Water_Potability_ML_Project

January 3, 2026

1 Water Potability Prediction System using Machine Learning

1.1 Project Information

Item	Details
Author	Sohaib Farooq
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Domain	Environmental Science / Public Health
Dataset	Water Potability Dataset (Kaggle)
Algorithms	Logistic Regression, Random Forest, XGBoost, LightGBM

1.2 Problem Statement

Access to safe drinking water is essential for health and is a basic human right. This project aims to **predict whether water is safe for human consumption** based on various water quality parameters using machine learning algorithms.

1.3 Dataset Download

Download Link: Kaggle - Water Potability Dataset

After downloading, place `water_potability.csv` in the same folder as this notebook.

## Step 1 & 2: Import Required Libraries

[43]:
```
# Install required packages (run this cell first time only)
# !pip install pandas numpy matplotlib seaborn scikit-learn
```

[44]:
```
# Import Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```python
import seaborn as sns

# Scikit-learn imports
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from sklearn.metrics import (accuracy_score, confusion_matrix,
                             classification_report, precision_score,
                             recall_score, f1_score)

# Settings
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline

print("All libraries imported successfully!")
```

```
All libraries imported successfully!
```

## Step 3: Domain and Problem Statement

1.3.1 Domain: Environmental Science / Public Health

1.3.2 Problem Statement:

To predict whether water is safe for human consumption based on various water quality parameters using machine learning algorithms.

1.3.3 Features Description:

Feature	Description	Unit
pH	Acidity/Alkalinity level	0-14
Hardness	Capacity to precipitate soap	mg/L
Solids	Total dissolved solids	ppm
Chloramines	Amount of chloramines	ppm
Sulfate	Sulfate dissolved	mg/L
Conductivity	Electrical conductivity	S/cm
Organic_carbon	Organic carbon amount	ppm
Trihalomethanes	THMs amount	g/L
Turbidity	Cloudiness measure	NTU
Potability	**Target: Safe (1) or Unsafe (0)**	-

## Step 4: Data Collection and Preprocessing

1.3.4 4.1 Load the Dataset

[45]:
```
# Load the dataset
df = pd.read_csv('water_potability.csv')

# Display basic info
print("="*60)
print("DATASET LOADED SUCCESSFULLY!")
print("="*60)
print(f"\nDataset Shape: {df.shape}")
print(f"Total Samples: {df.shape[0]}")
print(f"Total Features: {df.shape[1]}")
```

```
============================================================
DATASET LOADED SUCCESSFULLY!
============================================================

Dataset Shape: (3276, 10)
Total Samples: 3276
Total Features: 10
```

1.3.5 4.2 Explore the Dataset

[46]:
```
# Display first 5 rows
print("First 5 Rows of Dataset:")
df.head()
```

```
First 5 Rows of Dataset:
```

[46]:
```
         ph    Hardness        Solids  Chloramines     Sulfate  Conductivity  \
0       NaN  204.890455  20791.318981     7.300212  368.516441    564.308654
1  3.716080  129.422921  18630.057858     6.635246         NaN    592.885359
2  8.099124  224.236259  19909.541732     9.275884         NaN    418.606213
3  8.316766  214.373394  22018.417441     8.059332  356.886136    363.266516
4  9.092223  181.101509  17978.986339     6.546600  310.135738    398.410813

   Organic_carbon  Trihalomethanes  Turbidity  Potability
0       10.379783        86.990970   2.963135           0
1       15.180013        56.329076   4.500656           0
2       16.868637        66.420093   3.055934           0
3       18.436524       100.341674   4.628771           0
4       11.558279        31.997993   4.075075           0
```

[47]:
```
# Display last 5 rows
print("Last 5 Rows of Dataset:")
```

```
df.tail()
```

```
Last 5 Rows of Dataset:
```

[47]:
```
            ph    Hardness        Solids  Chloramines     Sulfate  \
3271  4.668102  193.681735  47580.991603     7.166639  359.948574
3272  7.808856  193.553212  17329.802160     8.061362         NaN
3273  9.419510  175.762646  33155.578218     7.350233         NaN
3274  5.126763  230.603758  11983.869376     6.303357         NaN
3275  7.874671  195.102299  17404.177061     7.509306         NaN

      Conductivity  Organic_carbon  Trihalomethanes  Turbidity  Potability
3271    526.424171       13.894419        66.687695   4.435821           1
3272    392.449580       19.903225              NaN   2.798243           1
3273    432.044783       11.039070        69.845400   3.298875           1
3274    402.883113       11.168946        77.488213   4.708658           1
3275    327.459760       16.140368        78.698446   2.309149           1
```

[48]:
```
# Dataset Information
print("Dataset Information:")
print("="*60)
df.info()
```

```
Dataset Information:
============================================================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3276 entries, 0 to 3275
Data columns (total 10 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ph               2785 non-null   float64
 1   Hardness         3276 non-null   float64
 2   Solids           3276 non-null   float64
 3   Chloramines      3276 non-null   float64
 4   Sulfate          2495 non-null   float64
 5   Conductivity     3276 non-null   float64
 6   Organic_carbon   3276 non-null   float64
 7   Trihalomethanes  3114 non-null   float64
 8   Turbidity        3276 non-null   float64
 9   Potability       3276 non-null   int64
dtypes: float64(9), int64(1)
memory usage: 256.1 KB
```

[49]:
```
# Statistical Summary
print("Statistical Summary:")
df.describe()
```

```
Statistical Summary:
```

[49]:
```
                ph     Hardness        Solids  Chloramines      Sulfate  \
count  2785.000000  3276.000000   3276.000000  3276.000000  2495.000000
mean      7.080795   196.369496  22014.092526     7.122277   333.775777
std       1.594320    32.879761   8768.570828     1.583085    41.416840
min       0.000000    47.432000    320.942611     0.352000   129.000000
25%       6.093092   176.850538  15666.690297     6.127421   307.699498
50%       7.036752   196.967627  20927.833607     7.130299   333.073546
75%       8.062066   216.667456  27332.762127     8.114887   359.950170
max      14.000000   323.124000  61227.196008    13.127000   481.030642

       Conductivity  Organic_carbon  Trihalomethanes    Turbidity   Potability
count   3276.000000     3276.000000      3114.000000  3276.000000  3276.000000
mean     426.205111       14.284970        66.396293     3.966786     0.390110
std       80.824064        3.308162        16.175008     0.780382     0.487849
min      181.483754        2.200000         0.738000     1.450000     0.000000
25%      365.734414       12.065801        55.844536     3.439711     0.000000
50%      421.884968       14.218338        66.622485     3.955028     0.000000
75%      481.792304       16.557652        77.337473     4.500320     1.000000
max      753.342620       28.300000       124.000000     6.739000     1.000000
```

[50]:
```python
# Check column names
print("Column Names:")
print(df.columns.tolist())
```

```
Column Names:
['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate', 'Conductivity',
'Organic_carbon', 'Trihalomethanes', 'Turbidity', 'Potability']
```

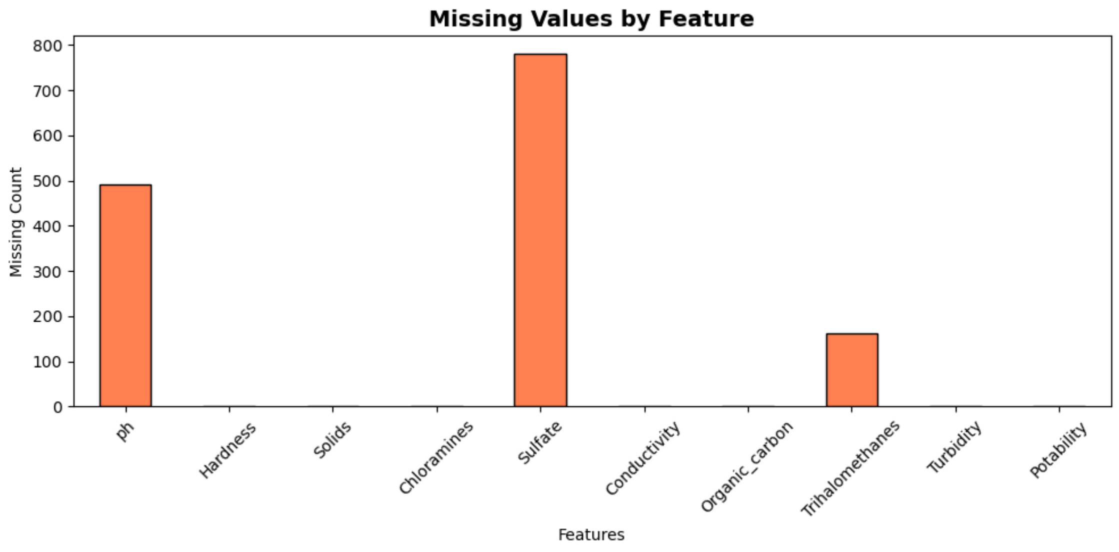
1.3.6 4.3 Check for Missing Values

[51]:
```python
# Check missing values
print("Missing Values in Each Column:")
print("="*60)
missing_values = df.isnull().sum()
missing_percent = (df.isnull().sum() / len(df) * 100).round(2)

missing_df = pd.DataFrame({
    'Missing Count': missing_values,
    'Percentage (%)': missing_percent
})
print(missing_df)
print(f"\nTotal Missing Values: {df.isnull().sum().sum()}")
```

```
Missing Values in Each Column:
============================================================
                 Missing Count  Percentage (%)
ph                         491           14.99
Hardness                     0            0.00
```

```
Solids                  0          0.00
Chloramines             0          0.00
Sulfate               781         23.84
Conductivity            0          0.00
Organic_carbon          0          0.00
Trihalomethanes       162          4.95
Turbidity               0          0.00
Potability              0          0.00

Total Missing Values: 1434
```

[52]:
```python
# Visualize missing values
plt.figure(figsize=(10, 5))
missing_values.plot(kind='bar', color='coral', edgecolor='black')
plt.title('Missing Values by Feature', fontsize=14, fontweight='bold')
plt.xlabel('Features')
plt.ylabel('Missing Count')
plt.xticks(rotation=45)
plt.tight_layout()
plt.show()
```



1.3.7 4.4 Handle Missing Values

[53]:
```python
# Fill missing values with median (robust to outliers)
print("Handling Missing Values (Filling with Median)...")
print("="*60)

for column in df.columns:
    if df[column].isnull().sum() > 0:
        median_value = df[column].median()
        df[column].fillna(median_value, inplace=True)
        print(f"{column}: Filled with median = {median_value:.2f}")

print("\n" + "="*60)
print("Missing Values After Treatment:")
print(df.isnull().sum())
```

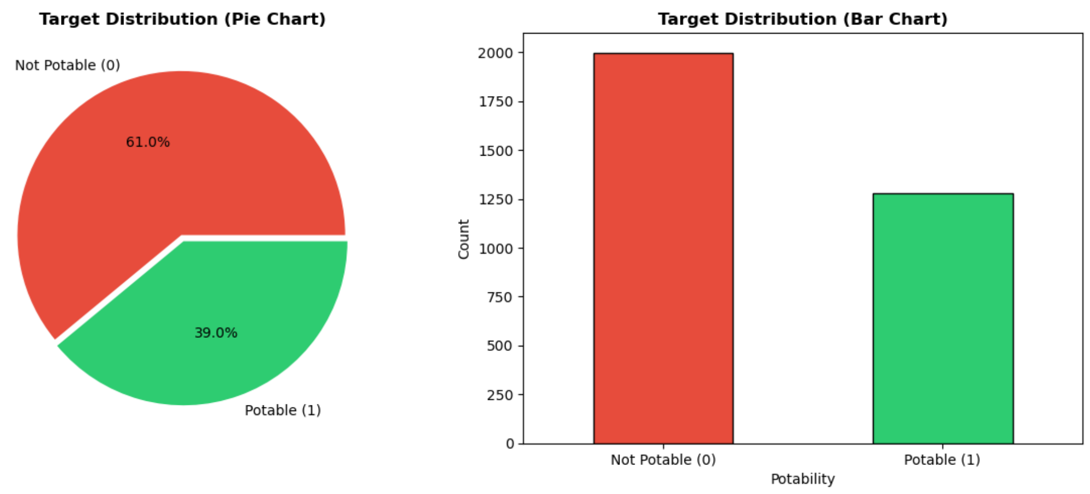
```
Handling Missing Values (Filling with Median)…
============================================================
ph: Filled with median = 7.04
Sulfate: Filled with median = 333.07
Trihalomethanes: Filled with median = 66.62

============================================================
Missing Values After Treatment:
ph                 0
Hardness           0
Solids             0
Chloramines        0
Sulfate            0
Conductivity       0
Organic_carbon     0
Trihalomethanes    0
Turbidity          0
Potability         0
dtype: int64
Sulfate: Filled with median = 333.07
Trihalomethanes: Filled with median = 66.62

============================================================
Missing Values After Treatment:
ph                 0
Hardness           0
Solids             0
Chloramines        0
Sulfate            0
Conductivity       0
Organic_carbon     0
Trihalomethanes    0
Turbidity          0
Potability         0
dtype: int64
```

1.3.8 4.5 Explore Target Variable

[54]:
```python
# Target variable distribution
print("Target Variable Distribution:")
print("="*60)
print(df['Potability'].value_counts())
print(f"\nClass 0 (Not Potable): {(df['Potability'] == 0).sum()} samples")
print(f"Class 1 (Potable): {(df['Potability'] == 1).sum()} samples")
```

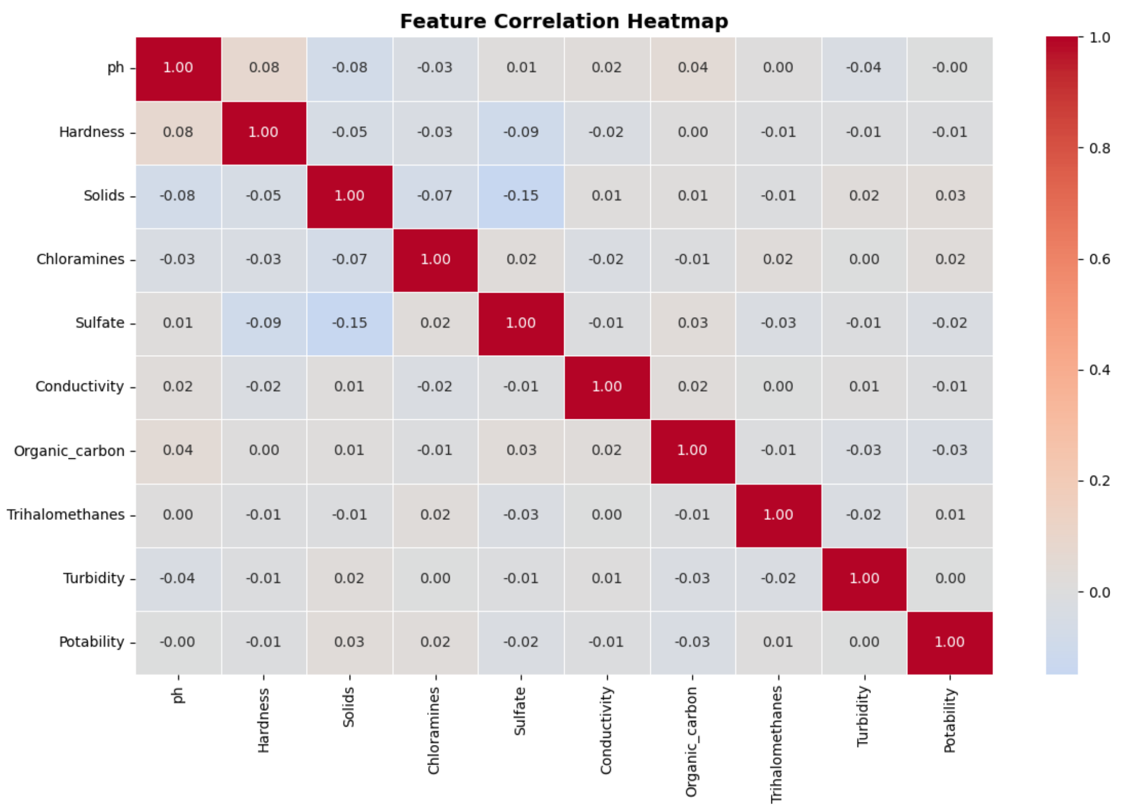
```
Target Variable Distribution:
============================================================
Potability
0    1998
1    1278
Name: count, dtype: int64

Class 0 (Not Potable): 1998 samples
Class 1 (Potable): 1278 samples
```

[55]:
```python
# Visualize target distribution
fig, axes = plt.subplots(1, 2, figsize=(12, 5))

# Pie Chart
colors = ['#e74c3c', '#2ecc71']
labels = ['Not Potable (0)', 'Potable (1)']
df['Potability'].value_counts().plot(kind='pie', ax=axes[0], colors=colors,
                                      autopct='%1.1f%%', labels=labels,
                                      explode=(0.02, 0.02))
axes[0].set_title('Target Distribution (Pie Chart)', fontsize=12,␣
 ↪fontweight='bold')
axes[0].set_ylabel('')

# Bar Chart
df['Potability'].value_counts().plot(kind='bar', ax=axes[1], color=colors,␣
 ↪edgecolor='black')
axes[1].set_title('Target Distribution (Bar Chart)', fontsize=12,␣
 ↪fontweight='bold')
axes[1].set_xlabel('Potability')
axes[1].set_ylabel('Count')
axes[1].set_xticklabels(labels, rotation=0)

plt.tight_layout()
plt.show()
```



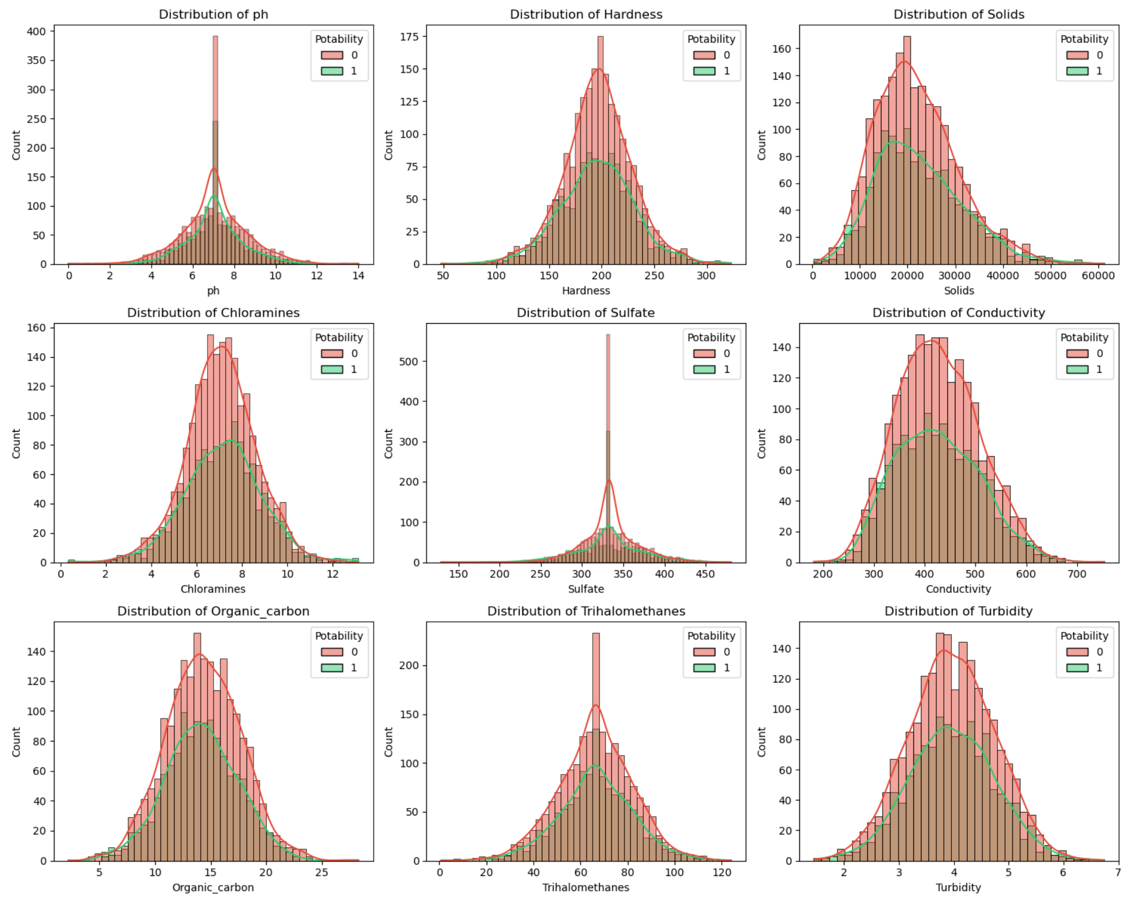
1.3.9 4.6 Data Visualization

[56]:
```
# Correlation Heatmap
plt.figure(figsize=(12, 8))
correlation_matrix = df.corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0,
            fmt='.2f', linewidths=0.5)
plt.title('Feature Correlation Heatmap', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```

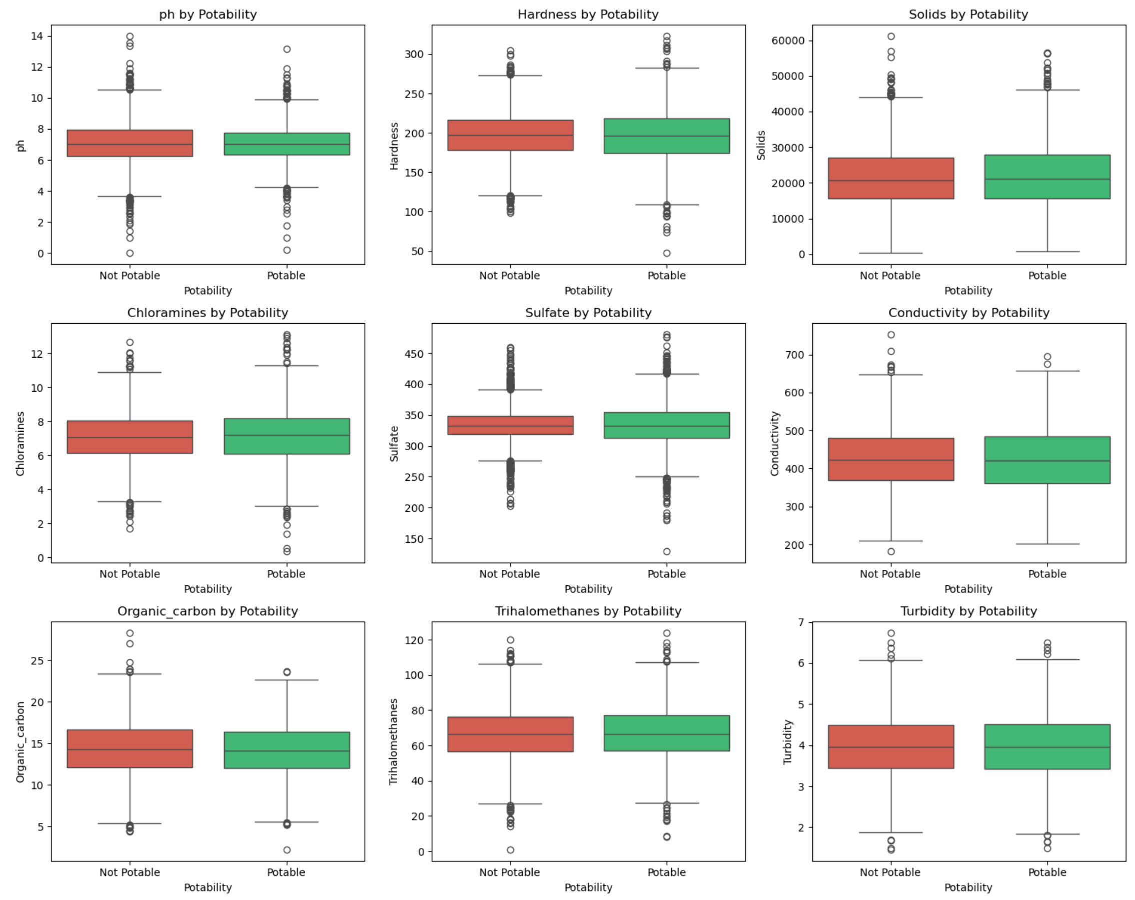


	ph	Hardness	Solids	Chloramines	Sulfate	Conductivity	Organic_carbon	Trihalomethanes	Turbidity	Potability
ph	1.00	0.08	-0.08	-0.03	0.01	0.02	0.04	0.00	-0.04	-0.00
Hardness	0.08	1.00	-0.05	-0.03	-0.09	-0.02	0.00	-0.01	-0.01	-0.01
Solids	-0.08	-0.05	1.00	-0.07	-0.15	0.01	0.01	-0.01	0.02	0.03
Chloramines	-0.03	-0.03	-0.07	1.00	0.02	-0.02	-0.01	0.02	0.00	0.02
Sulfate	0.01	-0.09	-0.15	0.02	1.00	-0.01	0.03	-0.03	-0.01	-0.02
Conductivity	0.02	-0.02	0.01	-0.02	-0.01	1.00	0.02	0.00	0.01	-0.01
Organic_carbon	0.04	0.00	0.01	-0.01	0.03	0.02	1.00	-0.01	-0.03	-0.03
Trihalomethanes	0.00	-0.01	-0.01	0.02	-0.03	0.00	-0.01	1.00	-0.02	0.01
Turbidity	-0.04	-0.01	0.02	0.00	-0.01	0.01	-0.03	-0.02	1.00	0.00
Potability	-0.00	-0.01	0.03	0.02	-0.02	-0.01	-0.03	0.01	0.00	1.00

[57]:
```python
# Distribution of all features
fig, axes = plt.subplots(3, 3, figsize=(15, 12))
features = df.columns[:-1]  # All columns except Potability

for idx, feature in enumerate(features):
    row = idx // 3
    col = idx % 3

    sns.histplot(data=df, x=feature, hue='Potability', kde=True,
                 ax=axes[row, col], palette=['#e74c3c', '#2ecc71'])
    axes[row, col].set_title(f'Distribution of {feature}')

plt.tight_layout()
plt.show()
```



[58]:
```python
# Box plots for all features
fig, axes = plt.subplots(3, 3, figsize=(15, 12))
features = df.columns[:-1]

for idx, feature in enumerate(features):
    row = idx // 3
    col = idx % 3

    sns.boxplot(data=df, x='Potability', y=feature, ax=axes[row, col],
                palette=['#e74c3c', '#2ecc71'])
    axes[row, col].set_title(f'{feature} by Potability')
    axes[row, col].set_xticklabels(['Not Potable', 'Potable'])

plt.tight_layout()
plt.show()
```



1.3.10 4.7 Prepare Data for Machine Learning

[59]:
```python
# Separate features (X) and target (y)
print("Separating Features and Target Variable...")
print("="*60)

X = df.drop('Potability', axis=1)
y = df['Potability']

print(f"Features (X) Shape: {X.shape}")
print(f"Target (y) Shape: {y.shape}")
print(f"\nFeature Names: {list(X.columns)}")
```

```
Separating Features and Target Variable…
============================================================
Features (X) Shape: (3276, 9)
Target (y) Shape: (3276,)

Feature Names: ['ph', 'Hardness', 'Solids', 'Chloramines', 'Sulfate',
'Conductivity', 'Organic_carbon', 'Trihalomethanes', 'Turbidity']
```

[60]:
```python
# Split data into training and testing sets (80% train, 20% test)
print("Splitting Data into Training and Testing Sets...")
print("="*60)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)

print(f"Training Set: {X_train.shape[0]} samples ({80}%)")
print(f"Testing Set: {X_test.shape[0]} samples ({20}%)")
```

```
Splitting Data into Training and Testing Sets…
============================================================
Training Set: 2620 samples (80%)
Testing Set: 656 samples (20%)
```

[61]:
```python
# Feature Scaling using StandardScaler
print("Feature Scaling (StandardScaler)...")
print("="*60)

scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

print("Feature scaling completed successfully!")
print(f"\nScaled Training Data Shape: {X_train_scaled.shape}")
print(f"Scaled Testing Data Shape: {X_test_scaled.shape}")
```

```
Feature Scaling (StandardScaler)…
============================================================
Feature scaling completed successfully!

Scaled Training Data Shape: (2620, 9)
Scaled Testing Data Shape: (656, 9)
```

## Step 5: Apply ML Algorithms (4 Algorithms)

---

[62]:
```python
# Dictionary to store all results
results = {}
```

1.3.11 Algorithm 1: Logistic Regression

[63]:
```python
print("="*60)
print("ALGORITHM 1: LOGISTIC REGRESSION")
print("="*60)
```

```
# Create and train the model with class_weight='balanced' to handle class␣
↪imbalance
lr_model = LogisticRegression(random_state=42, max_iter=1000,␣
↪class_weight='balanced')
lr_model.fit(X_train_scaled, y_train)

# Make predictions
lr_pred = lr_model.predict(X_test_scaled)

# Calculate metrics
lr_accuracy = accuracy_score(y_test, lr_pred)
lr_precision = precision_score(y_test, lr_pred)
lr_recall = recall_score(y_test, lr_pred)
lr_f1 = f1_score(y_test, lr_pred)

# Store results
results['Logistic Regression'] = {
    'Accuracy': lr_accuracy,
    'Precision': lr_precision,
    'Recall': lr_recall,
    'F1-Score': lr_f1,
    'Predictions': lr_pred
}

# Print results
print(f"\nResults:")
print(f"   Accuracy:  {lr_accuracy:.4f} ({lr_accuracy*100:.2f}%)")
print(f"   Precision: {lr_precision:.4f}")
print(f"   Recall:    {lr_recall:.4f}")
print(f"   F1-Score:  {lr_f1:.4f}")
```

```
============================================================
ALGORITHM 1: LOGISTIC REGRESSION
============================================================

Results:
   Accuracy:  0.5259 (52.59%)
   Precision: 0.4159
   Recall:    0.5312
   F1-Score:  0.4666
```

1.3.12 Algorithm 2: Random Forest Classifier

[64]:
```
print("="*60)
print("ALGORITHM 2: RANDOM FOREST CLASSIFIER")
print("="*60)
```

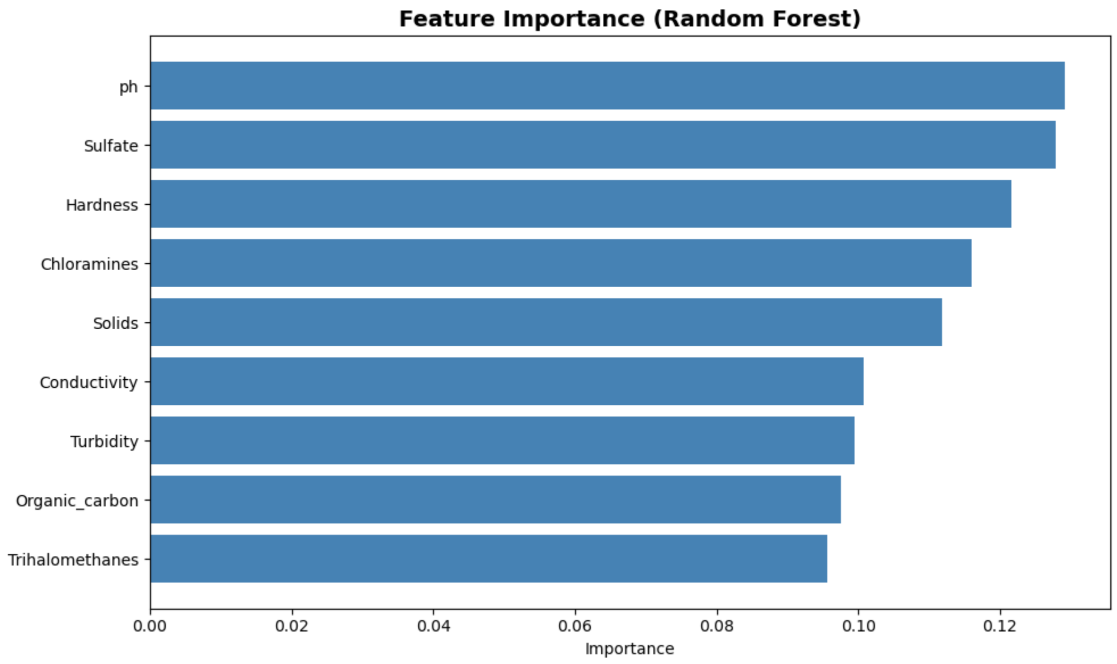
```python
# Create and train the model
rf_model = RandomForestClassifier(n_estimators=100, random_state=42)
rf_model.fit(X_train_scaled, y_train)

# Make predictions
rf_pred = rf_model.predict(X_test_scaled)

# Calculate metrics
rf_accuracy = accuracy_score(y_test, rf_pred)
rf_precision = precision_score(y_test, rf_pred)
rf_recall = recall_score(y_test, rf_pred)
rf_f1 = f1_score(y_test, rf_pred)

# Store results
results['Random Forest'] = {
    'Accuracy': rf_accuracy,
    'Precision': rf_precision,
    'Recall': rf_recall,
    'F1-Score': rf_f1,
    'Predictions': rf_pred
}

# Print results
print(f"\nResults:")
print(f"   Accuracy:  {rf_accuracy:.4f} ({rf_accuracy*100:.2f}%)")
print(f"   Precision: {rf_precision:.4f}")
print(f"   Recall:    {rf_recall:.4f}")
print(f"   F1-Score:  {rf_f1:.4f}")
```

```
============================================================
ALGORITHM 2: RANDOM FOREST CLASSIFIER
============================================================

Results:
   Accuracy:  0.6585 (65.85%)
   Precision: 0.6311
   Recall:    0.3008
   F1-Score:  0.4074
```

[65]:
```python
# Feature Importance from Random Forest
print("\nFeature Importance (Random Forest):")
print("="*60)

feature_importance = pd.DataFrame({
    'Feature': X.columns,
    'Importance': rf_model.feature_importances_
}).sort_values('Importance', ascending=False)
```

```
print(feature_importance.to_string(index=False))

# Visualize feature importance
plt.figure(figsize=(10, 6))
plt.barh(feature_importance['Feature'], feature_importance['Importance'],␣
  ↪color='steelblue')
plt.xlabel('Importance')
plt.title('Feature Importance (Random Forest)', fontsize=14, fontweight='bold')
plt.gca().invert_yaxis()
plt.tight_layout()
plt.show()
```

```
Feature Importance (Random Forest):
============================================================
        Feature  Importance
             ph    0.129132
        Sulfate    0.127858
       Hardness    0.121633
    Chloramines    0.116048
         Solids    0.111863
   Conductivity    0.100752
      Turbidity    0.099522
 Organic_carbon    0.097521
Trihalomethanes    0.095672
```



1.3.13 Algorithm 3: XGBoost Classifier

[66]:
```python
print("="*60)
print("ALGORITHM 3: XGBOOST CLASSIFIER")
print("="*60)

# Create and train the model
xgb_model = XGBClassifier(n_estimators=200, learning_rate=0.1, max_depth=5,␣
↪random_state=42, eval_metric='logloss')
xgb_model.fit(X_train_scaled, y_train)

# Make predictions
xgb_pred = xgb_model.predict(X_test_scaled)

# Calculate metrics
xgb_accuracy = accuracy_score(y_test, xgb_pred)
xgb_precision = precision_score(y_test, xgb_pred)
xgb_recall = recall_score(y_test, xgb_pred)
xgb_f1 = f1_score(y_test, xgb_pred)

# Store results
results['XGBoost'] = {
    'Accuracy': xgb_accuracy,
    'Precision': xgb_precision,
    'Recall': xgb_recall,
    'F1-Score': xgb_f1,
    'Predictions': xgb_pred
}

# Print results
print(f"\nResults:")
print(f"   Accuracy:  {xgb_accuracy:.4f} ({xgb_accuracy*100:.2f}%)")
print(f"   Precision: {xgb_precision:.4f}")
print(f"   Recall:    {xgb_recall:.4f}")
print(f"   F1-Score:  {xgb_f1:.4f}")
```

```
============================================================
ALGORITHM 3: XGBOOST CLASSIFIER
============================================================

Results:
   Accuracy:  0.6372 (63.72%)
   Precision: 0.5536
   Recall:    0.3633
   F1-Score:  0.4387
```

1.3.14 Algorithm 4: LightGBM Classifier

[67]:
```
print("="*60)
print("ALGORITHM 4: LIGHTGBM CLASSIFIER")
print("="*60)

# Create and train the model
lgbm_model = LGBMClassifier(n_estimators=200, learning_rate=0.1, max_depth=5,␣
↪random_state=42, verbose=-1)
lgbm_model.fit(X_train_scaled, y_train)

# Make predictions
lgbm_pred = lgbm_model.predict(X_test_scaled)

# Calculate metrics
lgbm_accuracy = accuracy_score(y_test, lgbm_pred)
lgbm_precision = precision_score(y_test, lgbm_pred)
lgbm_recall = recall_score(y_test, lgbm_pred)
lgbm_f1 = f1_score(y_test, lgbm_pred)

# Store results
results['LightGBM'] = {
    'Accuracy': lgbm_accuracy,
    'Precision': lgbm_precision,
    'Recall': lgbm_recall,
    'F1-Score': lgbm_f1,
    'Predictions': lgbm_pred
}

# Print results
print(f"\nResults:")
print(f"   Accuracy:  {lgbm_accuracy:.4f} ({lgbm_accuracy*100:.2f}%)")
print(f"   Precision: {lgbm_precision:.4f}")
print(f"   Recall:    {lgbm_recall:.4f}")
print(f"   F1-Score:  {lgbm_f1:.4f}")
```

```
============================================================
ALGORITHM 4: LIGHTGBM CLASSIFIER
============================================================

Results:
   Accuracy:  0.6463 (64.63%)
   Precision: 0.5750
   Recall:    0.3594
   F1-Score:  0.4423

Results:
   Accuracy:  0.6463 (64.63%)
```

```
Precision: 0.5750
Recall:    0.3594
F1-Score:  0.4423
```

## Step 6: Model Evaluation

1.3.15 6.1 Model Comparison Summary

[68]:
```
# Create comparison table
print("="*70)
print("MODEL COMPARISON SUMMARY")
print("="*70)

algorithms = ['Logistic Regression', 'Random Forest', 'XGBoost', 'LightGBM']

comparison_df = pd.DataFrame({
    'Algorithm': algorithms,
    'Accuracy': [results[algo]['Accuracy'] for algo in algorithms],
    'Precision': [results[algo]['Precision'] for algo in algorithms],
    'Recall': [results[algo]['Recall'] for algo in algorithms],
    'F1-Score': [results[algo]['F1-Score'] for algo in algorithms]
})

# Format as percentages
comparison_df_display = comparison_df.copy()
for col in ['Accuracy', 'Precision', 'Recall', 'F1-Score']:
    comparison_df_display[col] = comparison_df_display[col].apply(lambda x:␣
 ↪f"{x:.4f}")

print(comparison_df_display.to_string(index=False))

# Find best model
best_model_name = comparison_df.loc[comparison_df['Accuracy'].idxmax(),␣
 ↪'Algorithm']
best_accuracy = comparison_df['Accuracy'].max()

print("\n" + "="*70)
print(f"BEST MODEL: {best_model_name}")
print(f"BEST ACCURACY: {best_accuracy*100:.2f}%")
print("="*70)
```

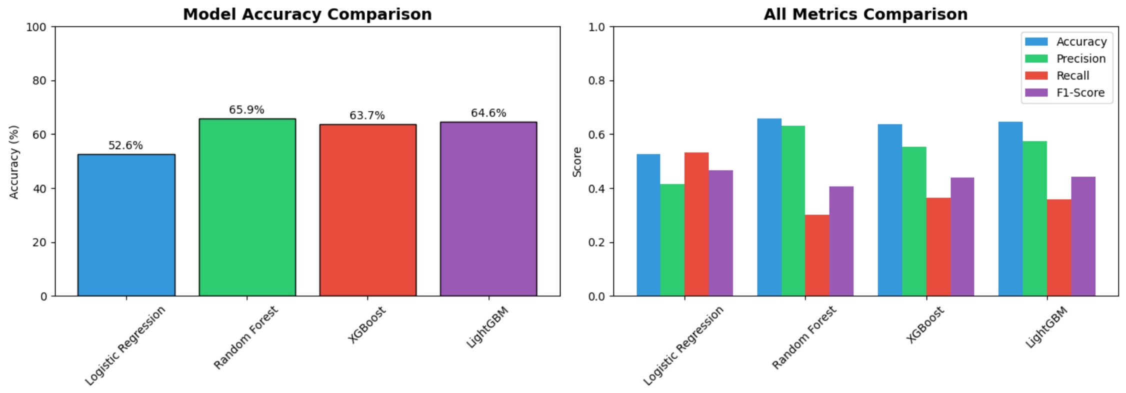
```
======================================================================
MODEL COMPARISON SUMMARY
======================================================================
          Algorithm Accuracy Precision Recall F1-Score
Logistic Regression   0.5259    0.4159 0.5312   0.4666
      Random Forest   0.6585    0.6311 0.3008   0.4074
```

```
           XGBoost   0.6372    0.5536 0.3633   0.4387
          LightGBM   0.6463    0.5750 0.3594   0.4423

======================================================================
BEST MODEL: Random Forest
BEST ACCURACY: 65.85%
======================================================================
```

[69]:

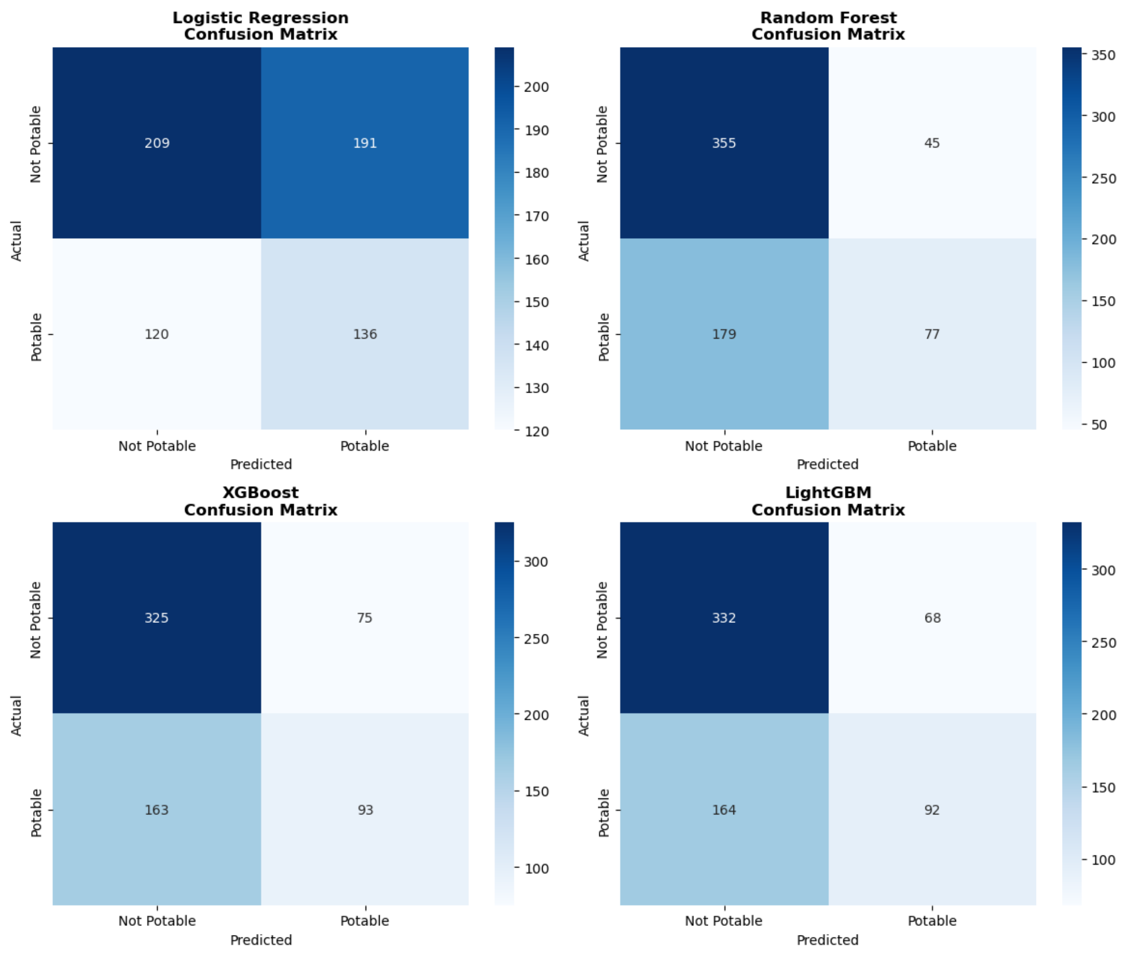
```python
# Visualize model comparison
fig, axes = plt.subplots(1, 2, figsize=(14, 5))

# Accuracy comparison bar chart
colors = ['#3498db', '#2ecc71', '#e74c3c', '#9b59b6']
bars = axes[0].bar(algorithms, comparison_df['Accuracy'] * 100, color=colors,␣
 ↪edgecolor='black')
axes[0].set_title('Model Accuracy Comparison', fontsize=14, fontweight='bold')
axes[0].set_ylabel('Accuracy (%)')
axes[0].set_ylim(0, 100)

# Add value labels on bars
for bar in bars:
    height = bar.get_height()
    axes[0].text(bar.get_x() + bar.get_width()/2., height + 1,
                 f'{height:.1f}%', ha='center', va='bottom', fontsize=10)

axes[0].tick_params(axis='x', rotation=45)

# All metrics comparison
x = np.arange(len(algorithms))
width = 0.2

axes[1].bar(x - 1.5*width, comparison_df['Accuracy'], width, label='Accuracy',␣
 ↪color='#3498db')
axes[1].bar(x - 0.5*width, comparison_df['Precision'], width,␣
 ↪label='Precision', color='#2ecc71')
axes[1].bar(x + 0.5*width, comparison_df['Recall'], width, label='Recall',␣
 ↪color='#e74c3c')
axes[1].bar(x + 1.5*width, comparison_df['F1-Score'], width, label='F1-Score',␣
 ↪color='#9b59b6')

axes[1].set_title('All Metrics Comparison', fontsize=14, fontweight='bold')
axes[1].set_ylabel('Score')
axes[1].set_xticks(x)
axes[1].set_xticklabels(algorithms, rotation=45)
axes[1].legend()
axes[1].set_ylim(0, 1)
```

```
plt.tight_layout()
plt.show()
```



1.3.16 6.2 Confusion Matrices

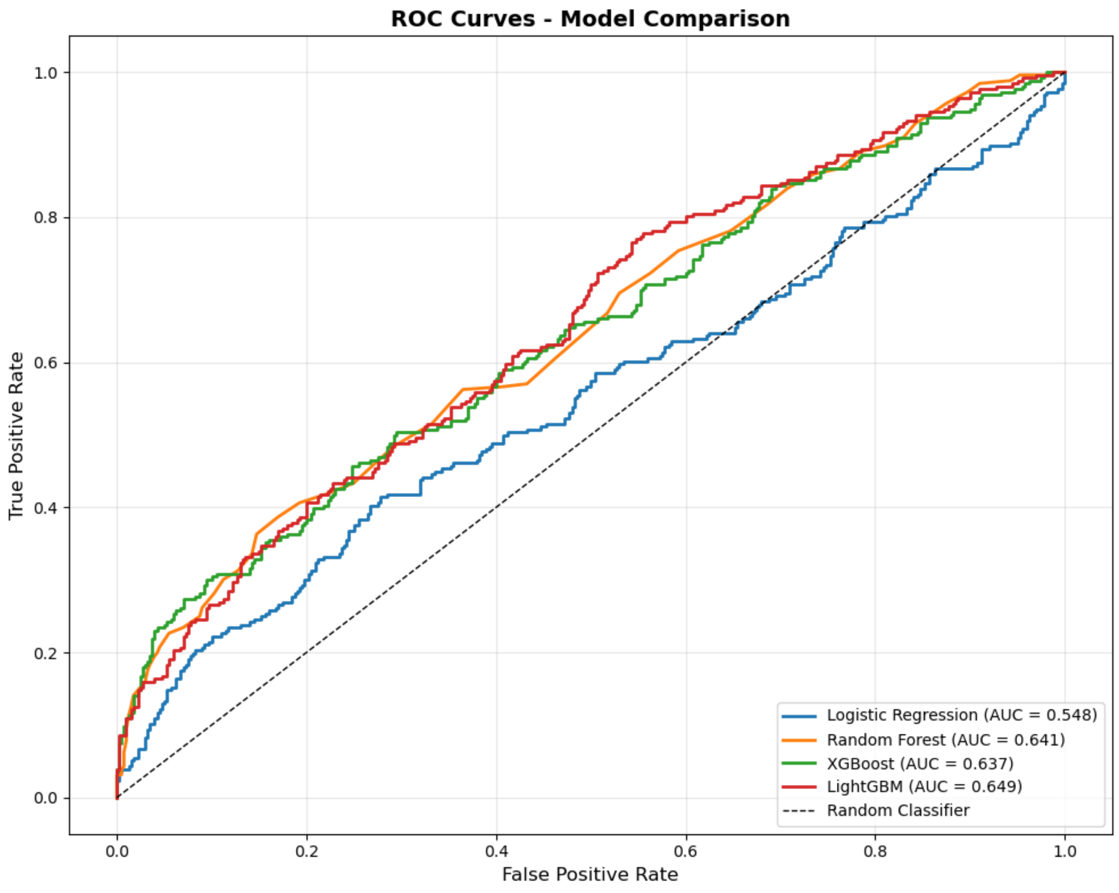
[70]:
```
# Plot confusion matrices for all models
fig, axes = plt.subplots(2, 2, figsize=(12, 10))

predictions = [lr_pred, rf_pred, xgb_pred, lgbm_pred]

for idx, (algo, pred) in enumerate(zip(algorithms, predictions)):
    row = idx // 2
    col = idx % 2

    cm = confusion_matrix(y_test, pred)
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[row, col],
                xticklabels=['Not Potable', 'Potable'],
                yticklabels=['Not Potable', 'Potable'])
    axes[row, col].set_title(f'{algo}\nConfusion Matrix', fontsize=12,␣
 ↪fontweight='bold')
    axes[row, col].set_xlabel('Predicted')
    axes[row, col].set_ylabel('Actual')

plt.tight_layout()
plt.show()
```



1.3.17 6.3 ROC Curves and AUC Scores

[71]:
```
from sklearn.metrics import roc_curve, auc, precision_recall_curve,␣
 ↪average_precision_score

# Get prediction probabilities for ROC curves
# For models that support predict_proba
lr_proba = lr_model.predict_proba(X_test_scaled)[:, 1]
rf_proba = rf_model.predict_proba(X_test_scaled)[:, 1]
xgb_proba = xgb_model.predict_proba(X_test_scaled)[:, 1]
lgbm_proba = lgbm_model.predict_proba(X_test_scaled)[:, 1]

# Calculate ROC curves
lr_fpr, lr_tpr, _ = roc_curve(y_test, lr_proba)
rf_fpr, rf_tpr, _ = roc_curve(y_test, rf_proba)
xgb_fpr, xgb_tpr, _ = roc_curve(y_test, xgb_proba)
lgbm_fpr, lgbm_tpr, _ = roc_curve(y_test, lgbm_proba)
```

```
# Calculate AUC scores
lr_auc = auc(lr_fpr, lr_tpr)
rf_auc = auc(rf_fpr, rf_tpr)
xgb_auc = auc(xgb_fpr, xgb_tpr)
lgbm_auc = auc(lgbm_fpr, lgbm_tpr)

# Plot ROC curves
plt.figure(figsize=(10, 8))

plt.plot(lr_fpr, lr_tpr, label=f'Logistic Regression (AUC = {lr_auc:.3f})',␣
 ↪linewidth=2)
plt.plot(rf_fpr, rf_tpr, label=f'Random Forest (AUC = {rf_auc:.3f})',␣
 ↪linewidth=2)
plt.plot(xgb_fpr, xgb_tpr, label=f'XGBoost (AUC = {xgb_auc:.3f})', linewidth=2)
plt.plot(lgbm_fpr, lgbm_tpr, label=f'LightGBM (AUC = {lgbm_auc:.3f})',␣
 ↪linewidth=2)

# Diagonal line (random classifier)
plt.plot([0, 1], [0, 1], 'k--', label='Random Classifier', linewidth=1)

plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curves - Model Comparison', fontsize=14, fontweight='bold')
plt.legend(loc='lower right', fontsize=10)
plt.grid(True, alpha=0.3)
plt.tight_layout()
plt.show()

# Print AUC scores
print("\nAUC Scores:")
print("="*50)
print(f"   Logistic Regression: {lr_auc:.4f}")
print(f"   Random Forest:       {rf_auc:.4f}")
print(f"   XGBoost:             {xgb_auc:.4f}")
print(f"   LightGBM:            {lgbm_auc:.4f}")
```

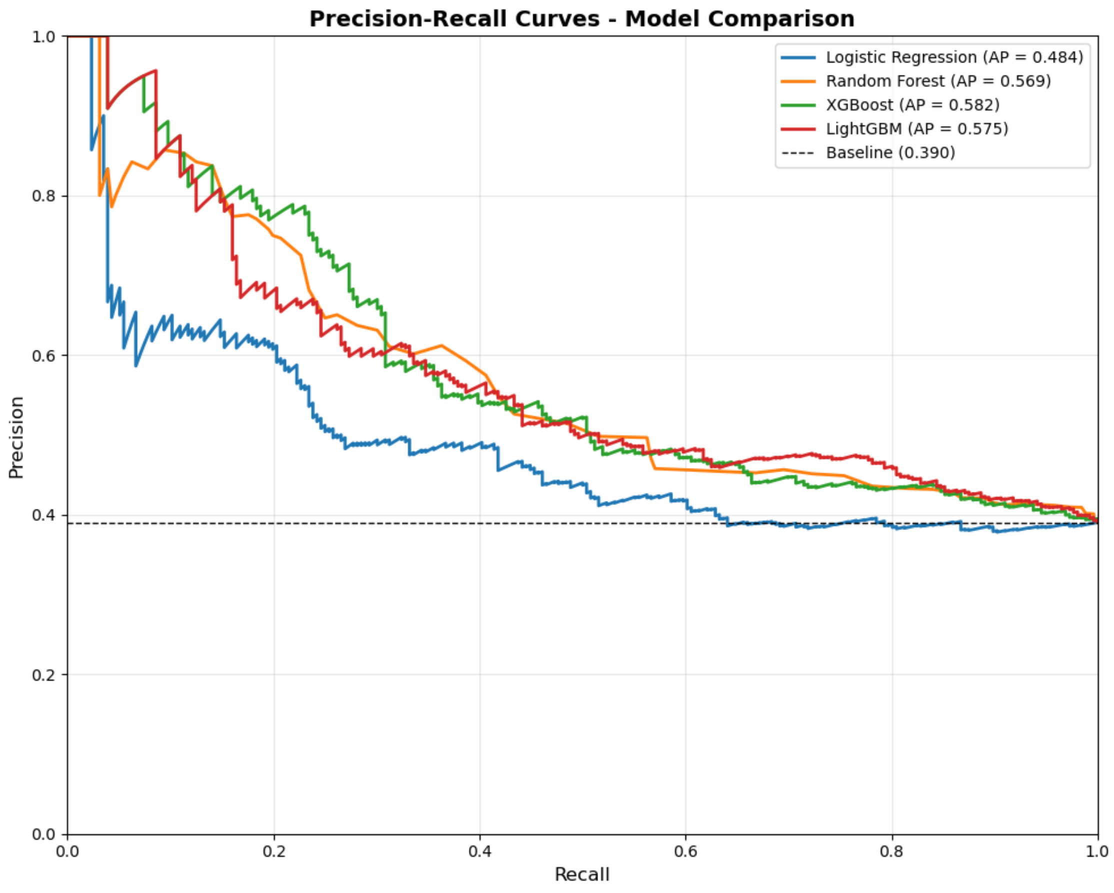


```
AUC Scores:
==================================================
   Logistic Regression: 0.5475
   Random Forest:       0.6407
   XGBoost:             0.6367
   LightGBM:            0.6487
```

1.3.18 6.4 Precision-Recall Curves

[72]:
```
# Calculate Precision-Recall curves
lr_precision_curve, lr_recall_curve, _ = precision_recall_curve(y_test,␣
 ↪lr_proba)
rf_precision_curve, rf_recall_curve, _ = precision_recall_curve(y_test,␣
 ↪rf_proba)
xgb_precision_curve, xgb_recall_curve, _ = precision_recall_curve(y_test,␣
 ↪xgb_proba)
lgbm_precision_curve, lgbm_recall_curve, _ = precision_recall_curve(y_test,␣
 ↪lgbm_proba)
```

```
# Calculate Average Precision scores
lr_ap = average_precision_score(y_test, lr_proba)
rf_ap = average_precision_score(y_test, rf_proba)
xgb_ap = average_precision_score(y_test, xgb_proba)
lgbm_ap = average_precision_score(y_test, lgbm_proba)

# Plot Precision-Recall curves
plt.figure(figsize=(10, 8))

plt.plot(lr_recall_curve, lr_precision_curve, label=f'Logistic Regression (AP =␣
 ↪{lr_ap:.3f})', linewidth=2)
plt.plot(rf_recall_curve, rf_precision_curve, label=f'Random Forest (AP =␣
 ↪{rf_ap:.3f})', linewidth=2)
plt.plot(xgb_recall_curve, xgb_precision_curve, label=f'XGBoost (AP = {xgb_ap:.
 ↪3f})', linewidth=2)
plt.plot(lgbm_recall_curve, lgbm_precision_curve, label=f'LightGBM (AP =␣
 ↪{lgbm_ap:.3f})', linewidth=2)

# Baseline (proportion of positive class)
baseline = y_test.sum() / len(y_test)
plt.axhline(y=baseline, color='k', linestyle='--', label=f'Baseline ({baseline:.
 ↪3f})', linewidth=1)

plt.xlabel('Recall', fontsize=12)
plt.ylabel('Precision', fontsize=12)
plt.title('Precision-Recall Curves - Model Comparison', fontsize=14,␣
 ↪fontweight='bold')
plt.legend(loc='upper right', fontsize=10)
plt.grid(True, alpha=0.3)
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.tight_layout()
plt.show()

# Print Average Precision scores
print("\nAverage Precision Scores:")
print("="*50)
print(f"   Logistic Regression: {lr_ap:.4f}")
print(f"   Random Forest:       {rf_ap:.4f}")
print(f"   XGBoost:             {xgb_ap:.4f}")
print(f"   LightGBM:            {lgbm_ap:.4f}")
```



```
Average Precision Scores:
==================================================
   Logistic Regression: 0.4841
   Random Forest:       0.5695
   XGBoost:             0.5816
   LightGBM:            0.5747
```

1.3.19 6.5 Classification Reports

[73]:
```
# Print detailed classification reports
for algo, pred in zip(algorithms, predictions):
    print("="*60)
    print(f"{algo} - CLASSIFICATION REPORT")
    print("="*60)
    print(classification_report(y_test, pred,
                                target_names=['Not Potable (0)', 'Potable (1)']))
    print()
```

```
============================================================
Logistic Regression - CLASSIFICATION REPORT
============================================================
                 precision    recall  f1-score   support

Not Potable (0)       0.64      0.52      0.57       400
    Potable (1)       0.42      0.53      0.47       256

       accuracy                           0.53       656
      macro avg       0.53      0.53      0.52       656
   weighted avg       0.55      0.53      0.53       656


============================================================
Random Forest - CLASSIFICATION REPORT
============================================================
                 precision    recall  f1-score   support

Not Potable (0)       0.66      0.89      0.76       400
    Potable (1)       0.63      0.30      0.41       256

       accuracy                           0.66       656
      macro avg       0.65      0.59      0.58       656
   weighted avg       0.65      0.66      0.62       656


============================================================
XGBoost - CLASSIFICATION REPORT
============================================================
                 precision    recall  f1-score   support

Not Potable (0)       0.67      0.81      0.73       400
    Potable (1)       0.55      0.36      0.44       256

       accuracy                           0.64       656
      macro avg       0.61      0.59      0.59       656
   weighted avg       0.62      0.64      0.62       656


============================================================
LightGBM - CLASSIFICATION REPORT
============================================================
                 precision    recall  f1-score   support

Not Potable (0)       0.67      0.83      0.74       400
    Potable (1)       0.57      0.36      0.44       256

       accuracy                           0.65       656
      macro avg       0.62      0.59      0.59       656
```

```
weighted avg       0.63      0.65      0.62       656
```

## Step 7: Save Results

[74]:
```
# Save comparison results to CSV
comparison_df.to_csv('model_comparison_results.csv', index=False)
print("Results saved to 'model_comparison_results.csv'")
```

```
Results saved to 'model_comparison_results.csv'
```

## Project Summary

[75]:
```
print("="*70)
print("                     PROJECT SUMMARY                              ")
print("="*70)
print(f"""
Project Title: Water Potability Prediction System using Machine Learning

Domain: Environmental Science / Public Health

Problem Statement:
   To predict whether water is safe for human consumption based on
   various water quality parameters using machine learning algorithms.

Dataset: Water Potability Dataset (Kaggle)
   - Total Samples: {len(df)}
   - Features: {len(df.columns) - 1}
   - Target: Potability (0 = Not Potable, 1 = Potable)

Features Used:
   1. pH              - Acidity/Alkalinity level (0-14)
   2. Hardness        - Water hardness in mg/L
   3. Solids          - Total dissolved solids in ppm
   4. Chloramines     - Chloramines amount in ppm
   5. Sulfate         - Sulfate dissolved in mg/L
   6. Conductivity - Electrical conductivity in  S/cm
   7. Organic_carbon - Organic carbon in ppm
   8. Trihalomethanes - THMs amount in  g/L
   9. Turbidity       - Cloudiness measure in NTU

Algorithms Applied:
   1. Logistic Regression - Accuracy: {results['Logistic␣
 ↪Regression']['Accuracy']*100:.2f}%
```

```
   2. Random Forest       - Accuracy: {results['Random Forest']['Accuracy']*100:
↪.2f}%
   3. XGBoost             - Accuracy: {results['XGBoost']['Accuracy']*100:.2f}%
   4. LightGBM            - Accuracy: {results['LightGBM']['Accuracy']*100:.2f}%

Best Performing Model: {best_model_name}
Best Accuracy: {best_accuracy*100:.2f}%
""")
print("="*70)
print("              PROJECT COMPLETED SUCCESSFULLY!                  ")
print("="*70)
```

```
======================================================================
                     PROJECT SUMMARY
======================================================================

Project Title: Water Potability Prediction System using Machine Learning

Domain: Environmental Science / Public Health

Problem Statement:
   To predict whether water is safe for human consumption based on
   various water quality parameters using machine learning algorithms.

Dataset: Water Potability Dataset (Kaggle)
   - Total Samples: 3276
   - Features: 9
   - Target: Potability (0 = Not Potable, 1 = Potable)

Features Used:
   1. pH              - Acidity/Alkalinity level (0-14)
   2. Hardness        - Water hardness in mg/L
   3. Solids          - Total dissolved solids in ppm
   4. Chloramines     - Chloramines amount in ppm
   5. Sulfate         - Sulfate dissolved in mg/L
   6. Conductivity - Electrical conductivity in  S/cm
   7. Organic_carbon - Organic carbon in ppm
   8. Trihalomethanes - THMs amount in  g/L
   9. Turbidity       - Cloudiness measure in NTU

Algorithms Applied:
   1. Logistic Regression - Accuracy: 52.59%
   2. Random Forest       - Accuracy: 65.85%
   3. XGBoost             - Accuracy: 63.72%
   4. LightGBM            - Accuracy: 64.63%

Best Performing Model: Random Forest
Best Accuracy: 65.85%
```

```
======================================================================
             PROJECT COMPLETED SUCCESSFULLY!
======================================================================
```

## References

1. **Dataset:** Kaggle - Water Potability
2. **Scikit-learn Documentation:** `https://scikit-learn.org/`
3. **WHO Water Quality Guidelines:** `https://www.who.int/`

Thank You!