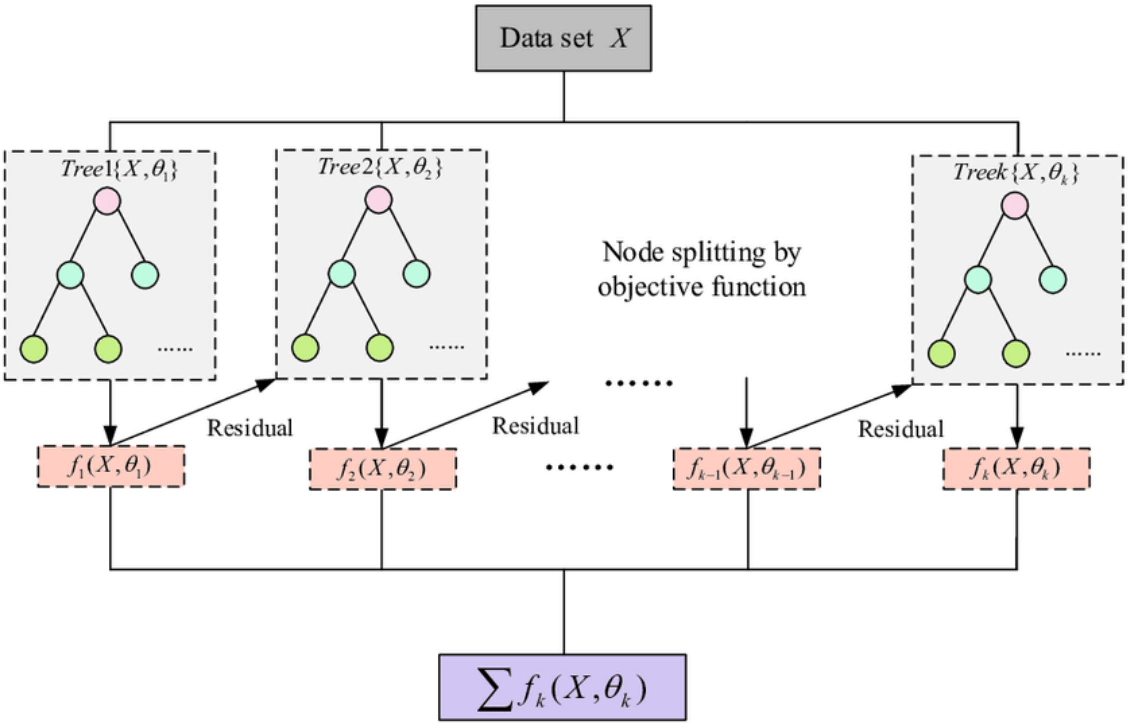
XGBoost from Scratch in Python



Import Required Libraries

In [1]:
```
# Base Libraries
import numpy as np
import pandas as pd

# Data Prep
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split

# Model Fine Tuning
import optuna

# Model Performance
from sklearn.metrics import classification_report

# Data Visualization
import plotly.express as px
```

Class Node

In [2]:
```
class Node:
    """
    A node class for a decision tree.
```

```
    """
    def __init__(self, x, gradient, hessian, idxs, subsample_cols=1 , min_le
        """
        Constructor to initialize the node with data and parameters.
        Parameters:
        - x: Input data for the node.
        - gradient: Gradient information for gradient boosting.
        - hessian: Hessian information for second-order optimization.
        - idxs: Indices of the data points in the node.
        - subsample_cols: Fraction of columns to consider for splitting.
        - min_leaf: Minimum number of samples required in a leaf node.
        - min_child_weight: Minimum sum of instance weight(hessian) needed i
        - depth: Maximum depth of the tree.
        - lambda_: Regularization parameter.
        - gamma: Minimum loss reduction required to make a further partition
        - eps: Epsilon value for quantile sketch method.
        """
        self.x, self.gradient, self.hessian = x, gradient, hessian
        self.idxs = idxs
        self.depth = depth
        self.min_leaf = min_leaf
        self.lambda_ = lambda_
        self.gamma  = gamma
        self.min_child_weight = min_child_weight
        self.row_count = len(idxs)
        self.col_count = x.shape[1]
        self.subsample_cols = subsample_cols
        self.eps = eps
        self.column_subsample = np.random.permutation(self.col_count)[:round
        self.val = self.compute_gamma(self.gradient[self.idxs], self.hessian
        self.score = float('-inf')
        self.find_varsplit()

    def compute_gamma(self, gradient, hessian):
        """
        Computes the gamma value for the node.
        Gamma is calculated as negative sum of gradient divided by the sum o

        Parameters:
        - gradient: Gradient information for gradient boosting.
        - hessian: Hessian information for second-order optimization.

        Returns:
        - gamma: Gamma value for the node.
        """
        return(-np.sum(gradient)/(np.sum(hessian) + self.lambda_))

    def find_varsplit(self):
        """
        Identifies the best variable to split on.
        Iterates through the subset of columns and finds the best greedy spl
        """
        for c in self.column_subsample: self.find_greedy_split(c)
        if self.is_leaf: return
        x = self.split_col
        lhs = np.nonzero(x <= self.split)[0]
```

```python
        rhs = np.nonzero(x > self.split)[0]
        self.lhs = Node(x = self.x, gradient = self.gradient, hessian = self
        self.rhs = Node(x = self.x, gradient = self.gradient, hessian = self

    def find_greedy_split(self, var_idx):
        """
        Finds the best split point for a given variable using a greedy appro
        Iterates through each row and evaluates potential splits.

        Parameters:
        - var_idx: Index of the variable to split on.
        """
        x = self.x[self.idxs, var_idx]
        for r in range(self.row_count):
            lhs = x <= x[r]
            rhs = x > x[r]
            lhs_indices = np.nonzero(lhs)[0]
            rhs_indices = np.nonzero(rhs)[0]
            lhs_sum = self.hessian[lhs_indices].sum()
            rhs_sum = self.hessian[rhs_indices].sum()
            # Ensures minimum leaf size and child weight before considering
            if(rhs.sum() < self.min_leaf or lhs.sum() < self.min_leaf
               or lhs_sum < self.min_child_weight
               or rhs_sum < self.min_child_weight): continue
            curr_score = self.gain(lhs, rhs)
            # Updates the best split if a better score is found.
            if curr_score > self.score:
                self.var_idx = var_idx
                self.score = curr_score
                self.split = x[r]

    def weighted_qauntile_sketch(self, var_idx):
        """
        Finds the best split point for a given variable using a weighted qua
        Iterates through each row and evaluates potential splits.

        Parameters:
        - var_idx: Index of the variable to split on.
        """
        x = self.x[self.idxs, var_idx]
        hessian_ = self.hessian[self.idxs]
        df = pd.DataFrame({'feature':x,'hess':hessian_})
        df.sort_values(by=['feature'], ascending = True, inplace = True)
        hess_sum = df['hess'].sum()
        df['rank'] = df.apply(lambda x : (1/hess_sum)*sum(df[df['feature'] <

        for row in range(df.shape[0]-1):
            # look at the current rank and the next ran
            rk_sk_j, rk_sk_j_1 = df['rank'].iloc[row:row+2]
            diff = abs(rk_sk_j - rk_sk_j_1)
            if(diff >= self.eps):
                continue

            split_value = (df['rank'].iloc[row+1] + df['rank'].iloc[row])/2
            lhs = x <= split_value
            rhs = x > split_value
```

```python
        lhs_indices = np.nonzero(x <= split_value)[0]
        rhs_indices = np.nonzero(x > split_value)[0]
        if(rhs.sum() < self.min_leaf or lhs.sum() < self.min_leaf
           or self.hessian[lhs_indices].sum() < self.min_child_weight
           or self.hessian[rhs_indices].sum() < self.min_child_weight):

        curr_score = self.gain(lhs, rhs)
        if curr_score > self.score:
            self.var_idx = var_idx
            self.score = curr_score
            self.split = split_value

    def gain(self, lhs, rhs):
        """
        Computes the gain in loss function for a given split.

        Parameters:
        - lhs: Left hand side of the split.
        - rhs: Right hand side of the split.

        Returns:
        - gain: Gain in loss function for the split.
        """
        gradient = self.gradient[self.idxs]
        hessian  = self.hessian[self.idxs]
        lhs_gradient = gradient[lhs].sum()
        lhs_hessian  = hessian[lhs].sum()
        rhs_gradient = gradient[rhs].sum()
        rhs_hessian  = hessian[rhs].sum()
        total_gradient = lhs_gradient + rhs_gradient
        total_hessian = lhs_hessian + rhs_hessian

        gain = 0.5 *( (lhs_gradient**2/(lhs_hessian + self.lambda_)) + (rhs_
        return(gain)

    @property
    def split_col(self):
        """
        Returns the column of the split variable.
        """
        return self.x[self.idxs , self.var_idx]

    @property
    def is_leaf(self):
        """
        Returns True if the node is a leaf node.
        """
        return self.score == float('-inf') or self.depth <= 0

    def predict(self, x):
        """
        Predicts the value for a given input.

        Parameters:
        - x: Input data.
```

```
        Returns:
        - np.array: Predicted values.
        """
        return np.array([self.predict_row(xi) for xi in x])

    def predict_row(self, xi):
        """
        Predicts the value for a given input row.

        Parameters:
        - xi: Input row.

        Returns:
        - np.array: Predicted value.
        """
        if self.is_leaf:
            return(self.val)

        node = self.lhs if xi[self.var_idx] <= self.split else self.rhs
        return node.predict_row(xi)
```

XGBoost Tree Class

In [3]:
```
class XGBoostTree:
    def fit(self, x, gradient, hessian, subsample_cols = 0.8 , min_leaf = 5,
        """
        Fits a decision tree to the data.

        Parameters:
        - x: Input data.
        - gradient: Gradient information for gradient boosting.
        - hessian: Hessian information for second-order optimization.
        - subsample_cols: Fraction of columns to consider for splitting.
        - min_leaf: Minimum number of samples required in a leaf node.
        - min_child_weight: Minimum sum of instance weight(hessian) needed i
        - depth: Maximum depth of the tree.
        - lambda_: Regularization parameter.
        - gamma: Minimum loss reduction required to make a further partition
        - eps: Epsilon value for quantile sketch method.

        Returns:
        - self: Trained decision tree.
        """
        self.dtree = Node(x, gradient, hessian, np.array(np.arange(len(x))),
        return self

    def predict(self, X):
        """
        Predicts the value for a given input.

        Parameters:
        - X: Input data.
```

```
        Returns:
        - np.array: Predicted values.
        """
        return self.dtree.predict(X)
```

XGBoost Classifier Class

In [4]:
```
class XGBoostClassifier:
    def __init__(self, random_state=None):
        self.estimators = []
        self.random_state = random_state
        np.random.seed(self.random_state)

    @staticmethod
    def sigmoid(x):
        """
        Computes the sigmoid function.

        Parameters:
        - x: Input data.

        Returns:
        - np.array: Sigmoid of the input data.
        """
        return 1 / (1 + np.exp(-x))

    def grad(self, preds, labels):
        """
        Computes the gradient of the log loss function.

        Parameters:
        - preds: Predicted values.
        - labels: Actual values.

        Returns:
        - np.array: Gradient of the log loss function.
        """
        preds = self.sigmoid(preds)
        return(preds - labels)

    def hess(self, preds, labels):
        """
        Computes the hessian of the log loss function.

        Parameters:
        - preds: Predicted values.

        Returns:
        - np.array: Hessian of the log loss function.
        """
        preds = self.sigmoid(preds)
        return(preds * (1 - preds))

    @staticmethod
```

```python
    def log_odds(column):
        """
        Computes the log odds of a binary variable.

        Parameters:
        - column: Binary variable.

        Returns:
        - np.array: Log odds of the binary variable.
        """
        binary_yes = np.count_nonzero(column == 1)
        binary_no  = np.count_nonzero(column == 0)
        return(np.log(binary_yes/binary_no))


    def fit(self, X, y, subsample_cols=1 , min_child_weight=1, depth=5, min_
        """
        Fits a gradient boosted decision tree to the data.

        Parameters:
        - X: Input data.
        - y: Target variable.
        - subsample_cols: Fraction of columns to consider for splitting.
        - min_leaf: Minimum number of samples required in a leaf node.
        - min_child_weight: Minimum sum of instance weight(hessian) needed i
        - depth: Maximum depth of the tree.
        - lambda_: Regularization parameter.
        - gamma: Minimum loss reduction required to make a further partition
        - eps: Epsilon value for quantile sketch method.
        - learning_rate: Learning rate for gradient boosting.
        - boosting_rounds: Number of boosting rounds.

        Returns:
        - self: Trained gradient boosted decision tree.
        """
        self.X, self.y = X, y
        self.depth = depth
        self.subsample_cols = subsample_cols
        self.eps = eps
        self.min_child_weight = min_child_weight
        self.min_leaf = min_leaf
        self.learning_rate = learning_rate
        self.boosting_rounds = boosting_rounds
        self.lambda_ = lambda_
        self.gamma  = gamma
        self.base_pred = np.full((X.shape[0], 1), 1).flatten().astype('float
        Grad = self.grad(self.base_pred, self.y)
        Hess = self.hess(self.base_pred, self.y)
        for _ in range(self.boosting_rounds):
            boosting_tree = XGBoostTree().fit(self.X, Grad, Hess, depth = se
            self.base_pred += self.learning_rate * boosting_tree.predict(sel
            self.estimators.append(boosting_tree)

    def predict_proba(self, X):
        """
        Predicts the probability of the positive class for a given input.
```

```
        Parameters:
        - X: Input data.

        Returns:
        - np.array: Predicted probabilities.
        """
        pred = np.zeros(X.shape[0])

        for estimator in self.estimators:
            pred += self.learning_rate * estimator.predict(X)

        return self.sigmoid(np.full((X.shape[0], 1), 1).flatten().astype('fl

    def predict(self, X):
        pred = np.zeros(X.shape[0])
        for estimator in self.estimators:
            pred += self.learning_rate * estimator.predict(X)

        predicted_probas = self.sigmoid(np.full((X.shape[0], 1), 1).flatten(
        preds = np.where(predicted_probas > np.mean(predicted_probas), 1, 0)
        return preds
```

Load Breast Cancer Data

In [5]:
```
data = load_breast_cancer()
df = pd.DataFrame(data.data, columns=data.feature_names)
```

EDA

Distribution of Mean Radius

In [6]:
```
fig = px.histogram(df, x="mean radius", nbins=20, title='Distribution of Mea
fig.update_layout(
    xaxis_title='Mean Radius',
    yaxis_title='Count',
    font=dict(
        family="Courier New, monospace",
        size=14,
        color="#7f7f7f"
    )
)
fig.show()
```

Box Plot of Mean Radius

In [7]:
```
# Calculate the quantiles
q1 = np.percentile(df['mean radius'], 25)
q3 = np.percentile(df['mean radius'], 75)
median = np.median(df['mean radius'])
```

```
fig = px.box(df, y="mean radius", title='Box Plot of Mean Radius', template=

# Customize the box plot
fig.update_traces(marker_color='#636EFA', line_color='#636EFA', boxmean=True
fig.update_layout(
    xaxis_title='Mean Radius',
    yaxis_title='Count',
    font=dict(
        family="Courier New, monospace",
        size=14,
        color="#7f7f7f"
    ),
    # Add annotations for the quantiles
    annotations=[
        dict(x=0.5, y=q1, xref='x', yref='y', text=f'Q1: {q1:.2f}', showarro
        dict(x=0.5, y=median, xref='x', yref='y', text=f'Median: {median:.2f
        dict(x=0.5, y=q3, xref='x', yref='y', text=f'Q3: {q3:.2f}', showarro
    ]
)

fig.show()
```

Scatter matrix of selected features

In [8]:

```
selected_features = ['mean radius', 'mean texture', 'mean perimeter', 'mean
fig = px.scatter_matrix(df[selected_features], title='Scatter matrix of sele

# Customize the scatter matrix plot
fig.update_traces(marker=dict(size=3, color='#636EFA'), diagonal_visible=Fal
fig.update_layout(
    title_font=dict(size=20),
    font=dict(family='Courier New, monospace', size=10, color='#7f7f7f'),
    width=800,
    height=800
)

fig.show()
```

Fit XGBoost

In [9]:

```
X, y = data.data, data.target
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2, ra

xgb = XGBoostClassifier(random_state=42)
xgb.fit(X_train, y_train, depth = 5, min_leaf = 5, lambda_ = 1.5, gamma = 1,
y_pred = xgb.predict(X_test)
print(f"Test Accuracy: {np.mean(y_pred == y_test):.2%}")
print(classification_report(y_test, y_pred))
```

```
Test Accuracy: 95.61%
              precision    recall  f1-score   support

           0       0.93      0.95      0.94        43
           1       0.97      0.96      0.96        71

    accuracy                           0.96       114
   macro avg       0.95      0.96      0.95       114
weighted avg       0.96      0.96      0.96       114
```

In [10]:

```
def objective(trial):
    depth = trial.suggest_int('depth', 3, 10)
    min_leaf = trial.suggest_int('min_leaf', 1, 10)
    lambda_ = trial.suggest_float('lambda_', 0.1, 2.0)
    gamma = trial.suggest_float('gamma', 0.1, 2.0)
    eps = trial.suggest_float('eps', 0.01, 0.5)
    min_child_weight = trial.suggest_int('min_child_weight', 1, 10)
    subsample_cols = trial.suggest_float('subsample_cols', 0.5, 1.0)
    learning_rate = trial.suggest_float('learning_rate', 0.1, 1.0)
    boosting_rounds = trial.suggest_int('boosting_rounds', 3, 10)

    xgb = XGBoostClassifier(random_state=42)
    xgb.fit(X_train, y_train, depth=depth, min_leaf=min_leaf, lambda_=lambda
    y_pred = xgb.predict(X_test)
    accuracy = (y_test == y_pred).mean()

    return accuracy

study = optuna.create_study(direction='maximize')
study.optimize(objective, n_trials=20)

best_params = study.best_params
best_accuracy = study.best_value
```

```
[I 2024-01-10 11:29:33,881] A new study created in memory with name: no-nam
e-fff7c5a4-0285-48d3-bb63-556f7bfe88be
[I 2024-01-10 11:29:36,035] Trial 0 finished with value: 0.9473684210526315
and parameters: {'depth': 3, 'min_leaf': 10, 'lambda_': 1.8837519939791678,
'gamma': 1.9326730633196363, 'eps': 0.12256918818403406, 'min_child_weigh
t': 4, 'subsample_cols': 0.5257156428787195, 'learning_rate': 0.29017095483
91574, 'boosting_rounds': 6}. Best is trial 0 with value: 0.947368421052631
5.
[I 2024-01-10 11:29:39,921] Trial 1 finished with value: 0.868421052631579
and parameters: {'depth': 8, 'min_leaf': 6, 'lambda_': 0.36060611230704076,
'gamma': 1.846850132917239, 'eps': 0.2364774657260346, 'min_child_weight':
6, 'subsample_cols': 0.9376645896648708, 'learning_rate': 0.95453687347993
1, 'boosting_rounds': 5}. Best is trial 0 with value: 0.9473684210526315.
[I 2024-01-10 11:29:42,257] Trial 2 finished with value: 0.9473684210526315
and parameters: {'depth': 7, 'min_leaf': 9, 'lambda_': 0.18871441767328337,
'gamma': 0.4647923212573605, 'eps': 0.4626819136346244, 'min_child_weight':
8, 'subsample_cols': 0.55926598905196, 'learning_rate': 0.3302686983634011
7, 'boosting_rounds': 6}. Best is trial 0 with value: 0.9473684210526315.
[I 2024-01-10 11:29:44,128] Trial 3 finished with value: 0.956140350877193
and parameters: {'depth': 9, 'min_leaf': 3, 'lambda_': 0.680610876793632,
'gamma': 1.557954705378749, 'eps': 0.418189028299309, 'min_child_weight':
6, 'subsample_cols': 0.5356702605264945, 'learning_rate': 0.269655514241123
55, 'boosting_rounds': 4}. Best is trial 3 with value: 0.956140350877193.
[I 2024-01-10 11:29:52,667] Trial 4 finished with value: 0.9385964912280702
and parameters: {'depth': 10, 'min_leaf': 5, 'lambda_': 0.6785220276077152,
'gamma': 0.18570768400765225, 'eps': 0.2755012234719525, 'min_child_weigh
t': 1, 'subsample_cols': 0.6543554272234244, 'learning_rate': 0.67909217678
76401, 'boosting_rounds': 8}. Best is trial 3 with value: 0.95614035087719
3.
[I 2024-01-10 11:29:55,132] Trial 5 finished with value: 0.9649122807017544
and parameters: {'depth': 7, 'min_leaf': 2, 'lambda_': 1.0829617552292672,
'gamma': 0.4342859807341465, 'eps': 0.2938299738146402, 'min_child_weight':
2, 'subsample_cols': 0.6996408919284733, 'learning_rate': 0.419453513981250
1, 'boosting_rounds': 3}. Best is trial 5 with value: 0.9649122807017544.
[I 2024-01-10 11:29:58,088] Trial 6 finished with value: 0.9122807017543859
and parameters: {'depth': 6, 'min_leaf': 8, 'lambda_': 1.0871034115359437,
'gamma': 1.3343094591777238, 'eps': 0.44314172424821846, 'min_child_weigh
t': 7, 'subsample_cols': 0.8147712898765599, 'learning_rate': 0.91352281981
26929, 'boosting_rounds': 5}. Best is trial 5 with value: 0.964912280701754
4.
[I 2024-01-10 11:30:03,225] Trial 7 finished with value: 0.9122807017543859
and parameters: {'depth': 7, 'min_leaf': 1, 'lambda_': 1.4935870331640198,
'gamma': 0.5629524309002316, 'eps': 0.4769367229011085, 'min_child_weight':
8, 'subsample_cols': 0.7503779008691946, 'learning_rate': 0.266836586642835
5, 'boosting_rounds': 9}. Best is trial 5 with value: 0.9649122807017544.
[I 2024-01-10 11:30:08,376] Trial 8 finished with value: 0.9473684210526315
and parameters: {'depth': 6, 'min_leaf': 4, 'lambda_': 1.210688349837596,
'gamma': 0.8583706144167854, 'eps': 0.16262323222343628, 'min_child_weigh
t': 6, 'subsample_cols': 0.6453480741860826, 'learning_rate': 0.69607924714
49857, 'boosting_rounds': 10}. Best is trial 5 with value: 0.96491228070175
44.
[I 2024-01-10 11:30:11,379] Trial 9 finished with value: 0.8859649122807017
and parameters: {'depth': 5, 'min_leaf': 5, 'lambda_': 1.9190617408610273,
'gamma': 1.938461354637322, 'eps': 0.14714806616080398, 'min_child_weight':
9, 'subsample_cols': 0.9338744185703332, 'learning_rate': 0.188881538965250
56, 'boosting_rounds': 5}. Best is trial 5 with value: 0.9649122807017544.
```

```
[I 2024-01-10 11:30:13,698] Trial 10 finished with value: 0.956140350877193
and parameters: {'depth': 4, 'min_leaf': 1, 'lambda_': 1.4147294649291882,
'gamma': 0.10704013019772096, 'eps': 0.061694229396454386, 'min_child_weigh
t': 1, 'subsample_cols': 0.830742418262602, 'learning_rate': 0.494858988532
05046, 'boosting_rounds': 3}. Best is trial 5 with value: 0.964912280701754
4.
[I 2024-01-10 11:30:15,740] Trial 11 finished with value: 0.947368421052631
5 and parameters: {'depth': 9, 'min_leaf': 3, 'lambda_': 0.760148794269271
5, 'gamma': 1.2493491122070677, 'eps': 0.3471305182858102, 'min_child_weigh
t': 4, 'subsample_cols': 0.6248548431135975, 'learning_rate': 0.42998984269
08067, 'boosting_rounds': 3}. Best is trial 5 with value: 0.964912280701754
4.
[I 2024-01-10 11:30:17,660] Trial 12 finished with value: 0.964912280701754
4 and parameters: {'depth': 9, 'min_leaf': 3, 'lambda_': 0.780595430204518
6, 'gamma': 1.5083290840988517, 'eps': 0.3564700893061117, 'min_child_weigh
t': 3, 'subsample_cols': 0.5224278996202384, 'learning_rate': 0.15456456642
554905, 'boosting_rounds': 3}. Best is trial 5 with value: 0.96491228070175
44.
[I 2024-01-10 11:30:20,353] Trial 13 finished with value: 0.956140350877193
and parameters: {'depth': 8, 'min_leaf': 2, 'lambda_': 0.8906888430724932,
'gamma': 0.9290666545944087, 'eps': 0.35008785264021536, 'min_child_weigh
t': 3, 'subsample_cols': 0.6997018158740044, 'learning_rate': 0.10331604118
227555, 'boosting_rounds': 3}. Best is trial 5 with value: 0.96491228070175
44.
[I 2024-01-10 11:30:23,356] Trial 14 finished with value: 0.947368421052631
5 and parameters: {'depth': 10, 'min_leaf': 3, 'lambda_': 0.559538258583641
5, 'gamma': 1.0877613868875913, 'eps': 0.30401866434655445, 'min_child_weig
ht': 3, 'subsample_cols': 0.6078879852517559, 'learning_rate': 0.3969435120
735249, 'boosting_rounds': 4}. Best is trial 5 with value: 0.96491228070175
44.
[I 2024-01-10 11:30:27,754] Trial 15 finished with value: 0.964912280701754
4 and parameters: {'depth': 8, 'min_leaf': 7, 'lambda_': 0.932664017033692
6, 'gamma': 1.467028065215887, 'eps': 0.380384362626983, 'min_child_weigh
t': 2, 'subsample_cols': 0.5031985570780932, 'learning_rate': 0.10184012095
016437, 'boosting_rounds': 7}. Best is trial 5 with value: 0.96491228070175
44.
[I 2024-01-10 11:30:30,155] Trial 16 finished with value: 0.947368421052631
5 and parameters: {'depth': 9, 'min_leaf': 2, 'lambda_': 0.500606535730917,
'gamma': 0.7830650423200627, 'eps': 0.24139869949901643, 'min_child_weigh
t': 4, 'subsample_cols': 0.5775594259956663, 'learning_rate': 0.53814713098
14936, 'boosting_rounds': 4}. Best is trial 5 with value: 0.964912280701754
4.
[I 2024-01-10 11:30:32,192] Trial 17 finished with value: 0.973684210526315
8 and parameters: {'depth': 5, 'min_leaf': 4, 'lambda_': 1.108237040552457,
'gamma': 1.6249386096671368, 'eps': 0.3936850691142478, 'min_child_weight':
2, 'subsample_cols': 0.6933452380097069, 'learning_rate': 0.205227817954976
88, 'boosting_rounds': 3}. Best is trial 17 with value: 0.9736842105263158.
[I 2024-01-10 11:30:36,963] Trial 18 finished with value: 0.956140350877193
and parameters: {'depth': 5, 'min_leaf': 6, 'lambda_': 1.1064403517400772,
'gamma': 1.706906783286374, 'eps': 0.4906919579559388, 'min_child_weight':
2, 'subsample_cols': 0.703667031248543, 'learning_rate': 0.377516512411581,
'boosting_rounds': 7}. Best is trial 17 with value: 0.9736842105263158.
[I 2024-01-10 11:30:38,717] Trial 19 finished with value: 0.929824561403508
8 and parameters: {'depth': 5, 'min_leaf': 4, 'lambda_': 1.226890279047565
5, 'gamma': 1.1469387939055184, 'eps': 0.40657862701455527, 'min_child_weig
ht': 10, 'subsample_cols': 0.748309197633104, 'learning_rate': 0.2136211780
```

```
1005437, 'boosting_rounds': 4}. Best is trial 17 with value: 0.973684210526
3158.
```

In [11]:
```
print("Best Parameters:", best_params)
print(f"Best Accuracy on Test Data: {best_accuracy:.2%}")
print(classification_report(y_test, y_pred))
```

```
Best Parameters: {'depth': 5, 'min_leaf': 4, 'lambda_': 1.108237040552457,
'gamma': 1.6249386096671368, 'eps': 0.3936850691142478, 'min_child_weight':
2, 'subsample_cols': 0.6933452380097069, 'learning_rate': 0.205227817954976
88, 'boosting_rounds': 3}
Best Accuracy on Test Data: 97.37%
              precision    recall  f1-score   support

           0       0.93      0.95      0.94        43
           1       0.97      0.96      0.96        71

    accuracy                           0.96       114
   macro avg       0.95      0.96      0.95       114
weighted avg       0.96      0.96      0.96       114
```