```
In [3]: import pandas as pd
    from sklearn.model_selection import train_test_split
    from sklearn.preprocessing import StandardScaler , LabelEncoder
    from sklearn.metrics import accuracy_score,confusion_matrix,classification_rep
    from sklearn.svm import SVC
    from sklearn.neighbors import KNeighborsClassifier
    from sklearn.linear_model import LogisticRegression
```

In [5]: #Load dataset

iphone=pd.read_csv(r"C:\Users\mamun\OneDrive\iphone_purchase_records.csv")
iphone.head()

Out[5]:

	Gender	Age	Salary	Purchase Iphone
() Male	19	19000	0
1	I Male	35	20000	0
2	2 Female	26	43000	0
3	B Female	27	57000	0
2	1 Male	19	76000	0

```
In [6]: #encode the 'Gender' column
label = LabelEncoder()
iphone['Gender']=label.fit_transform(iphone['Gender'])
iphone.head()
```

Out[6]:

	Gender	Age	Salary	Purchase Iphone
0	1	19	19000	0
1	1	35	20000	0
2	0	26	43000	0
3	0	27	57000	0
4	1	19	76000	0

```
In [7]: #separate features and target variable
X = iphone[['Gender','Age','Salary']]
y = iphone['Purchase Iphone']
```

```
In [8]: #splitting data into tarining and testing set
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.25,random_state)
```

```
In [9]: #feature scaling
scaler=StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
In [10]: #initialize model
    models = {
        "SVM": SVC(kernel='linear',random_state=0),
        "KNN": KNeighborsClassifier(n_neighbors=5),
        "Logistic Regression": LogisticRegression(random_state=0)
}
```

```
In [12]: #train, predict and evaluate each model
         for name, model in models.items():
             print(f"\nModel:{name}")
             #train the model
             model.fit(X_train,y_train)
             #make predictions
             y_pred=model.predict(X_test)
             #calculate accuracy
             accuracy = accuracy_score(y_test, y_pred)
             print(f"Accuracy:{accuracy * 100:.2f}%")
             #confusion matrix and classification report
             cm= confusion_matrix(y_test,y_pred)
             report = classification_report(y_test,y_pred)
             print("confusion_matrix:\n",cm)
             print("classification_report:\n",report)
             #print correct and incorrect predictions
             correct_predictions = [(i,pred) for i,(pred,true) in enumerate(zip(y_pred,
             incorrect_predictions = [(i,pred) for i,(pred,true) in enumerate(zip(y_pred))
             print("Correct predictions:",correct_predictions)
             print("\nIncorrect predictions:",incorrect_predictions)
```

Model:SVM
Accuracy:89.00%
confusion_matrix:
[[66 2]
[9 23]]
classification_report:

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		precision	recall	f1-score	support
	0	0.88	0.97	0.92	68
	1	0.92	0.72	0.81	32
accur	acy			0.89	100
macro	avg	0.90	0.84	0.87	100
weighted	avg	0.89	0.89	0.89	100

Correct predictions: [(0, 0), (1, 0), (2, 0), (3, 0), (4, 0), (5, 0), (6, 0), (7, 1), (8, 0), (9, 0), (10, 0), (11, 0), (12, 0), (13, 0), (14, 0), (15, 0), (16, 0), (17, 0), (18, 1), (19, 0), (20, 0), (21, 1), (22, 0), (23, 1), (24, 0), (25, 1), (26, 0), (27, 0), (28, 0), (29, 0), (30, 0), (32, 1), (33, 0), (34, 0), (35, 0), (36, 0), (37, 0), (38, 0), (40, 0), (41, 0), (42, 0), (43, 0), (44, 1), (45, 0), (46, 0), (47, 1), (48, 0), (49, 1), (50, 1), (51, 0), (52, 0), (53, 0), (54, 1), (56, 0), (57, 0), (59, 0), (60, 0), (61, 1), (62, 0), (64, 0), (65, 1), (66, 0), (67, 0), (68, 0), (69, 0), (70, 1), (71, 0), (72, 0), (74, 0), (75, 0), (77, 0), (78, 1), (79, 1), (80, 1), (82, 0), (83, 0), (84, 1), (85, 1), (86, 0), (87, 1), (89, 0), (90, 0), (91, 1), (92, 0), (93, 0), (94, 0), (96, 0), (98, 1), (99, 1)]

Incorrect predictions: [(31, 0), (39, 0), (55, 0), (58, 0), (63, 0), (73, 0), (76, 1), (81, 1), (88, 0), (95, 0), (97, 0)]

Model:KNN
Accuracy:93.00%
confusion_matrix:
[[64 4]
[3 29]]

classification_report:

	precision	recall	f1-score	support
0	0.96	0.94	0.95	68
1	0.88	0.91	0.89	32
accuracy			0.93	100
macro avg	0.92	0.92	0.92	100
weighted avg	0.93	0.93	0.93	100

Correct predictions: [(0, 0), (1, 0), (2, 0), (3, 0), (4, 0), (5, 0), (6, 0), (7, 1), (8, 0), (10, 0), (11, 0), (12, 0), (13, 0), (14, 0), (16, 0), (17, 0), (18, 1), (19, 0), (20, 0), (21, 1), (22, 0), (23, 1), (24, 0), (25, 1), (26, 0), (27, 0), (28, 0), (29, 0), (30, 0), (32, 1), (33, 0), (34, 0), (35, 0), (36, 0), (37, 0), (38, 0), (39, 1), (40, 0), (41, 0), (42, 0), (43, 0), (44, 1), (45, 0), (46, 0), (47, 1), (48, 0), (49, 1), (50, 1), (51, 0), (52, 0), (54, 1), (55, 1), (56, 0), (57, 0), (58, 1), (59, 0), (60, 0), (61, 1), (62, 0), (63, 1), (64, 0), (65, 1), (66, 0), (67, 0), (68, 0), (69, 0), (70, 1), (71, 0), (72, 0), (73, 1), (74, 0), (75, 0), (76, 0), (77, 0), (78, 1), (79, 1), (80, 1), (82, 0), (83, 0), (84, 1), (86, 0), (87, 1), (88, 1), (89, 0), (90, 0), (91, 1), (92, 0), (93, 0), (94, 0), (96, 0), (97, 1), (98, 1),

(99, 1)

Incorrect predictions: [(9, 1), (15, 1), (31, 0), (53, 1), (81, 1), (85, 0), (95, 0)]

Model:Logistic Regression

Accuracy:90.00% confusion_matrix:

[[65 3] [7 25]]

classification report:

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	precision	recall	f1-score	support
0	0.90	0.96	0.93	68
1	0.89	0.78	0.83	32
accuracy			0.90	100
macro avg	0.90	0.87	0.88	100
weighted avg	0.90	0.90	0.90	100

Correct predictions: [(0, 0), (1, 0), (2, 0), (3, 0), (4, 0), (5, 0), (6, 0), (7, 1), (8, 0), (10, 0), (11, 0), (12, 0), (13, 0), (14, 0), (15, 0), (16, 0), (17, 0), (18, 1), (19, 0), (20, 0), (21, 1), (22, 0), (23, 1), (24, 0), (25, 1), (26, 0), (27, 0), (28, 0), (29, 0), (30, 0), (32, 1), (33, 0), (34, 0), (35, 0), (36, 0), (37, 0), (38, 0), (39, 1), (40, 0), (41, 0), (42, 0), (43, 0), (44, 1), (45, 0), (46, 0), (47, 1), (48, 0), (49, 1), (50, 1), (51, 0), (52, 0), (53, 0), (54, 1), (56, 0), (57, 0), (58, 1), (59, 0), (60, 0), (61, 1), (62, 0), (64, 0), (65, 1), (66, 0), (67, 0), (68, 0), (69, 0), (70, 1), (71, 0), (72, 0), (74, 0), (75, 0), (77, 0), (78, 1), (79, 1), (80, 1), (82, 0), (83, 0), (84, 1), (85, 1), (86, 0), (87, 1), (89, 0), (90, 0), (91, 1), (92, 0), (93, 0), (94, 0), (96, 0), (98, 1), (99, 1)]

Incorrect predictions: [(9, 1), (31, 0), (55, 0), (63, 0), (73, 0), (76, 1), (81, 1), (88, 0), (95, 0), (97, 0)]

In []: