

	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
...
48837	27	Private	257302	Assoc-acdm	12	Married-civ-spouse	Tech-support	Wife	White	Female	0	0	38	United-States	<=50K
48838	40	Private	154374	HS-grad	9	Married-civ-spouse	Machine-op-inspct	Husband	White	Male	0	0	40	United-States	>50K
48839	58	Private	151910	HS-grad	9	Widowed	Adm-clerical	Unmarried	White	Female	0	0	40	United-States	<=50K
48840	22	Private	201490	HS-grad	9	Never-married	Adm-clerical	Own-child	White	Male	0	0	20	United-States	<=50K
48841	52	Self-emp-inc	287927	HS-grad	9	Married-civ-spouse	Exec-managerial	Wife	White	Female	15024	0	40	United-States	>50K

48842 rows × 15 columns

```
[ ] data.isnull().sum() # it retrieve all the count the null value is available
```



	0
age	0
workclass	0
fnlwgt	0
education	0
educational-num	0
marital-status	0
occupation	0
relationship	0
race	0
gender	0
capital-gain	0
capital-loss	0
hours-per-week	0
native-country	0
income	0

dtype: int64



data



	age	workclass	fnlwgt	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country	income
0	25	2	226802	7	4	5	3	2	1	0	0	40	37	<=50K
1	38	2	89814	9	2	3	0	4	1	0	0	50	37	<=50K
2	28	1	336951	12	2	10	0	4	1	0	0	40	37	>50K
3	44	2	160323	10	2	5	0	2	1	7688	0	40	37	>50K
4	18	6	103497	10	4	6	3	4	0	0	0	30	37	<=50K
...
48837	27	2	257302	12	2	12	5	4	0	0	0	38	37	<=50K
48838	40	2	154374	9	2	5	0	4	1	0	0	40	37	>50K
48839	58	2	151910	9	6	0	4	4	0	0	0	40	37	<=50K
48840	22	2	201490	9	4	0	3	4	1	0	0	20	37	<=50K
48841	52	3	287927	9	2	2	5	4	0	15024	0	40	37	>50K

47603 rows × 14 columns

```
[ ] X = data.drop(columns=["income"]) # input
    y = data["income"] # outut
    x
```



	age	workclass	fnlwgt	educational-num	marital-status	occupation	relationship	race	gender	capital-gain	capital-loss	hours-per-week	native-country
0	25	2	226802	7	4	5	3	2	1	0	0	40	37
1	38	2	89814	9	2	3	0	4	1	0	0	50	37
2	28	1	336951	12	2	10	0	4	1	0	0	40	37
3	44	2	160323	10	2	5	0	2	1	7688	0	40	37
4	18	6	103497	10	4	6	3	4	0	0	0	30	37
...
48837	27	2	257302	12	2	12	5	4	0	0	0	38	37
48838	40	2	154374	9	2	5	0	4	1	0	0	40	37
48839	58	2	151910	9	6	0	4	4	0	0	0	40	37
48840	22	2	201490	9	4	0	3	4	1	0	0	20	37
48841	52	3	287927	9	2	2	5	4	0	15024	0	40	37

47603 rows × 13 columns



Logistic Regression Accuracy :0.830795

	precision	recall	f1-score	support
<=50K	0.85	0.95	0.89	7236
>50K	0.73	0.46	0.57	2285
accuracy			0.83	9521
macro avg	0.79	0.71	0.73	9521
weighted avg	0.82	0.83	0.82	9521

Random Forest Accuracy :0.860939

	precision	recall	f1-score	support
<=50K	0.89	0.93	0.91	7236
>50K	0.75	0.64	0.69	2285
accuracy			0.86	9521
macro avg	0.82	0.78	0.80	9521
weighted avg	0.86	0.86	0.86	9521

Gradient Boosting Accuracy :0.869446

	precision	recall	f1-score	support
<=50K	0.89	0.95	0.92	7236
>50K	0.79	0.62	0.69	2285
accuracy			0.87	9521
macro avg	0.84	0.78	0.81	9521
weighted avg	0.86	0.87	0.86	9521

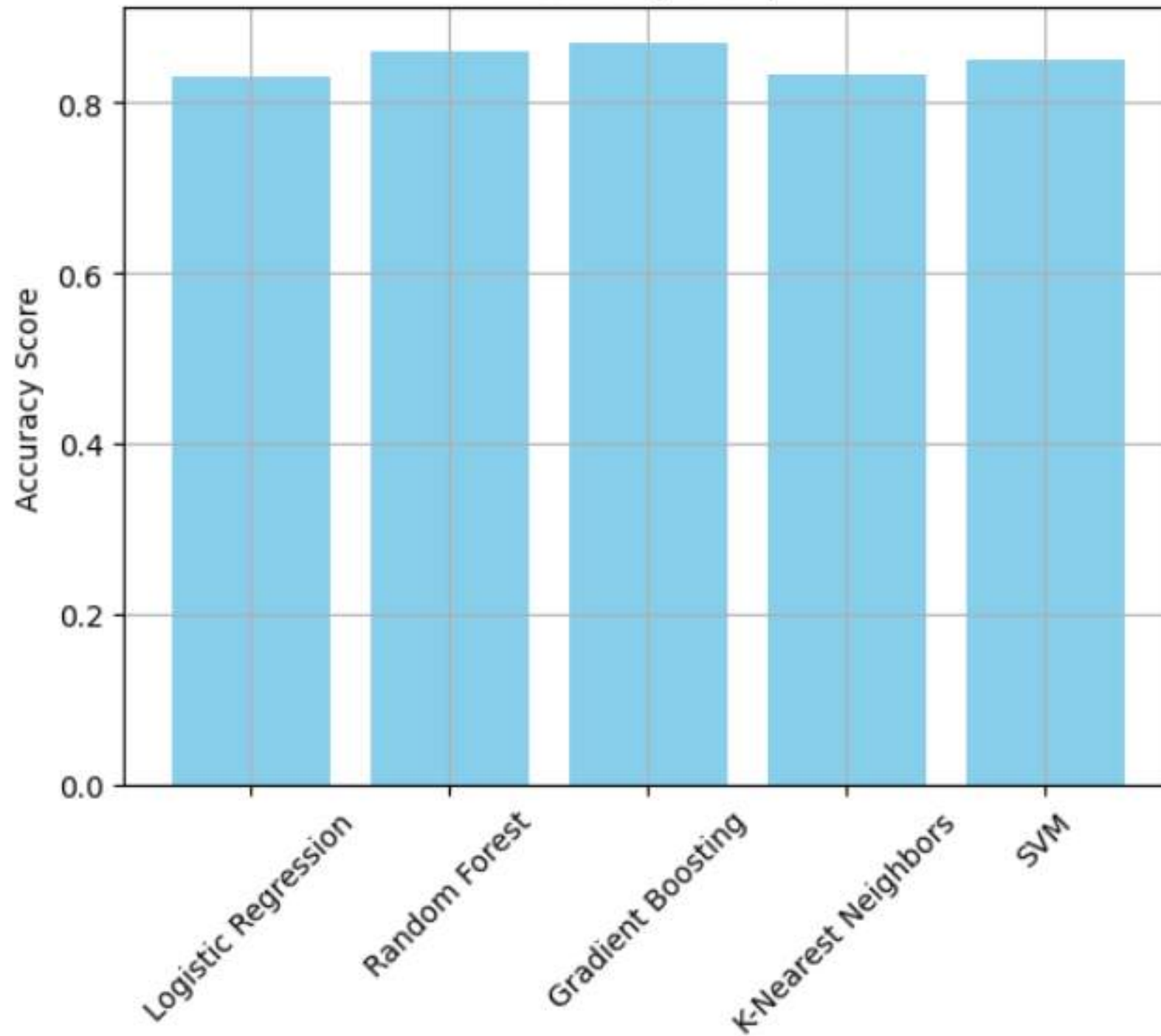
K-Nearest Neighbors Accuracy :0.832581

	precision	recall	f1-score	support
<=50K	0.88	0.91	0.89	7236
>50K	0.67	0.60	0.63	2285
accuracy			0.83	9521
macro avg	0.77	0.75	0.76	9521
weighted avg	0.83	0.83	0.83	9521

SVM Accuracy :0.851381

	precision	recall	f1-score	support
<=50K	0.87	0.95	0.91	7236
>50K	0.76	0.55	0.64	2285
accuracy			0.85	9521
macro avg	0.82	0.75	0.77	9521
weighted avg	0.84	0.85	0.84	9521

Model Accuracy Comparison



LogisticRegression: 0.8308

RandomForest: 0.8599

KNN: 0.8326

SVM: 0.8514

GradientBoosting: 0.8694

✅ Best model: GradientBoosting with accuracy 0.8694

✅ Saved best model as best_model.pkl



warnings.warn

Traceback (most recent call last)

/usr/local/lib/python3.11/dist-packages/streamlit/runtime/scriptrunner/exec_code.py:
128 in exec_func_with_error_handling

/usr/local/lib/python3.11/dist-packages/streamlit/runtime/scriptrunner/script_runner
.py:669 in code_to_exec

/content/app.py:55 in <module>

```
52 if uploaded_file is not None:
53     batch_data = pd.read_csv(uploaded_file)
54     st.write("Uploaded data preview:", batch_data.head())
55     batch_preds = model.predict(batch_data)
56     batch_data['PredictedClass'] = batch_preds
57     st.write("✅ Predictions:")
58     st.write(batch_data.head())
```

/usr/local/lib/python3.11/dist-packages/sklearn/ensemble/_gb.py:1623 in predict

```
1620 |         y : ndarray of shape (n_samples,)
1621 |         |         The predicted values.
1622 |         |         """
1623 |         raw_predictions = self.decision_function(X)
1624 |         if raw_predictions.ndim == 1: # decision_function already squeezed i
1625 |             encoded_classes = (raw_predictions >= 0).astype(int)
1626 |         else:
```

/usr/local/lib/python3.11/dist-packages/sklearn/ensemble/_gb.py:1576 in
decision_function

```
1573 |         :term:`classes_`. Regression and binary classification produce an
1574 |         array of shape (n_samples,).
1575 |         """
```

Years of Experience

5

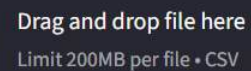
0 40

Predict whether an employee earns $>50K$ or $\leq 50K$ based on input features.

	age	education	occupation	hours-per-week	experience
0	30	Bachelors	Tech-support	40	5

Predict Salary Class

Upload a CSV file for batch prediction



Browse files