Deploy a Trained Machine Learning Model as a REST API Using Flask or FastAPI

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Description

This guide provides instructions for setting up a FastAPI-based application that predicts laptop prices based on various features. The model is trained using a Random Forest Regressor, and the trained model along with necessary label encoders are saved for deployment.

Problem Statement

As the laptop market expands, consumers struggle to determine fair prices based on specifications, as prices can vary widely among similar models. This project aims to develop a predictive model that estimates laptop prices using key features such as brand, type, screen size, processor, RAM, GPU, operating system, and weight. By leveraging machine learning, we can provide a reliable tool to help users make informed purchasing decisions.

Prerequisites

Completion of all previous lab guides (up to Lab Guide-09) is required before proceeding with Lab Guide-10.

Software Required

- **Python**: Ensure Python 3.11.9 is installed on your system.
- **Visual Studio Code (VSCode)**: A code editor to write and manage your Python scripts.
- **Postman or cURL**: Tools for testing the API requests.

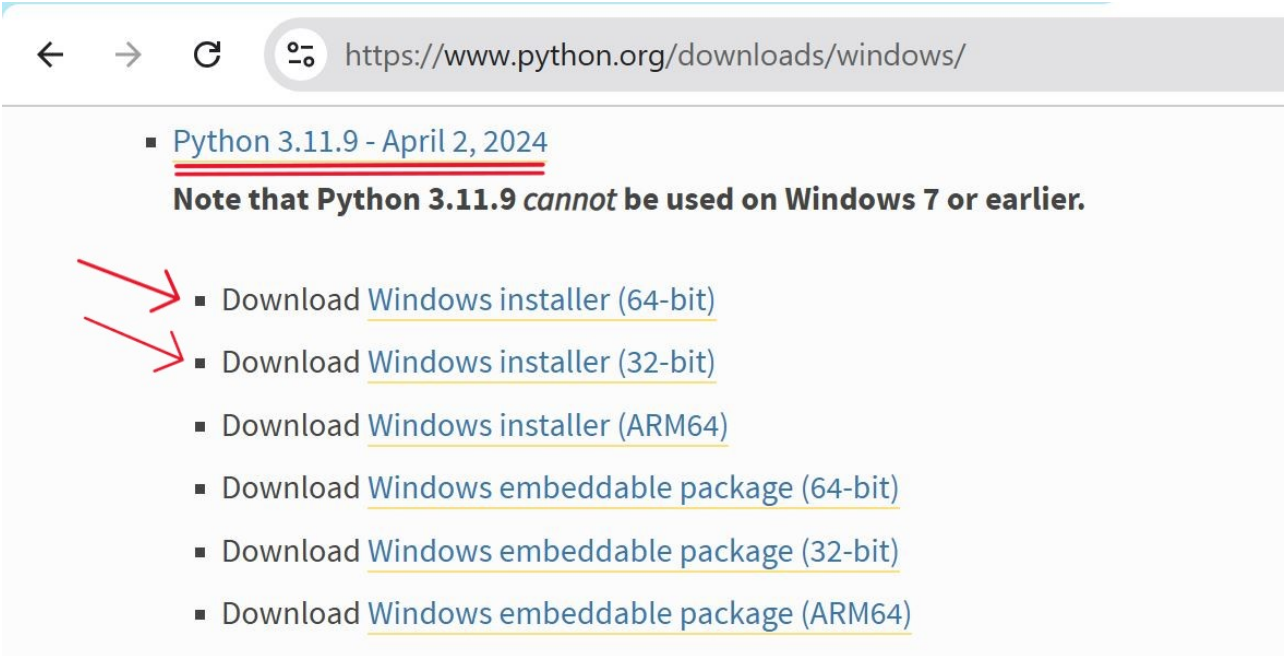
Hardware Requirements

- **Minimum System Requirements**:
  - CPU: Intel Core i3 or equivalent
  - RAM: 4 GB (8 GB recommended)
  - Disk Space: 1 GB for Python and libraries

Setup Instructions

Install Python:

- You can download and install Python 3.11.9 from the official Python website:
  - Visit the **official Python website**.
  - Locate a reliable version of Python 3, **"Download Python 3.11.9"**.
  - Choose the correct link for your device from the options provided: either Windows installer (64-bit) or Windows installer (32-bit) and proceed to download the executable file.



Install Visual Studio Code (VSCode):

- Download and install VSCode from the official Visual Studio Code website: **Download Visual Studio Code**

Install the necessary libraries using `pip`

- **Create a new folder**
  - Create a folder named `Fastapi` and open that folder in your `VScode`

```
pip install numpy pandas scikit-learn flask fastapi uvicorn joblib
```

```
PS C:\Users\Administrator\Desktop\AIML> pip install numpy pandas scikit-learn fastapi uvicorn joblib
Requirement already satisfied: numpy in c:\program files\python311\lib\site-packages (2.1.2)
Requirement already satisfied: pandas in c:\program files\python311\lib\site-packages (2.2.3)
Requirement already satisfied: scikit-learn in c:\program files\python311\lib\site-packages (1.5.2)
Collecting fastapi
  Downloading fastapi-0.115.2-py3-none-any.whl.metadata (27 kB)
Collecting uvicorn
  Downloading uvicorn-0.32.0-py3-none-any.whl.metadata (6.6 kB)
Requirement already satisfied: joblib in c:\program files\python311\lib\site-packages (1.4.2)
Requirement already satisfied: python-dateutil>=2.8.2 in c:\program files\python311\lib\site-packages (from pandas) (2.9.0.post0
)
Requirement already satisfied: pytz>=2020.1 in c:\program files\python311\lib\site-packages (from pandas) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in c:\program files\python311\lib\site-packages (from pandas) (2024.2)
Requirement already satisfied: scipy>=1.6.0 in c:\program files\python311\lib\site-packages (from scikit-learn) (1.14.1)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\program files\python311\lib\site-packages (from scikit-learn) (3.5.0)
Collecting starlette<0.41.0,>=0.37.2 (from fastapi)
  Downloading starlette-0.40.0-py3-none-any.whl.metadata (6.0 kB)
Collecting pydantic!=1.8,!=1.8.1,!=2.0.0,!=2.0.1,!=2.1.0,<3.0.0,>=1.7.4 (from fastapi)
  Downloading pydantic-2.9.2-py3-none-any.whl.metadata (149 kB)
     ---------------------------------------- 149.4/149.4 kB 3.0 MB/s eta 0:00:00
Requirement already satisfied: typing-extensions>=4.8.0 in c:\program files\python311\lib\site-packages (from fastapi) (4.12.2)
Collecting click>=7.0 (from uvicorn)
  Downloading click-8.1.7-py3-none-any.whl.metadata (3.0 kB)
Collecting h11>=0.8 (from uvicorn)
  Downloading h11-0.14.0-py3-none-any.whl.metadata (8.2 kB)
Collecting colorama (from click>=7.0->uvicorn)
  Downloading colorama-0.4.6-py2.py3-none-any.whl.metadata (17 kB)
Collecting annotated-types>=0.6.0 (from pydantic!=1.8,!=1.8.1,!=2.0.0,!=2.0.1,!=2.1.0,<3.0.0,>=1.7.4->fastapi)
  Downloading annotated_types-0.7.0-py3-none-any.whl.metadata (15 kB)
Collecting pydantic-core==2.23.4 (from pydantic!=1.8,!=1.8.1,!=2.0.0,!=2.0.1,!=2.1.0,<3.0.0,>=1.7.4->fastapi)
  Downloading pydantic_core-2.23.4-cp311-none-win_amd64.whl.metadata (6.7 kB)
Requirement already satisfied: six>=1.5 in c:\program files\python311\lib\site-packages (from python-dateutil>=2.8.2->pandas) (1
.16.0)
Collecting anyio<5,>=3.4.0 (from starlette<0.41.0,>=0.37.2->fastapi)
```

```
PS C:\Users\Administrator\Desktop\AIML> pip install flask
Collecting flask
  Downloading flask-3.0.3-py3-none-any.whl.metadata (3.2 kB)
Collecting Werkzeug>=3.0.0 (from flask)
  Downloading werkzeug-3.0.4-py3-none-any.whl.metadata (3.7 kB)
Requirement already satisfied: Jinja2>=3.1.2 in c:\program files\python311\lib\site-packages (from flask) (3.1.4)
Collecting itsdangerous>=2.1.2 (from flask)
  Downloading itsdangerous-2.2.0-py3-none-any.whl.metadata (1.9 kB)
Requirement already satisfied: click>=8.1.3 in c:\program files\python311\lib\site-packages (from flask) (8.1.7)
Collecting blinker>=1.6.2 (from flask)
  Downloading blinker-1.8.2-py3-none-any.whl.metadata (1.6 kB)
Requirement already satisfied: colorama in c:\program files\python311\lib\site-packages (from click>=8.1.3->flask) (0.4.6)
Requirement already satisfied: MarkupSafe>=2.0 in c:\program files\python311\lib\site-packages (from Jinja2>=3.1.2->flask) (3.0.
1)
Downloading flask-3.0.3-py3-none-any.whl (101 kB)
     ---------------------------------------- 101.7/101.7 kB 1.9 MB/s eta 0:00:00
Downloading blinker-1.8.2-py3-none-any.whl (9.5 kB)
Downloading itsdangerous-2.2.0-py3-none-any.whl (16 kB)
Downloading werkzeug-3.0.4-py3-none-any.whl (227 kB)
     ---------------------------------------- 227.6/227.6 kB 7.0 MB/s eta 0:00:00
Installing collected packages: Werkzeug, itsdangerous, blinker, flask
Successfully installed Werkzeug-3.0.4 blinker-1.8.2 flask-3.0.3 itsdangerous-2.2.0
```

Step 2: Verify Library Installation

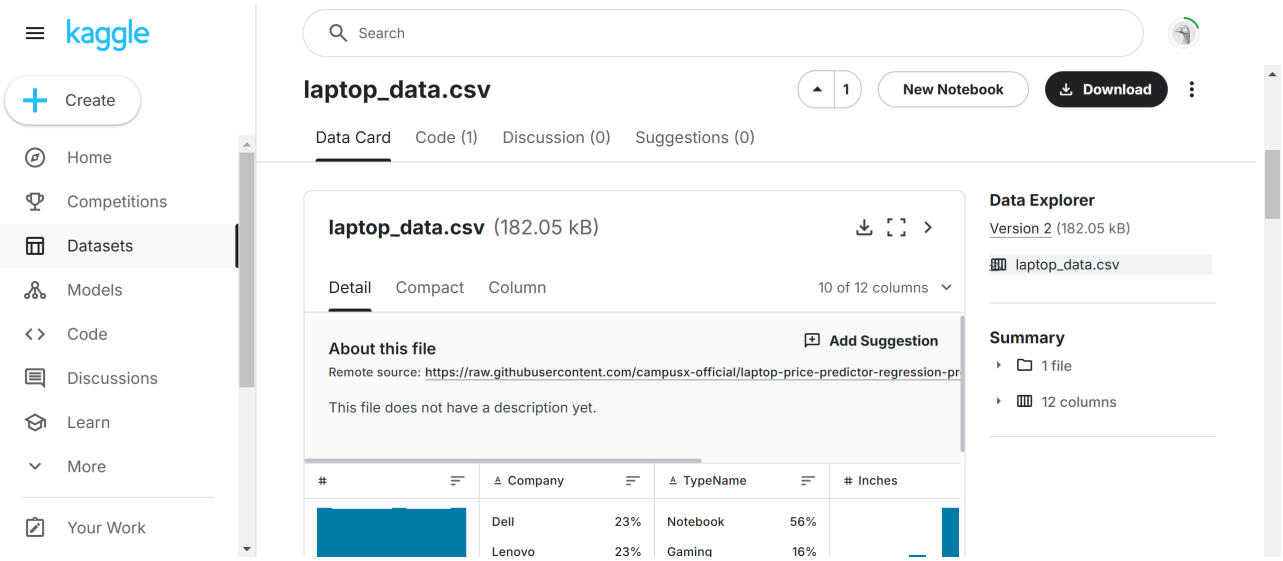
Run the following commands in a Python environment to check if the libraries are installed correctly:

```
import numpy
import pandas
import sklearn
import flask
import fastapi
```

If no errors are raised, the libraries are installed correctly.

Model Training

- **Create a new file**
  - Create a Python file named `model_training.py` inside your Fastapi folder.
  - Add the following code to `model_training.py`
- **Downloading the Dataset**
  - Go to the **Kaggle website** and sign in to your account. If you don't have an account, create one.
  - Navigate to the **Laptop Data csv file** competition page.



  - Click on the "Data Card" tab and download the `laptop_data.csv` file (the dataset used for training).
  - Move the downloaded `laptop_data.csv` file into your project directory.

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.preprocessing import LabelEncoder
import joblib

# Load the data
data = pd.read_csv('laptop_data.csv')

# Print the columns to see what was read
print("Columns in the dataset:", data.columns.tolist())

# Strip whitespace from column names
data.columns = data.columns.str.strip()

# Check if the required columns exist
required_columns = ['Company', 'TypeName', 'Inches', 'ScreenResolution', 'Cpu',
'Ram', 'Gpu', 'OpSys', 'Weight', 'Price']
for col in required_columns:
    if col not in data.columns:
```

```
        raise ValueError(f"The required column '{col}' is not present in the CSV
file.")

# Encode categorical variables
le_company = LabelEncoder()
le_typename = LabelEncoder()
le_cpu = LabelEncoder()
le_opsys = LabelEncoder()
le_gpu = LabelEncoder()
le_screenresolution = LabelEncoder()

data['Company'] = le_company.fit_transform(data['Company'])
data['TypeName'] = le_typename.fit_transform(data['TypeName'])
data['Cpu'] = le_cpu.fit_transform(data['Cpu'])
data['OpSys'] = le_opsys.fit_transform(data['OpSys'])
data['Gpu'] = le_gpu.fit_transform(data['Gpu'])
data['ScreenResolution'] =
le_screenresolution.fit_transform(data['ScreenResolution'])

# Convert 'Ram' and 'Weight' to numeric values
data['Ram'] = data['Ram'].str.replace('GB', '').astype(float)  # Assuming ram is
in "8GB" format
data['Weight'] = data['Weight'].str.replace('kg', '').str.strip().astype(float)  #
Ensure weight is numeric

# Prepare features and target variable
X = data[['Company', 'TypeName', 'Inches', 'ScreenResolution', 'Cpu', 'Ram',
'Gpu', 'OpSys', 'Weight']]
y = data['Price']

# Split the dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)

# Train the model
model = RandomForestRegressor()
model.fit(X_train, y_train)

# Save the model and label encoders
joblib.dump(model, 'laptop_price_model.joblib')
joblib.dump(le_company, 'label_encoder_company.joblib')
joblib.dump(le_typename, 'label_encoder_typename.joblib')
joblib.dump(le_cpu, 'label_encoder_cpu.joblib')
joblib.dump(le_opsys, 'label_encoder_opsys.joblib')
joblib.dump(le_gpu, 'label_encoder_gpu.joblib')
joblib.dump(le_screenresolution, 'label_encoder_screenresolution.joblib')
```

joblib

`joblib` is a Python library used for saving and loading Python objects efficiently. In simple terms, it helps you **store trained machine learning models and other data** to your disk so you can easily load them later without needing to retrain or recompute them.

Running the Training Script

Run the script to train and save the model:

```
python model_training.py
```

Output

```
PS C:\Users\Administrator\Desktop\FASTAPI> python model_training.py
```

The columns of laptop_data.csv

```
Columns in the dataset: ['Unnamed: 0', 'Company', 'TypeName', 'Inches',
'ScreenResolution', 'Cpu', 'Ram', 'Memory', 'Gpu', 'OpSys', 'Weight', 'Price']
```

Deploying the Model

Using FastAPI

Once you have the model trained and saved, you can use the following code to create a FastAPI application:

Create a FastAPI API:

- **Create a new file:**
  - Create a new file named `fastapi_app.py` in Fastapi folder and add the following code:

```
from fastapi import FastAPI, HTTPException
from pydantic import BaseModel
import joblib
import numpy as np

app = FastAPI()

# Load the model and label encoders
model = joblib.load('laptop_price_model.joblib')
le_company = joblib.load('label_encoder_company.joblib')
le_typename = joblib.load('label_encoder_typename.joblib')
le_cpu = joblib.load('label_encoder_cpu.joblib')
le_opsys = joblib.load('label_encoder_opsys.joblib')
le_gpu = joblib.load('label_encoder_gpu.joblib')
le_screenresolution = joblib.load('label_encoder_screenresolution.joblib')

# Define input data model
class LaptopFeatures(BaseModel):
```

```
    Company: str
    TypeName: str
    Inches: float  # in inches
    ScreenResolution: str
    Cpu: str
    Ram: float  # in GB
    Gpu: str
    OpSys: str
    Weight: float  # in kg

@app.post('/predict_price')
def predict_price(features: LaptopFeatures):
    try:
        # Prepare the input data for prediction
        input_data = np.array([[
            le_company.transform([features.Company])[0],
            le_typename.transform([features.TypeName])[0],
            features.Inches,
            le_screenresolution.transform([features.ScreenResolution])[0],
            le_cpu.transform([features.Cpu])[0],
            features.Ram,
            le_gpu.transform([features.Gpu])[0],
            le_opsys.transform([features.OpSys])[0],
            features.Weight
        ]])

        # Make prediction
        prediction = model.predict(input_data)
        return {'predicted_price': prediction[0]}

    except ValueError as e:
        raise HTTPException(status_code=400, detail=str(e))
    except Exception as e:
        raise HTTPException(status_code=500, detail="An unexpected error
occurred.")

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

Run the FastAPI application:

In the terminal, run the following command:

```
python -m uvicorn fastapi_app:app --reload
```

Output

```
PS C:\Users\Administrator\Desktop\FASTAPI> python -m uvicorn fastapi_app:app --reload
INFO:     Will watch for changes in these directories: ['C:\\Users\\Administrator\\Desktop\\FASTA
PI']
INFO:     Uvicorn running on http://127.0.0.1:8000 (Press CTRL+C to quit)
INFO:     Started reloader process [4384] using StatReload
INFO:     Started server process [10756]
INFO:     Waiting for application startup.
INFO:     Application startup complete.
INFO:     127.0.0.1:51550 - "GET / HTTP/1.1" 200 OK
```

Testing the API

You can test the deployed API using **Swagger UI**.

Using Swagger UI

FastAPI automatically generates interactive API documentation accessible via Swagger UI.

What is Swagger UI?

Swagger UI is an open-source tool that automatically generates interactive documentation for your RESTful APIs based on the OpenAPI specification. In the context of FastAPI, Swagger UI is seamlessly integrated, providing a user-friendly interface to visualize, interact with, and test your API endpoints without writing any additional client code.

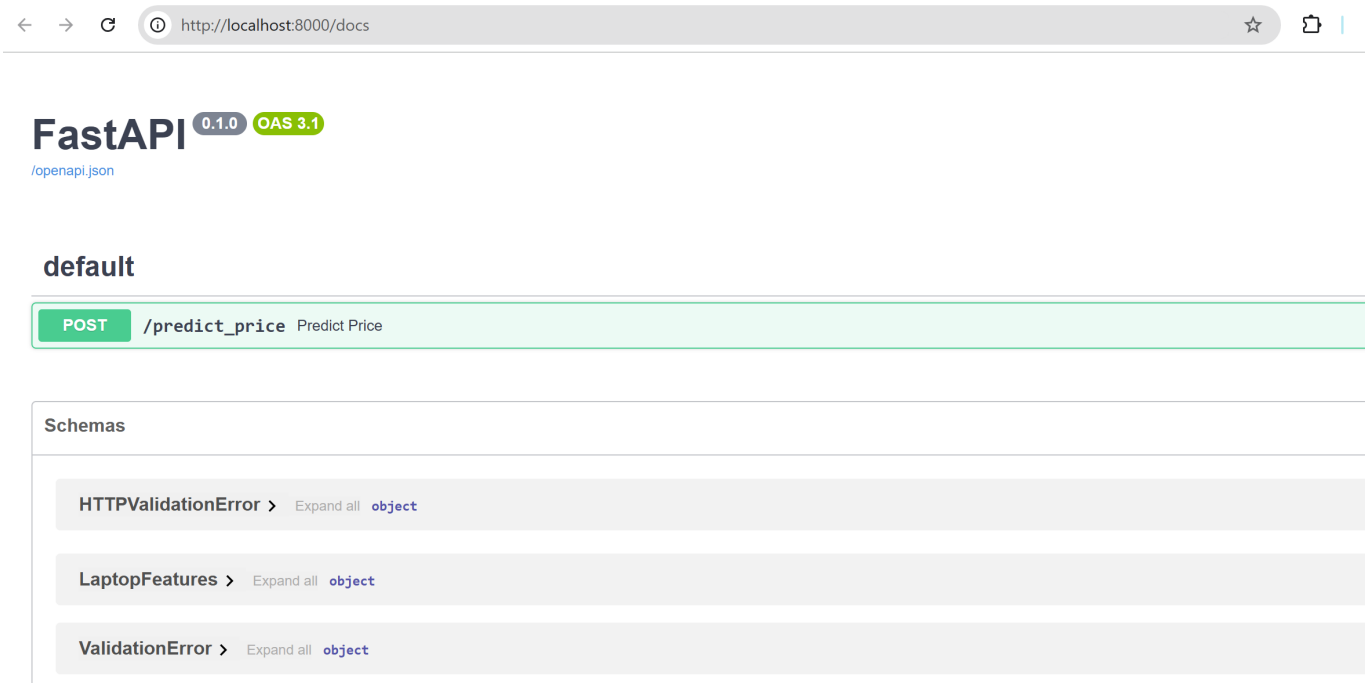
Key Features of Swagger UI

- **Interactive API Documentation**: Allows you to interact with the API directly from your browser.
- **Input Validation**: Automatically validates the input data against the defined Pydantic models.
- **Response Formats**: Displays the response formats for different endpoints.

Access Swagger UI:

Open your web browser and navigate to:

```
http://localhost:8000/docs
```



POST /predict_price

Endpoint: `/predict_price`

Method: `POST`

Description: Predicts the price of a laptop based on the provided features.

Request Body:

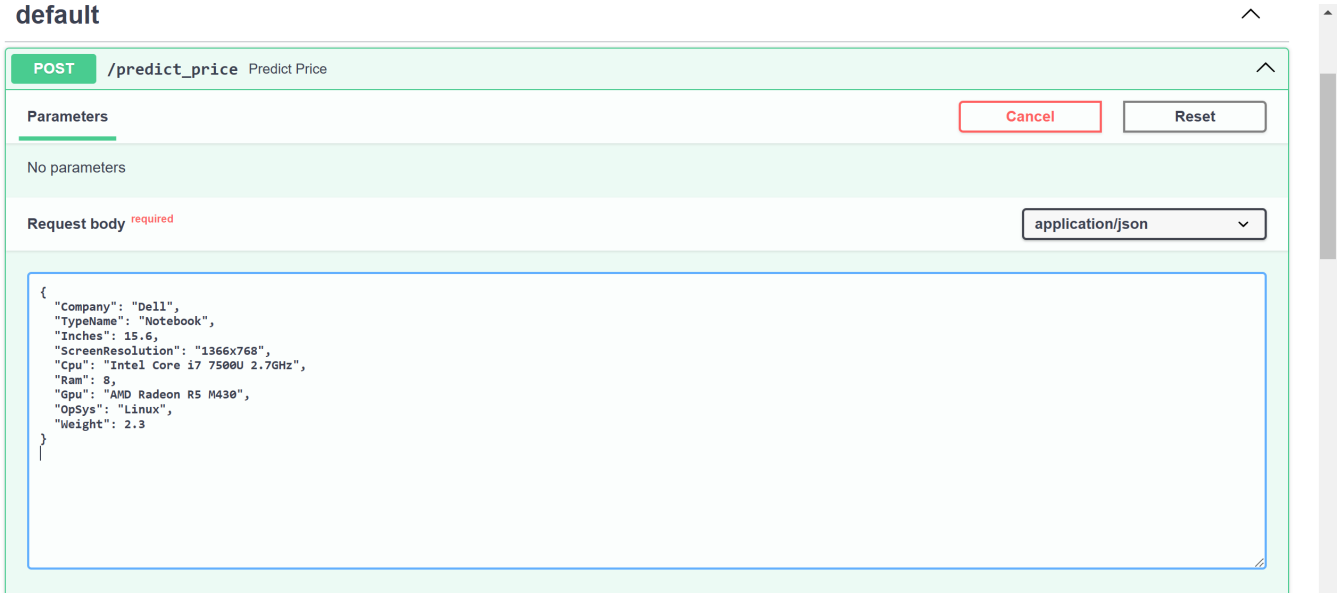
Requires a JSON payload that matches the `LaptopFeatures` model defined in the FastAPI application. Here is an example of the expected input format:

```
{
  "Company": "Dell",
```

```
  "TypeName": "Notebook",
  "Inches": 15.6,
  "ScreenResolution": "1366x768",
  "Cpu": "Intel Core i7 7500U 2.7GHz",
  "Ram": 8,
  "Gpu": "AMD Radeon R5 M430",
  "OpSys": "Linux",
  "Weight": 2.3
}
```

How to Test:

1. Click on the `POST /predict_price` endpoint to expand its details.
2. Click on the **"Try it out"** button.



3. In the text area provided, enter a valid JSON object as per the example above.
4. Click **"Execute"**.

Response: You should receive a JSON response containing the predicted price, similar to:

Error Handling:

- If the input is invalid (e.g., missing required fields or wrong data types), you will receive a 400 Bad Request response with a detailed error message.
- For unexpected errors, a 500 Internal Server Error response will be returned, indicating that something went wrong on the server side.

Here are a few key points about joblib

- **Serialization**: It allows you to serialize (convert) complex Python objects, such as NumPy arrays, pandas DataFrames, and machine learning models, into a binary format that can be saved as a file.
- **Speed**: `joblib` is optimized for large numerical arrays, making it faster than other serialization libraries (like `pickle`) for these types of data.
- **Easy to Use**: You can save an object to a file with `joblib.dump()` and load it back with `joblib.load()`.

Reference

- FastAPI Documentation: FastAPI
- Scikit-learn Documentation: Scikit-learn
- Pandas Documentation: Pandas
- Joblib Documentation: Joblib