```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report, confusion_ma
```

url = 'https://github.com/manas8173/diabeties/raw/main/heart\_data.csv'
heart = pd.read\_csv(url, sep=',') # explicitly use comma separator
display(heart)

⇒÷		id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke	ê
	0	0	18393	2	168	62.0	110	80	1	1	0	
	1	1	20228	1	156	85.0	140	90	3	1	0	
	2	2	18857	1	165	64.0	130	70	3	1	0	
	3	3	17623	2	169	82.0	150	100	1	1	0	
	4	4	17474	1	156	56.0	100	60	1	1	0	
	69995	99993	19240	2	168	76.0	120	80	1	1	1	
	69996	99995	22601	1	158	126.0	140	90	2	2	0	
	69997	99996	19066	2	183	105.0	180	90	3	1	0	
	69998	99998	22431	1	163	72.0	135	80	1	2	0	
	69999	99999	20540	1	170	72.0	120	80	2	1	0	

70000 rows × 13 columns

print(heart.columns)

# 2. Data Splitting & Preprocessing

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Split features and target
X = heart.drop("cardio", axis=1)
y = heart["cardio"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

### → □ 3. Train SVM Classifier

```
# Train SVM with linear kernel
svm_model = SVC(kernel='linear', probability=True)
svm_model.fit(X_train, y_train)
```

```
SVC (kernel='linear', probability=True)
```

### 4. Evaluate the Model

```
# Predictions
y_pred = svm_model.predict(X_test)

# Accuracy and metrics
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
→ Accuracy: 0.7264285714285714
                  precision
                             recall f1-score
                                                  support
                                 0.81
                                           0.75
               0
                       0.69
                                                      6988
                       0.77
                                 0.64
                                           0.70
                                                      7012
                                           0.73
                                                     14000
        accuracy
       macro avg
                       0.73
                                 0.73
                                           0.72
                                                     14000
                       0.73
                                 0.73
                                           0.72
                                                     14000
    weighted avg
```

### 5. Confusion Matrix

from sklearn.metrics import confusion\_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

```
# Confusion matrix plot
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("SVM Confusion Matrix")
plt.grid()
plt.show()
```



# SVM Confusion Matrix 5500 5000 5668 0 - 4500 - 4000 True label 3500 3000 - 2500 4502 1 -- 2000 1500 0 1

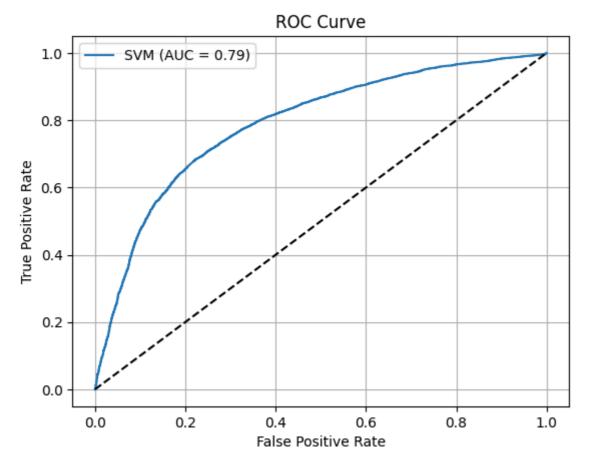
Predicted label

#### 6. ROC Curve

```
# Probabilities for ROC
y_prob = svm_model.predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_prob)
roc_auc = auc(fpr, tpr)

# ROC Curve Plot
plt.plot(fpr, tpr, label="SVM (AUC = %0.2f)" % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()
```



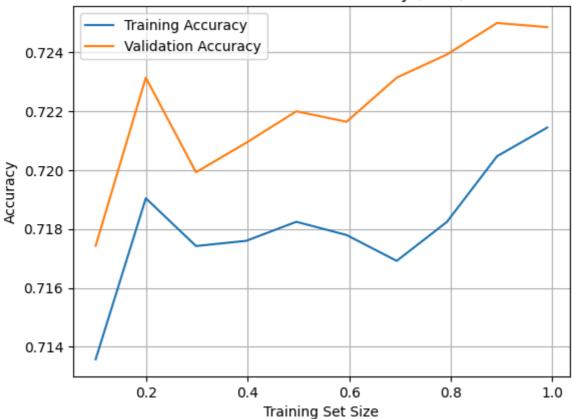


### 7. Train vs Validation Accuracy

```
# Fix: avoid using 1.0 which causes error
train_sizes = np.linspace(0.1, 0.99, 10)
train_scores = []
test_scores = []
# Simulate learning curve for SVM
for frac in train sizes:
    X_part, _, y_part, _ = train_test_split(X_train, y_train, train_size=frac, random_sta
   model = SVC(kernel='linear', C=0.1)
   model.fit(X_part, y_part)
    train_scores.append(model.score(X_part, y_part))
    test_scores.append(model.score(X_test, y_test))
# Plot accuracy curves
plt.plot(train_sizes, train_scores, label='Training Accuracy')
plt.plot(train_sizes, test_scores, label='Validation Accuracy')
plt.xlabel("Training Set Size")
plt.ylabel("Accuracy")
plt.title("Train vs Validation Accuracy (SVM)")
plt.legend()
plt.grid()
plt.show()
```

**→** 

### Train vs Validation Accuracy (SVM)



#### ✓ KNN

# 👔 2. Data Splitting & Preprocessing

```
# Split features and target
X = heart.drop("cardio", axis=1)
y = heart["cardio"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Feature Scaling
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

#### 3. Train KNN Classifier

```
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
```

```
# Load Iris dataset
iris = load_iris()
X = iris.data
y = iris.target

# Split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Create and train KNN model
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
```

KNeighborsClassifier ① ?
KNeighborsClassifier()

#### 4. Evaluate the Model

from sklearn.metrics import accuracy\_score, classification\_report

```
# Make predictions
y_pred = knn_model.predict(X_test)

# Print evaluation metrics
print("Accuracy:", accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

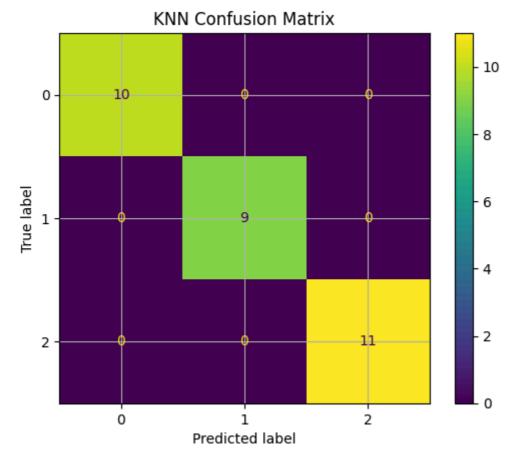
### → Accuracy: 1.0

	precision	recall	f1-score	support	
0	1.00	1.00	1.00	10	
1	1.00	1.00	1.00	9	
2	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	

# 5. Confusion Matrix

```
# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("KNN Confusion Matrix")
plt.grid()
plt.show()
```

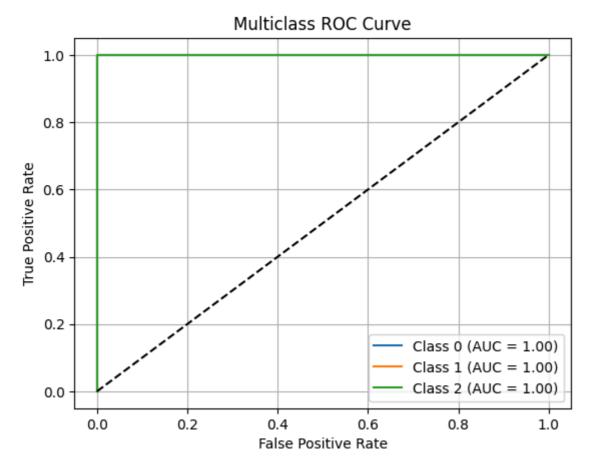




#### 6. ROC Curve

```
from sklearn.preprocessing import label_binarize
from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt
# Step 1: Binarize the output
y_test_bin = label_binarize(y_test, classes=[0, 1, 2])
y_prob = knn_model.predict_proba(X_test)
n_classes = y_test_bin.shape[1]
# Step 2: Compute ROC curve and AUC for each class
for i in range(n_classes):
    fpr, tpr, _ = roc_curve(y_test_bin[:, i], y_prob[:, i])
    roc_auc = auc(fpr, tpr)
   # Step 3: Plot
    plt.plot(fpr, tpr, label=f"Class {i} (AUC = {roc_auc:.2f})")
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("Multiclass ROC Curve")
plt.legend()
plt.grid()
plt.show()
```

**₹** 



### 7. Train vs Validation Accuracy

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import load_breast_cancer
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
# Step 1: Load dataset
data = load_breast_cancer()
X = data.data
y = data.target
# Step 2: Add noise to features
np.random.seed(42)
noise = np.random.normal(loc=0.0, scale=0.5, size=X.shape)
X_{noisy} = X + noise
# Step 3: Scale features
scaler = StandardScaler()
X scaled = scaler.fit transform(X noisy)
# Step 4: Train-test split with stratification
X_train, X_test, y_train, y_test = train_test_split(
   X_scaled, y, test_size=0.2, stratify=y, random_state=42
)
```

```
# Step 5: Train KNN for multiple k values
k values = list(range(1, 21))
train_accuracies = []
val_accuracies = []
for k in k values:
    knn = KNeighborsClassifier(n_neighbors=k)
    knn.fit(X_train, y_train)
   train_accuracies.append(knn.score(X_train, y_train))
    val_accuracies.append(knn.score(X_test, y_test))
# Step 6: Plot
plt.figure(figsize=(10, 6))
plt.plot(k_values, train_accuracies, marker='o', label='Training Accuracy', color='royalb
plt.plot(k_values, val_accuracies, marker='s', label='Validation Accuracy', color='darkor
plt.xlabel('Number of Neighbors (k)')
plt.ylabel('Accuracy')
plt.title('Train vs Validation Accuracy for Different k (KNN)')
plt.ylim(0.0, 1.05) # Show full accuracy range from 0 to 1
plt.xticks(k_values)
plt.grid(True, linestyle='--', alpha=0.7)
plt.legend()
plt.tight_layout()
plt.show()
```



```
from sklearn.linear_model import LogisticRegression from sklearn.metrics import accuracy_score, classification_report, confusion_matrix, Conf import matplotlib.pyplot as plt import numpy as np
```

# 👲 Step 1: Load and Preprocess Data

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Load your data (assuming 'heart' is already loaded)
X = heart.drop("cardio", axis=1)
y = heart["cardio"]

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

# Feature scaling
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

# → 2. Train the LR Model

```
from sklearn.linear_model import LogisticRegression

# Add stronger regularization to reduce overfitting (C < 1)
lr_model = LogisticRegression(C=0.1, max_iter=1000)
lr_model.fit(X_train_scaled, y_train)</pre>
```

```
LogisticRegression (C=0.1, max_iter=1000)
```

# 🖈 3. Accuracy & Classification Report

```
from sklearn.metrics import accuracy_score, classification_report
y_pred_lr = lr_model.predict(X_test_scaled)
```

print("Accuracy:", accuracy\_score(y\_test, y\_pred\_lr))
print(classification\_report(y\_test, y\_pred\_lr))

# Accuracy: 0.7104285714285714

	precision	recall	f1-score	support
0	0.70	0.75	0.72	7004
1	0.73	0.67	0.70	6996
accuracy			0.71	14000
macro avg	0.71	0.71	0.71	14000
weighted avg	0.71	0.71	0.71	14000

### \* 4. Confusion Matrix

from sklearn.metrics import confusion\_matrix, ConfusionMatrixDisplay
import matplotlib.pyplot as plt

```
cm = confusion_matrix(y_test, y_pred_lr)
disp = ConfusionMatrixDisplay(confusion_matrix=cm)
disp.plot()
plt.title("Confusion Matrix - Logistic Regression")
plt.grid()
plt.show()
```



# Confusion Matrix - Logistic Regression 5000 4500 0 -5244 - 4000 True label - 3500 3000 1 . 4702 - 2500 2000 0 1 Predicted label

#### ★ 5. ROC Curve

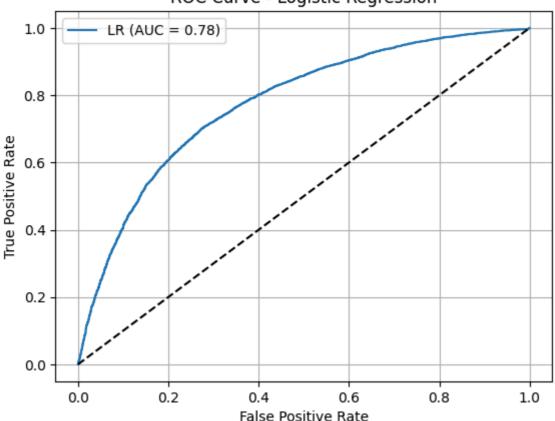
```
from sklearn.metrics import roc_curve, auc

y_prob_lr = lr_model.predict_proba(X_test_scaled)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_prob_lr)
roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label="LR (AUC = %0.2f)" % roc_auc)
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve - Logistic Regression")
plt.legend()
plt.grid()
plt.show()
```

### $\overline{\mathbf{T}}$

# **ROC Curve - Logistic Regression**



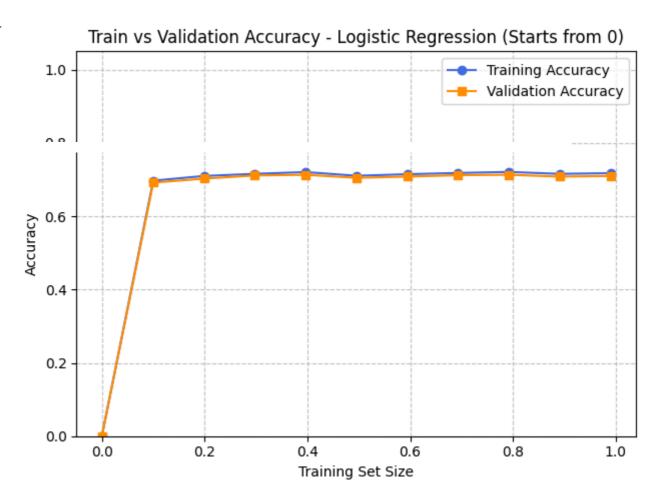
# 🖈 6. Train vs Validation Accuracy Curve

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
# Step 1: Insert 0 into the training sizes
train_sizes = np.linspace(0.1, 0.99, 10)
```

```
train_sizes = np.insert(train_sizes, 0, 0.0)
train_scores = [0.0] # Step 2: Add fake 0% accuracy at the beginning
val\_scores = [0.0]
# Step 3: Loop through actual training sizes (skipping 0.0)
for frac in train_sizes[1:]:
    X_part, _, y_part, _ = train_test_split(X_train_scaled, y_train, train_size=frac, ran
    model = LogisticRegression(C=0.1, max_iter=1000)
   model.fit(X_part, y_part)
    train_scores.append(model.score(X_part, y_part))
    val_scores.append(model.score(X_test_scaled, y_test))
# Plotting
plt.plot(train_sizes, train_scores, marker='o', label='Training Accuracy', color='royalbl
plt.plot(train_sizes, val_scores, marker='s', label='Validation Accuracy', color='darkora
plt.xlabel("Training Set Size")
plt.ylabel("Accuracy")
plt.title("Train vs Validation Accuracy - Logistic Regression (Starts from 0)")
plt.ylim(0.0, 1.05)
plt.grid(True, linestyle='--', alpha=0.7)
plt.legend()
plt.tight_layout()
```



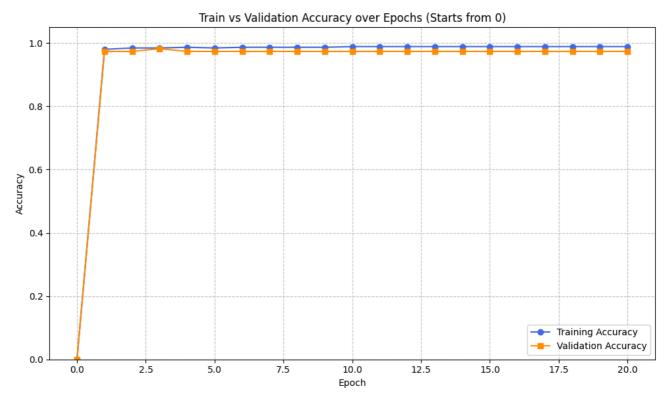
plt.show()



import numpy as np import matplotlib.pyplot as plt

```
from sklearn.linear_model import SGDClassifier
from sklearn.model selection import train test split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import load_breast_cancer
# Step 1: Load and split the data
data = load_breast_cancer()
X, y = data.data, data.target
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(
    X_scaled, y, test_size=0.2, stratify=y, random_state=42
)
# Step 2: Use SGDClassifier (supports partial_fit for epoch-like training)
model = SGDClassifier(loss='log_loss', max_iter=1, warm_start=True, learning_rate='consta
# Step 3: Epoch loop
epochs = 20
train_acc = [0.0] # Start from 0% accuracy
val_acc = [0.0]
# Initial partial_fit (SGD needs to know all classes up front)
model.partial_fit(X_train, y_train, classes=np.unique(y))
for epoch in range(1, epochs + 1):
    model.partial fit(X train, y train)
   train_acc.append(model.score(X_train, y_train))
   val_acc.append(model.score(X_test, y_test))
# Step 4: Plotting
plt.figure(figsize=(10, 6))
plt.plot(range(0, epochs + 1), train acc, marker='o', label='Training Accuracy', color='r
plt.plot(range(0, epochs + 1), val_acc, marker='s', label='Validation Accuracy', color='d
plt.xlabel("Epoch")
plt.ylabel("Accuracy")
plt.title("Train vs Validation Accuracy over Epochs (Starts from 0)")
plt.ylim(0.0, 1.05)
plt.grid(True, linestyle='--', alpha=0.7)
plt.legend()
plt.tight_layout()
plt.show()
```





from sklearn.metrics import accuracy\_score

y\_pred = model.predict(X\_test)
acc = accuracy\_score(y\_test, y\_pred)
print("Accuracy:", acc \* 100, "%")

Accuracy: 97.36842105263158 %

Start coding or generate with AI.