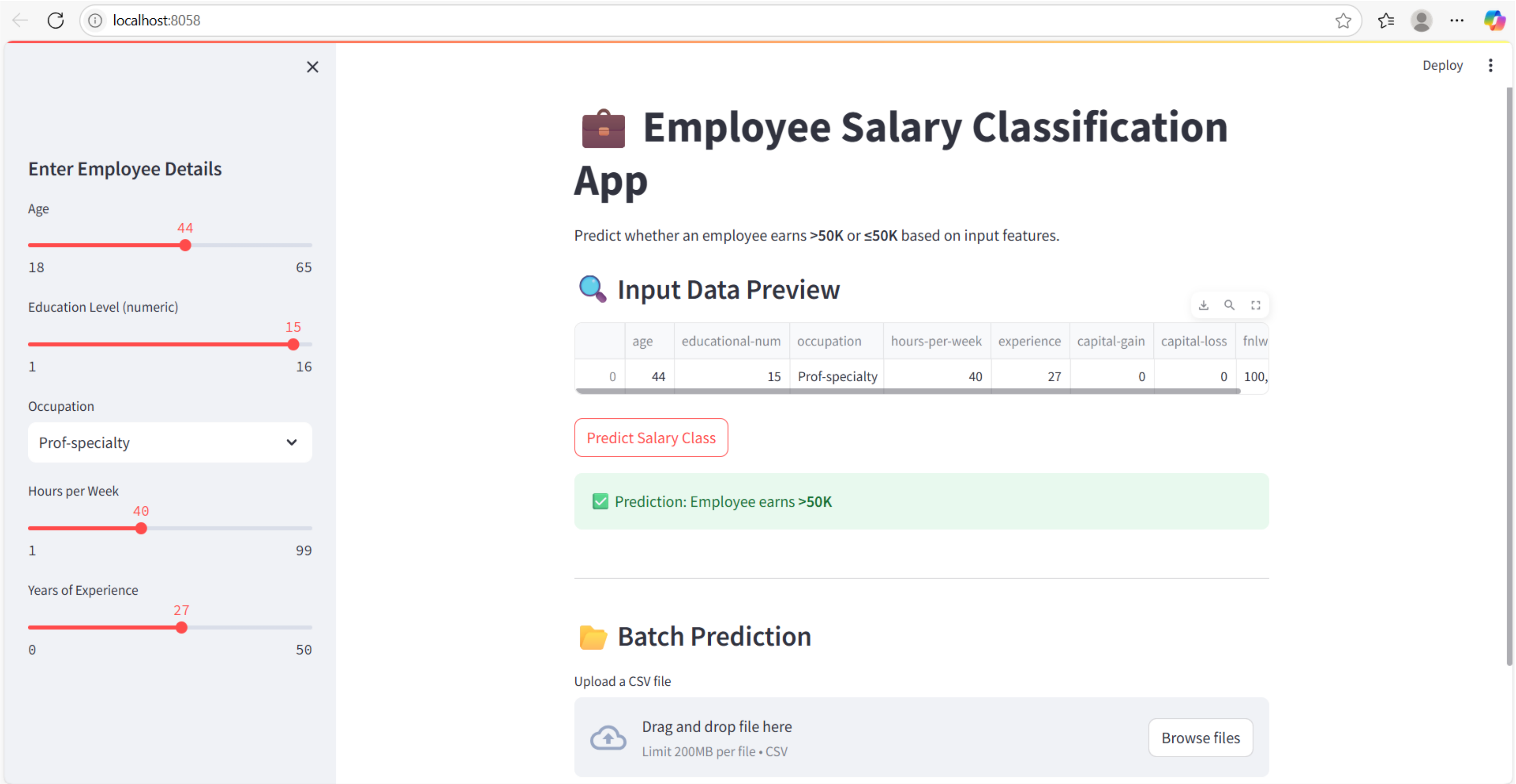
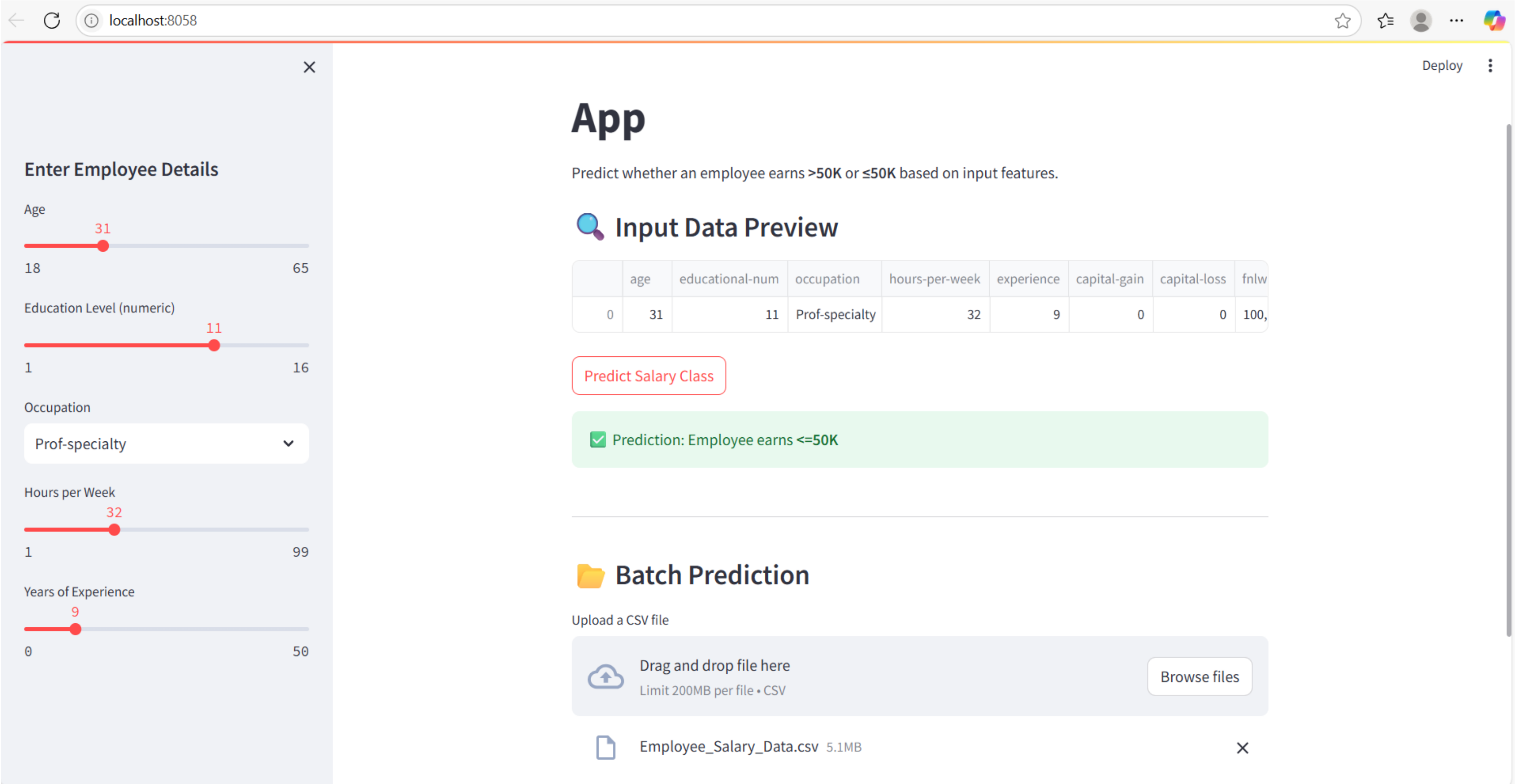

localhost:8058
Deploy
Enter Employee Details
Age
44
18
65
Education Level (numeric)
15
1
16
Occupation
Prof-specialty
Hours per Week
40
1
99
Years of Experience
27
0
50
Employee Salary Classification App
Predict whether an employee earns >50K or ≤50K based on input features.
Input Data Preview
age | educational-num | occupation | hours-per-week | experience | capital-gain | capital-loss | fnlw
0 | 44 | 15 | Prof-specialty | 40 | 27 | 0 | 0 | 100,
Predict Salary Class
Prediction: Employee earns >50K
Batch Prediction
Upload a CSV file
Drag and drop file here
Limit 200MB per file • CSV
Browse files


localhost:8058
Deploy
Enter Employee Details
Age
31
18
65
Education Level (numeric)
11
1
16
Occupation
Prof-specialty
Hours per Week
32
1
99
Years of Experience
9
0
50
App
Predict whether an employee earns >50K or ≤50K based on input features.
Input Data Preview
age | educational-num | occupation | hours-per-week | experience | capital-gain | capital-loss | fnlw
0 | 31 | 11 | Prof-specialty | 32 | 9 | 0 | 0 | 100,
Predict Salary Class
Prediction: Employee earns <=50K
Batch Prediction
Upload a CSV file
Drag and drop file here
Limit 200MB per file • CSV
Browse files
Employee_Salary_Data.csv 5.1MB

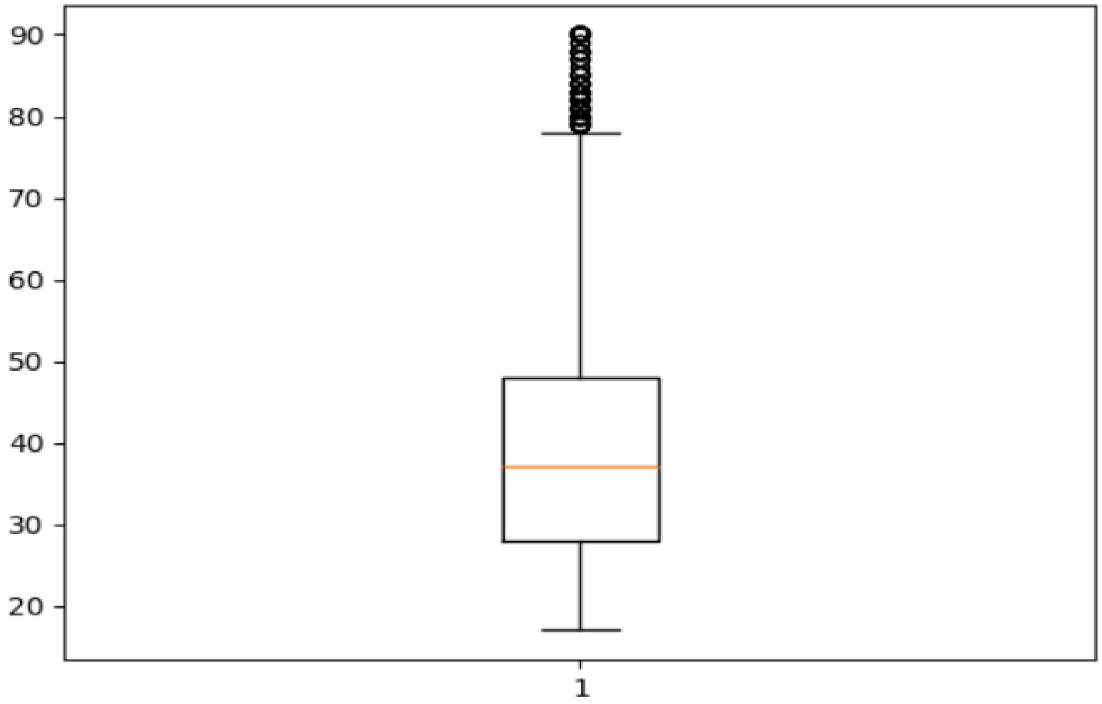
[8]:
```
data.head(6)
```

[8]:

	age	workclass	fnlwgt	education	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income
0	25	Private	226802	11th	7	Never-married	Machine-op-inspct	Own-child	Black	Male	0	0	40	United-States	<=50K
1	38	Private	89814	HS-grad	9	Married-civ-spouse	Farming-fishing	Husband	White	Male	0	0	50	United-States	<=50K
2	28	Local-gov	336951	Assoc-acdm	12	Married-civ-spouse	Protective-serv	Husband	White	Male	0	0	40	United-States	>50K
3	44	Private	160323	Some-college	10	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	7688	0	40	United-States	>50K
4	18	?	103497	Some-college	10	Never-married	?	Own-child	White	Female	0	0	30	United-States	<=50K
5	34	Private	198693	10th	6	Never-married	Other-service	Not-in-family	White	Male	0	0	30	United-States	<=50K

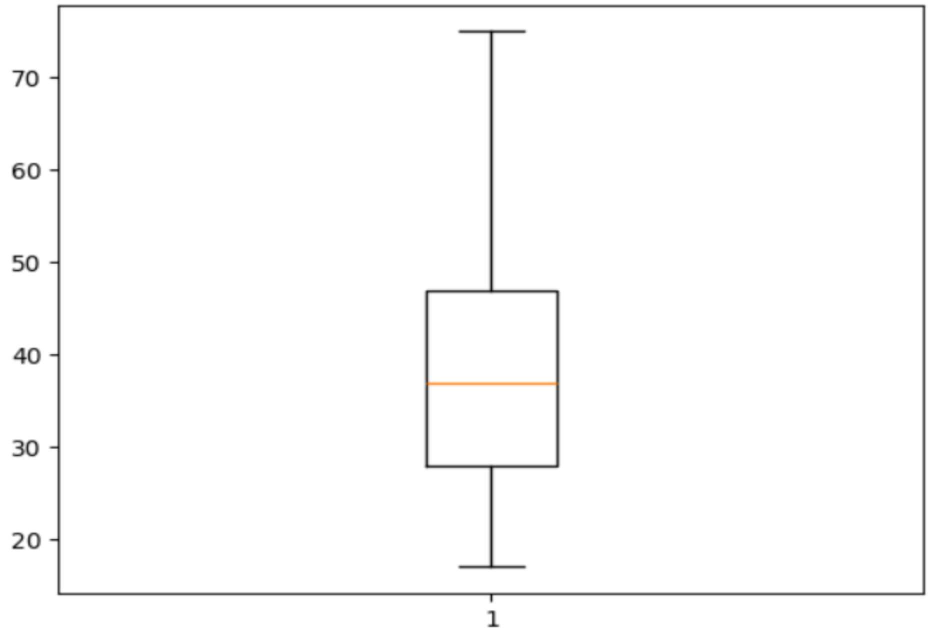
To remove Outliers:

```
import matplotlib.pyplot as plt
plt.boxplot(data['age'])
plt.show()
```




```
[79]: data=data[(data['age']<=75) & (data['age']>=17)]
```

```
[82]: #to check whether the outliers are removed or not
plt.boxplot(data['age'])
plt.show()
```



Comparing Model Accuracy:

LogisticRegression Accuracy: 0.8283

	precision	recall	f1-score	support
<=50K	0.85	0.94	0.89	7277
>50K	0.70	0.47	0.56	2247
accuracy			0.83	9524
macro avg	0.78	0.70	0.73	9524
weighted avg	0.82	0.83	0.82	9524

RandomForest Accuracy: 0.8658

	precision	recall	f1-score	support
<=50K	0.89	0.93	0.91	7277
>50K	0.75	0.64	0.69	2247
accuracy			0.87	9524
macro avg	0.82	0.79	0.80	9524
weighted avg	0.86	0.87	0.86	9524

KNN Accuracy: 0.8340

	precision	recall	f1-score	support
<=50K	0.88	0.91	0.89	7277
>50K	0.66	0.60	0.63	2247
accuracy			0.83	9524
macro avg	0.77	0.75	0.76	9524
weighted avg	0.83	0.83	0.83	9524

SVM Accuracy: 0.8563

	precision	recall	f1-score	support
<=50K	0.88	0.95	0.91	7277
>50K	0.76	0.57	0.65	2247
accuracy			0.86	9524
macro avg	0.82	0.76	0.78	9524
weighted avg	0.85	0.86	0.85	9524

GradientBoosting Accuracy: 0.8710

	precision	recall	f1-score	support
<=50K	0.89	0.95	0.92	7277
>50K	0.79	0.61	0.69	2247
accuracy			0.87	9524
macro avg	0.84	0.78	0.81	9524
weighted avg	0.87	0.87	0.86	9524