Week 3 – ML Model Development (Logistic Regression From Scratch)

This week, we train a machine learning model using the cleaned dataset.
We implement **Logistic Regression from scratch using NumPy** to understand how the algorithm works internally and compare its performance with Scikit-Learn's LogisticRegression.

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Objectives of Week 3

- Train a machine learning model on the cleaned dataset.
- Implement Logistic Regression from scratch using NumPy.
- Evaluate the model using accuracy, precision, recall, F1 score, and ROC-AUC.
- Compare the scratch model with Scikit-Learn's LogisticRegression.
- Save the trained model weights and bias for Week-4 Flask deployment.

1. Import Libraries

In [1]:
```
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.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.linear_model import LogisticRegression
```

2. Load Dataset

In [2]:
```
df = pd.read_csv("../data/processed/clean_cardio.csv")
df.head()
```

Out[2]:

	id	age	gender	height	weight	ap_hi	ap_lo	cholesterol	gluc	smoke
0	0	18393	2	0.453998	-0.848131	-0.998901	-0.138532	1	1	0
1	1	20228	1	-1.073987	0.762418	0.797987	0.919187	3	1	0
2	2	18857	1	0.072002	-0.708084	0.199024	-1.196251	3	1	0
3	3	17623	2	0.581330	0.552347	1.396950	1.976906	1	1	0
4	4	17474	1	-1.073987	-1.268275	-1.597864	-2.253970	1	1	0

3. Define Features & Target

We select the relevant features for modeling.

The target variable is **cardio** (0 = No disease, 1 = Disease).

In [4]:
```
feature_cols = [
    'age_years', 'height', 'weight', 'ap_hi', 'ap_lo', 'bmi',
    'cholesterol', 'gluc', 'smoke', 'alco', 'active'
]

X = df[feature_cols].values
y = df['cardio'].values
```

4. Split Dataset

In [7]:
```
x_train, x_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

x_train.shape, x_test.shape
```

Out[7]:
```
((54864, 11), (13717, 11))
```

Choosing the Appropriate Algorithm

The target variable **cardio** is binary (0 = no disease, 1 = disease).
Since we want to predict the probability of a patient having cardiovascular disease based on multiple numerical and categorical features, this becomes a **binary classification problem**.

For this type of problem, **Logistic Regression** is one of the most suitable and widely used algorithms because:

- It models the probability of a binary outcome.
- It works well with medical datasets and interpretable features.

- It handles linear decision boundaries effectively.
- It allows us to analyze feature importance easily.
- It performs well when data is properly scaled (as in Week 2).

Therefore, we choose **Logistic Regression** as the appropriate algorithm and implement it **from scratch using NumPy**, as required.

5. Logistic Regression From Scratch

We implement:

- Sigmoid function
- Loss (Binary Cross-Entropy)
- Gradient computation
- Weight & bias update

In [9]:
```
class LogisticRegressionScratch:

    def __init__(self, lr=0.01, n_iters=2000):
        self.lr = lr
        self.n_iters = n_iters

    def sigmoid(self, z):
        return 1 / (1 + np.exp(-z))

    def fit(self, x, y):
        n_samples, n_features = x.shape
        self.weights = np.zeros(n_features)
        self.bias = 0
        self.loss_history = []

        for _ in range(self.n_iters):
            # linear model
            linear_model = np.dot(x, self.weights) + self.bias
            y_pred = self.sigmoid(linear_model)

            # gradients
            dw = (1/n_samples) * np.dot(x.T, (y_pred - y))
            db = (1/n_samples) * np.sum(y_pred - y)

            # update weights & bias
            self.weights -= self.lr * dw
            self.bias -= self.lr * db

            # compute loss (binary cross-entropy)
            loss = -np.mean(
                y*np.log(y_pred + 1e-8) + (1 - y)*np.log(1 - y_pred + 1e-8)
            )
            self.loss_history.append(loss)

    def predict_proba(self, x):
        linear_model = np.dot(x, self.weights) + self.bias
        return self.sigmoid(linear_model)

    def predict(self, x, threshold=0.5):
        proba = self.predict_proba(x)
        return (proba >= threshold).astype(int)
```

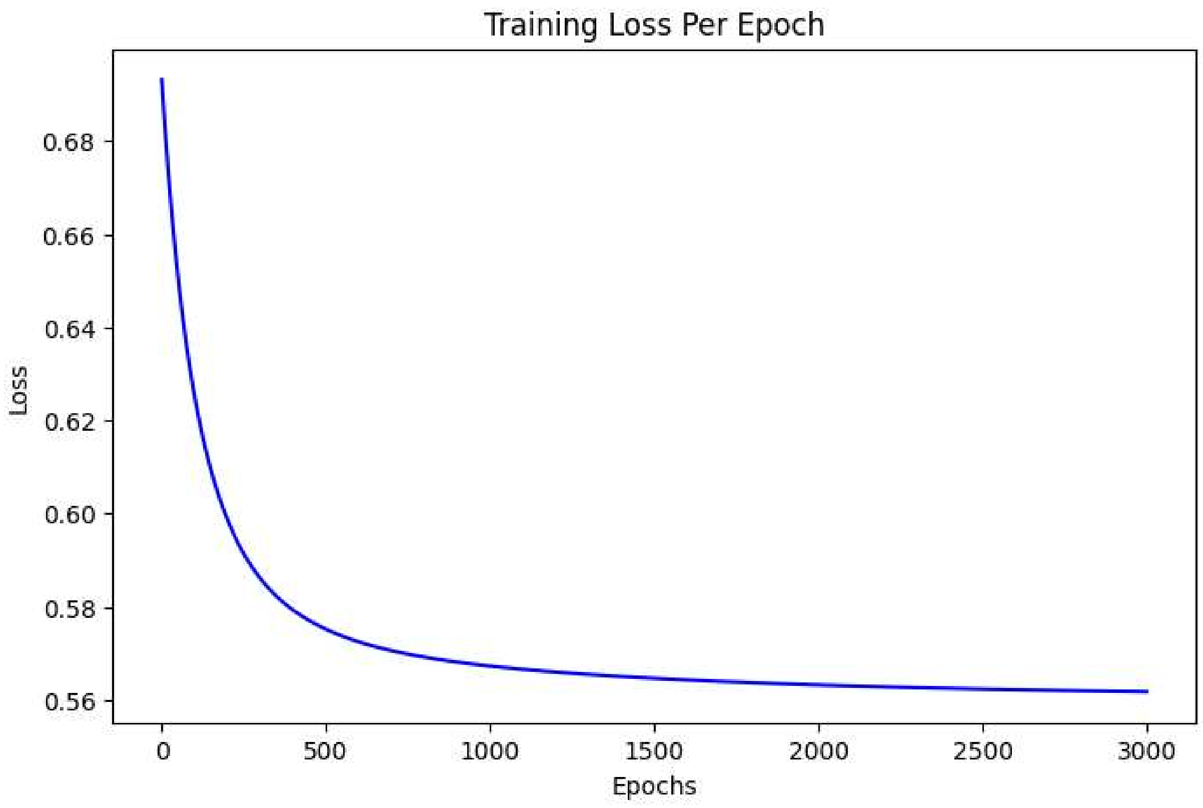
In [10]:
```
model_scratch = LogisticRegressionScratch(lr=0.01, n_iters=3000)
model_scratch.fit(x_train, y_train)

print("Training complete!")
```

```
Training complete!
```

6. Plot Training Loss

In [11]:
```
plt.figure(figsize=(8,5))
plt.plot(model_scratch.loss_history, color='blue')
plt.title("Training Loss Per Epoch")
plt.xlabel("Epochs")
plt.ylabel("Loss")
plt.show()
```



7. Evaluate Scratch Model

In [12]:
```
y_pred = model_scratch.predict(x_test)
y_proba = model_scratch.predict_proba(x_test)
```

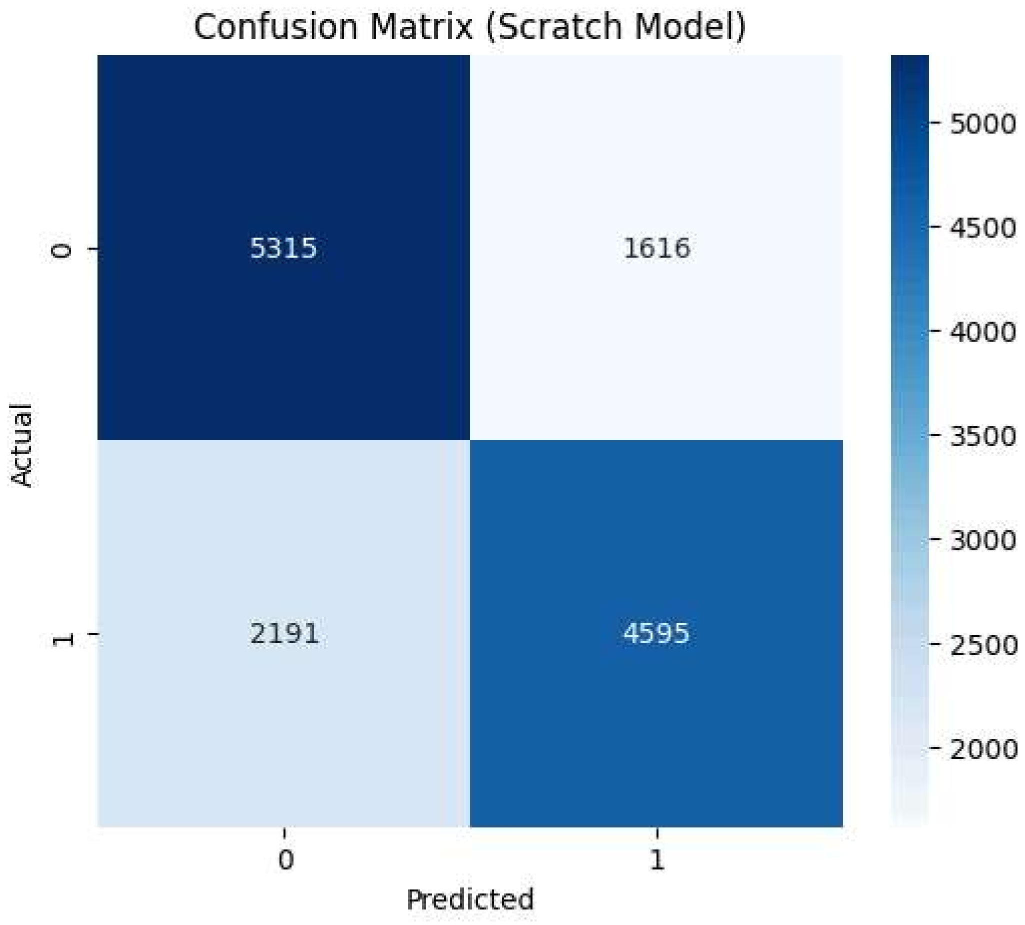
```
print("Accuracy:", accuracy_score(y_test, y_pred))
print("Precision:", precision_score(y_test, y_pred))
print("Recall:", recall_score(y_test, y_pred))
print("F1 Score:", f1_score(y_test, y_pred))
```

```
Accuracy: 0.7224611795582124
Precision: 0.7398164546771856
Recall: 0.6771293840259357
F1 Score: 0.7070862506732323
```

8. Confusion Matrix

In [13]:
```
cm = confusion_matrix(y_test, y_pred)

plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
plt.title("Confusion Matrix (Scratch Model)")
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.show()
```

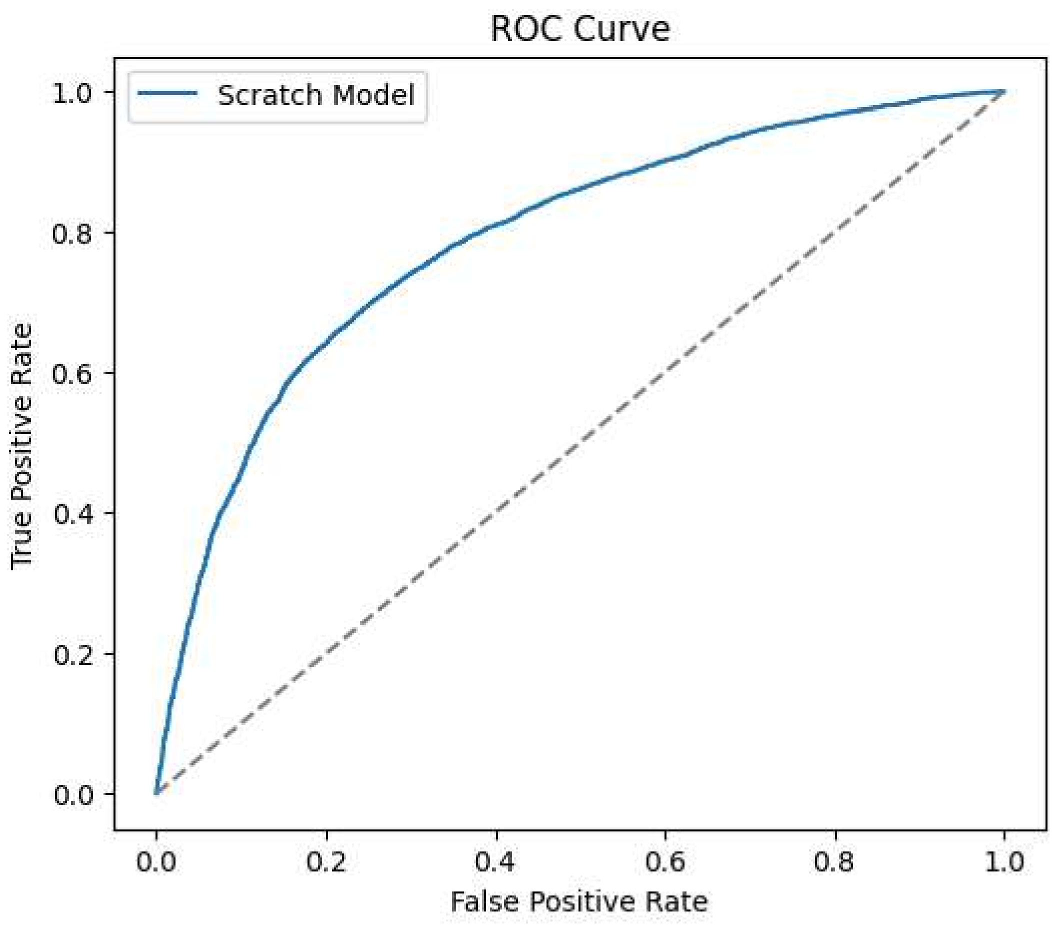


9. ROC Curve

In [14]:
```
fpr, tpr, _ = roc_curve(y_test, y_proba)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, label="Scratch Model")
plt.plot([0,1], [0,1], linestyle='--', color='gray')
plt.title("ROC Curve")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.legend()
plt.show()

print("AUC Score:", roc_auc_score(y_test, y_proba))
```



```
AUC Score: 0.7882303215949155
```

10. Compare with sklearn LogisticRegression

In [15]:
```
sk_model = LogisticRegression(max_iter=5000)
sk_model.fit(X_train, y_train)

sk_pred = sk_model.predict(X_test)
sk_proba = sk_model.predict_proba(X_test)[:,1]

print("Accuracy:", accuracy_score(y_test, sk_pred))
print("Precision:", precision_score(y_test, sk_pred))
print("Recall:", recall_score(y_test, sk_pred))
print("F1 Score:", f1_score(y_test, sk_pred))
print("AUC:", roc_auc_score(y_test, sk_proba))
```

```
Accuracy: 0.7242108332725815
Precision: 0.7477313974591652
Recall: 0.6678455643972885
F1 Score: 0.7055343659998443
AUC: 0.7896826399144818
```

11. Save Model Parameters

These weights will be used in **Week-4 Flask App**.

In [17]:
```
import os

os.makedirs("../models", exist_ok=True)

np.save("../models/logistic_weights.npy", model_scratch.weights)
np.save("../models/logistic_bias.npy", np.array([model_scratch.bias]))

print("Model parameters saved!")
```

```
Model parameters saved!
```

Week 3 Completed Successfully

- Loaded cleaned dataset
- Performed train-test split
- Implemented **Logistic Regression from scratch** using NumPy
- Trained model with gradient descent
- Visualized loss curve
- Evaluated model using multiple metrics
- Drew confusion matrix & ROC curve
- Compared results with sklearn model
- Saved model weights for deployment

In [ ]: