uksouth-01.azurewebsites.net/api/predict



Test the API: Test Success

Once deployed, test the API to ensure it's working correctly.

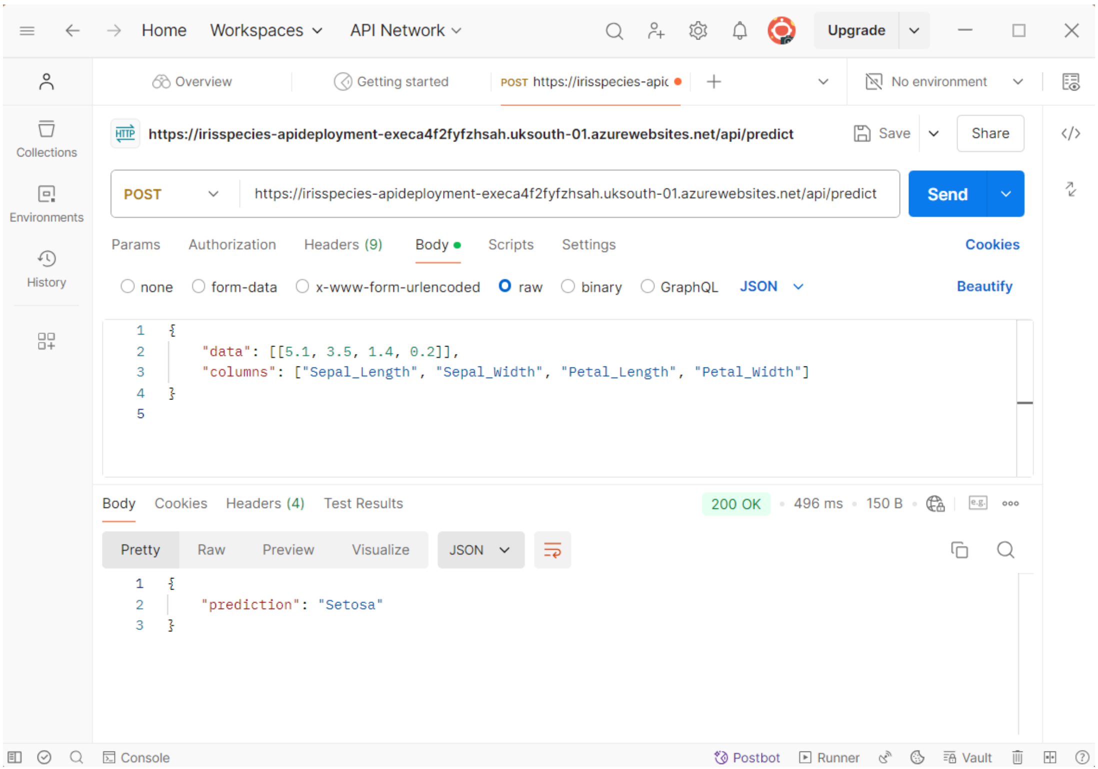
1. **Get the API URL**:
   - After deployment, Azure will provide a URL for the API, which is '`https://irisspecies-apideployment-execa4f2fyfzhsah.uksouth-01.azurewebsites.net`'
2. **Send a POST Request**:
   - Use a tool like **Postman** or **curl** to send a POST request to the API with sample data.

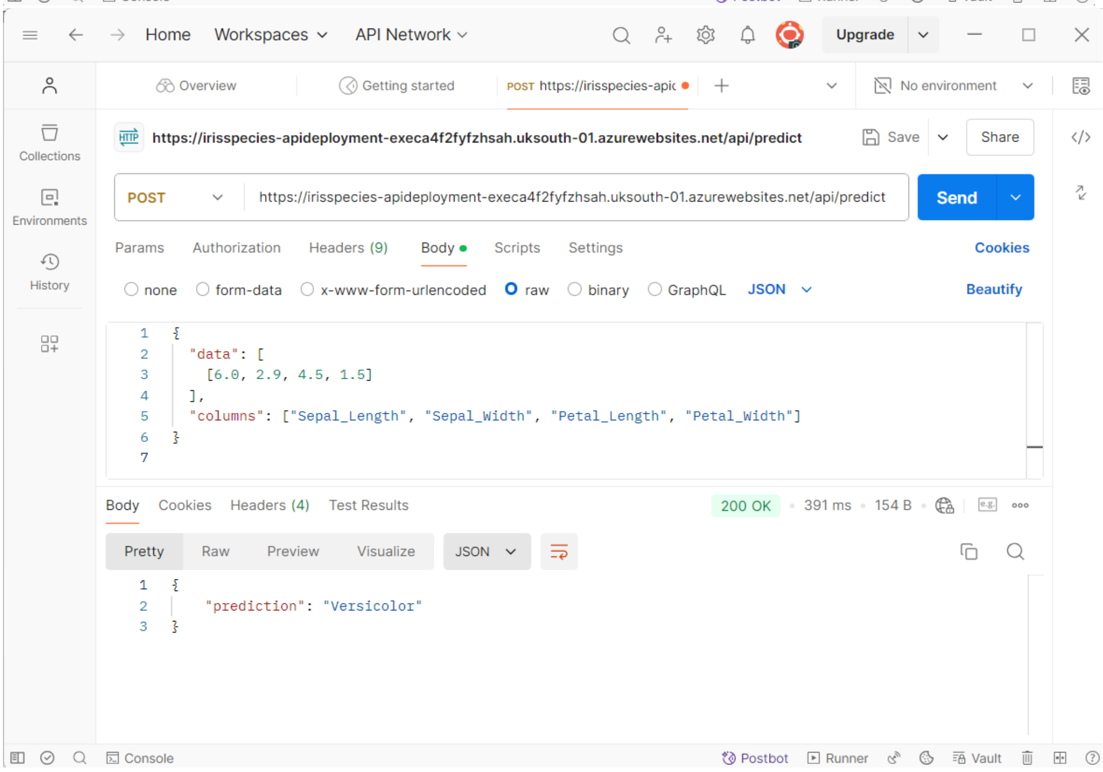
Using Postman:

- Open Postman and create a new POST request.
- Set the method to **POST**.
- Set the URL to 'https://irisspecies-apideployment-execa4f2fyfzhsah.uksouth-01.azurewebsites.net/api/predict'
- Set the `Content-Type` header to the value `application/json`.
- In the Body tab, select `raw` and `JSON` as the format, then paste in your JSON payload:

```
{
    "data": [[5.1, 3.5, 1.4, 0.2]],
    "columns": ["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"]
}
```

- Click **Send** and observe the response.





api_app.py (Used in Azure App Services)

```
from flask import Flask, request, jsonify
import pandas as pd
import pickle
import logging

# Set up logging
logging.basicConfig(level=logging.INFO)

# Import the trained model
model = pickle.load(open('model.pkl', 'rb'))

# Create the Flask app for the API
app = Flask(__name__)

@app.route("/")
def home():
    return "API is up and running!"

@app.route("/api/predict", methods=['POST'])
def api_predict():
    try:
        data = request.get_json(force=True)
        logging.info(f"Received data: {data}")

        # Extract features from JSON
        if 'data' not in data or 'columns' not in data:
            raise ValueError("JSON must contain 'data' and 'columns' keys")

        # Create a DataFrame with the incoming data
        features = pd.DataFrame(data['data'], columns=data['columns'])
        logging.info(f"Features DataFrame: {features}")

        # Check if the columns match what the model was trained with
        expected_columns = ["Sepal_Length", "Sepal_Width", "Petal_Length", "Petal_Width"]
        if list(features.columns) != expected_columns:
            raise ValueError(f"Expected columns: {expected_columns}, but got: {list(features.columns)}")

        # Make predictions
        prediction = model.predict(features)
        logging.info(f"Prediction: {prediction}")

        # Return the prediction in JSON format
        return jsonify({'prediction': prediction[0]})
    except Exception as e:
        logging.error(f"Error occurred: {str(e)}")
        return jsonify({'error': str(e)}), 500

if __name__ == "__main__":
    app.run(host='0.0.0.0', port=8000)
```