Employee Attrition Prediction

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This notebook contains the complete code for Employee Attrition Prediction using Machine Learning and Explainable AI.

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1. Import Libraries

```
# ==========================================
# STEP 1: IMPORT ALL REQUIRED LIBRARIES
# ==========================================

# Data manipulation
import pandas as pd
import numpy as np

# Visualization
import matplotlib.pyplot as plt
import seaborn as sns
```

```
# Machine Learning
from sklearn.model_selection import train_test_split, GridSearchCV, cross_val_s
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn.metrics import (
    accuracy_score, precision_score, recall_score, f1_score,
    roc_auc_score, confusion_matrix, classification_report, roc_curve
)

# XGBoost
import xgboost as xgb

# SHAP for explainability
import shap

# Utilities
import pickle
import warnings
warnings.filterwarnings('ignore')

# Set visualization style
plt.style.use('seaborn-v0_8-whitegrid')
sns.set_palette("husl")

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

```
✅ All libraries imported successfully!
```

2. Load Dataset

```
# ==========================================
# STEP 2: LOAD THE DATASET
# ==========================================

df = pd.read_csv('WA_Fn-UseC_-HR-Employee-Attrition.csv')

print("="*50)
print("DATASET LOADED SUCCESSFULLY")
print("="*50)
print(f"\nShape: {df.shape[0]} rows × {df.shape[1]} columns")
print(f"\nFirst 5 rows:")
df.head()
```

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

Shape: 1470 rows × 35 columns

First 5 rows:
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Edu
0	41	Yes	Travel_Rarely	1102	Sales	1	
1	49	No	Travel_Frequently	279	Research & Development	8	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	
4	27	No	Travel_Rarely	591	Research & Development	2	

5 rows × 35 columns

3. Data Exploration

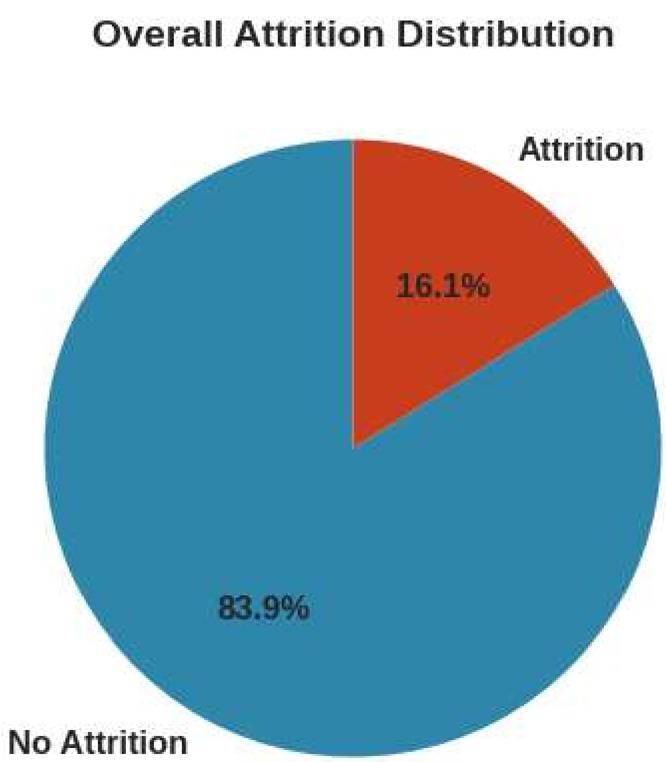
```
# ==========================================
# STEP 3: EXPLORE THE DATA
# ==========================================

print("="*50)
print("DATA EXPLORATION")
print("="*50)

# Column names
print(f"\nColumns ({len(df.columns)}):")
print(list(df.columns))

# Data types
print("\nData Types:")
print(df.dtypes)

# Missing values
print("\nMissing Values:")
missing = df.isnull().sum()
print(missing[missing > 0] if missing.sum() > 0 else "No missing values found!"
```

```
# Duplicates
print(f"\nDuplicate Rows: {df.duplicated().sum()}")
```

```
==================================================
DATA EXPLORATION
==================================================

Columns (35):
['Age', 'Attrition', 'BusinessTravel', 'DailyRate', 'Department', 'DistanceFromH

Data Types:
Age                          int64
Attrition                   object
BusinessTravel              object
DailyRate                    int64
Department                  object
DistanceFromHome             int64
Education                    int64
EducationField              object
EmployeeCount                int64
EmployeeNumber               int64
EnvironmentSatisfaction      int64
Gender                      object
HourlyRate                   int64
JobInvolvement               int64
JobLevel                     int64
JobRole                     object
JobSatisfaction              int64
MaritalStatus               object
MonthlyIncome                int64
MonthlyRate                  int64
NumCompaniesWorked           int64
Over18                      object
OverTime                    object
PercentSalaryHike            int64
PerformanceRating            int64
RelationshipSatisfaction     int64
StandardHours                int64
StockOptionLevel             int64
TotalWorkingYears            int64
TrainingTimesLastYear        int64
WorkLifeBalance              int64
YearsAtCompany               int64
YearsInCurrentRole           int64
YearsSinceLastPromotion      int64
YearsWithCurrManager         int64
dtype: object

Missing Values:
No missing values found!

Duplicate Rows: 0
```

```
# Check target variable distribution
print("\n" + "="*50)
print("TARGET VARIABLE (ATTRITION) DISTRIBUTION")
print("="*50)

attrition_counts = df['Attrition'].value_counts()
print(f"\n{attrition_counts}")
print(f"\nAttrition Rate: {attrition_counts['Yes'] / len(df) * 100:.1f}%")

# Plot
plt.figure(figsize=(8, 5))
colors = ['#2E86AB', '#C73E1D']
plt.pie(attrition_counts, labels=['No Attrition', 'Attrition'],
        autopct='%1.1f%%', colors=colors, startangle=90,
        textprops={'fontsize': 12, 'fontweight': 'bold'})
plt.title('Overall Attrition Distribution', fontsize=14, fontweight='bold')
plt.show()
```

```
==================================================
TARGET VARIABLE (ATTRITION) DISTRIBUTION
==================================================

Attrition
No     1233
Yes     237
Name: count, dtype: int64

Attrition Rate: 16.1%
```



4. Data Preprocessing

```
# ==========================================
# STEP 4: DATA PREPROCESSING
# ==========================================

print("="*50)
print("DATA PREPROCESSING")
print("="*50)

# Create a copy for preprocessing
df_processed = df.copy()

# 4.1: Encode target variable (Attrition)
df_processed['Attrition'] = df_processed['Attrition'].map({'Yes': 1, 'No': 0})
print("\n1. Target variable encoded: Yes=1, No=0")

# 4.2: Remove unnecessary columns
columns_to_drop = ['EmployeeCount', 'EmployeeNumber', 'Over18', 'StandardHours'
df_processed = df_processed.drop(columns=columns_to_drop, errors='ignore')
print(f"2. Dropped columns: {columns_to_drop}")

# 4.3: Encode categorical variables
categorical_cols = df_processed.select_dtypes(include=['object']).columns.tolis
if 'Attrition' in categorical_cols:
    categorical_cols.remove('Attrition')

label_encoders = {}
for col in categorical_cols:
    le = LabelEncoder()
    df_processed[col] = le.fit_transform(df_processed[col].astype(str))
    label_encoders[col] = le

print(f"3. Encoded {len(categorical_cols)} categorical columns")
print(f"   Columns: {categorical_cols}")

print(f"\nProcessed dataset shape: {df_processed.shape}")
df_processed.head()
```

```
==================================================
DATA PREPROCESSING
==================================================

1. Target variable encoded: Yes=1, No=0
2. Dropped columns: ['EmployeeCount', 'EmployeeNumber', 'Over18', 'StandardHours
3. Encoded 7 categorical columns
   Columns: ['BusinessTravel', 'Department', 'EducationField', 'Gender', 'JobRol

Processed dataset shape: (1470, 31)
```

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Educ
0	41	1	2	1102	2	1	
1	49	0	1	279	1	8	
2	37	1	2	1373	1	2	
3	33	0	1	1392	1	3	
4	27	0	2	591	1	2	

5 rows × 31 columns

5. Feature Engineering

```
# ==========================================
# STEP 5: FEATURE ENGINEERING
# ==========================================

print("="*50)
print("FEATURE ENGINEERING")
print("="*50)

# 5.1: Create derived features

# Average years per company
df_processed['AverageYearsPerCompany'] = df_processed['TotalWorkingYears'] / (
    df_processed['NumCompaniesWorked'] + 1
)

# Years since last promotion ratio
df_processed['YearsSinceLastPromotionRatio'] = df_processed['YearsSinceLastProm
    df_processed['YearsAtCompany'] + 1
)

# Income per year of experience
df_processed['IncomePerYearExperience'] = df_processed['MonthlyIncome'] / (
    df_processed['TotalWorkingYears'] + 1
```

```
)

# Age groups
df_processed['AgeGroup'] = pd.cut(
    df_processed['Age'],
    bins=[0, 30, 40, 50, 100],
    labels=[0, 1, 2, 3]
).astype(int)

# Overall satisfaction score
df_processed['OverallSatisfaction'] = (
    df_processed['JobSatisfaction'] +
    df_processed['EnvironmentSatisfaction'] +
    df_processed['WorkLifeBalance']
) / 3

print("Created 5 new features:")
print("  1. AverageYearsPerCompany")
print("  2. YearsSinceLastPromotionRatio")
print("  3. IncomePerYearExperience")
print("  4. AgeGroup")
print("  5. OverallSatisfaction")

print(f"\nFinal dataset shape: {df_processed.shape}")
```

```
==================================================
FEATURE ENGINEERING
==================================================
Created 5 new features:
  1. AverageYearsPerCompany
  2. YearsSinceLastPromotionRatio
  3. IncomePerYearExperience
  4. AgeGroup
  5. OverallSatisfaction

Final dataset shape: (1470, 36)
```

---

6. Train-Test Split

```
# ==========================================
# STEP 6: SPLIT DATA INTO TRAIN AND TEST
# ==========================================

print("="*50)
print("TRAIN-TEST SPLIT")
print("="*50)

# Separate features and target
X = df_processed.drop('Attrition', axis=1)
```

```
y = df_processed['Attrition']

# Split data
X_train, X_test, y_train, y_test = train_test_split(
    X, y,
    test_size=0.2,      # 80% train, 20% test
    random_state=42,     # For reproducibility
    stratify=y           # Maintain class distribution
)

print(f"\nTraining set: {X_train.shape[0]} samples")
print(f"Test set: {X_test.shape[0]} samples")

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

# Convert back to DataFrame
X_train_scaled = pd.DataFrame(X_train_scaled, columns=X.columns, index=X_train.
X_test_scaled = pd.DataFrame(X_test_scaled, columns=X.columns, index=X_test.inc

print("\nFeatures scaled using StandardScaler")
print("\n✅ Data ready for model training!")
```

```
==================================================
TRAIN-TEST SPLIT
==================================================

Training set: 1176 samples
Test set: 294 samples

Features scaled using StandardScaler

✅ Data ready for model training!
```

7. Model Training

```
# ==========================================
# STEP 7: TRAIN MULTIPLE MODELS
# ==========================================

print("="*50)
print("MODEL TRAINING")
print("="*50)

# Dictionary to store models and results
models = {}
results = {}
```

```
# 7.1: Logistic Regression
print("\n1. Training Logistic Regression...")
lr = LogisticRegression(max_iter=1000, random_state=42, class_weight='balanced'
lr.fit(X_train_scaled, y_train)
models['Logistic Regression'] = lr

# Cross-validation score
cv_scores = cross_val_score(lr, X_train_scaled, y_train, cv=5, scoring='roc_auc
results['Logistic Regression'] = {'cv_score': cv_scores.mean()}
print(f"   CV ROC-AUC: {cv_scores.mean():.4f}")
```

```
==================================================
MODEL TRAINING
==================================================

1. Training Logistic Regression...
   CV ROC-AUC: 0.8042
```

```
# 7.2: Decision Tree
print("\n2. Training Decision Tree...")
dt = DecisionTreeClassifier(
    max_depth=10,
    min_samples_split=5,
    random_state=42,
    class_weight='balanced'
)
dt.fit(X_train_scaled, y_train)
models['Decision Tree'] = dt

cv_scores = cross_val_score(dt, X_train_scaled, y_train, cv=5, scoring='roc_auc
results['Decision Tree'] = {'cv_score': cv_scores.mean()}
print(f"   CV ROC-AUC: {cv_scores.mean():.4f}")
```

```

2. Training Decision Tree...
   CV ROC-AUC: 0.6118
```

```
# 7.3: Random Forest
print("\n3. Training Random Forest...")
rf = RandomForestClassifier(
    n_estimators=100,
    max_depth=15,
    random_state=42,
    class_weight='balanced'
)
rf.fit(X_train_scaled, y_train)
models['Random Forest'] = rf

cv_scores = cross_val_score(rf, X_train_scaled, y_train, cv=5, scoring='roc_auc
```

```
results['Random Forest'] = {'cv_score': cv_scores.mean()}
print(f"   CV ROC-AUC: {cv_scores.mean():.4f}")
```

```
3. Training Random Forest...
   CV ROC-AUC: 0.7917
```

```
# 7.4: Gradient Boosting
print("\n4. Training Gradient Boosting...")
gb = GradientBoostingClassifier(
    n_estimators=100,
    learning_rate=0.1,
    max_depth=5,
    random_state=42
)
gb.fit(X_train_scaled, y_train)
models['Gradient Boosting'] = gb

cv_scores = cross_val_score(gb, X_train_scaled, y_train, cv=5, scoring='roc_auc
results['Gradient Boosting'] = {'cv_score': cv_scores.mean()}
print(f"   CV ROC-AUC: {cv_scores.mean():.4f}")
```

```
4. Training Gradient Boosting...
   CV ROC-AUC: 0.7730
```

```
# 7.5: XGBoost (Best Model)
print("\n5. Training XGBoost...")
xgb_model = xgb.XGBClassifier(
    learning_rate=0.1,
    max_depth=6,
    n_estimators=200,
    subsample=0.8,
    colsample_bytree=0.8,
    random_state=42,
    eval_metric='logloss'
)
xgb_model.fit(X_train_scaled, y_train)
models['XGBoost'] = xgb_model

cv_scores = cross_val_score(xgb_model, X_train_scaled, y_train, cv=5, scoring='
results['XGBoost'] = {'cv_score': cv_scores.mean()}
print(f"   CV ROC-AUC: {cv_scores.mean():.4f}")
```

```
5. Training XGBoost...
   CV ROC-AUC: 0.8008
```

```
# Print training summary
print("\n" + "="*50)
```

```
print("TRAINING SUMMARY")
print("="*50)

for name, result in results.items():
    print(f"{name}: {result['cv_score']:.4f}")

# Find best model
best_model_name = max(results, key=lambda x: results[x]['cv_score'])
best_model = models[best_model_name]

print(f"\n✅ Best Model: {best_model_name}")
print(f"   CV ROC-AUC: {results[best_model_name]['cv_score']:.4f}")
```

```
==================================================
TRAINING SUMMARY
==================================================
Logistic Regression: 0.8042
Decision Tree: 0.6118
Random Forest: 0.7917
Gradient Boosting: 0.7730
XGBoost: 0.8008

✅ Best Model: Logistic Regression
   CV ROC-AUC: 0.8042
```

8. Model Evaluation

```
# ==========================================
# STEP 8: EVALUATE ALL MODELS
# ==========================================

print("="*50)
print("MODEL EVALUATION")
print("="*50)

evaluation_results = []

for name, model in models.items():
    # Make predictions
    y_pred = model.predict(X_test_scaled)
    y_pred_proba = model.predict_proba(X_test_scaled)[:, 1]

    # Calculate metrics
    metrics = {
        'Model': name,
        'Accuracy': accuracy_score(y_test, y_pred),
        'Precision': precision_score(y_test, y_pred),
        'Recall': recall_score(y_test, y_pred),
```

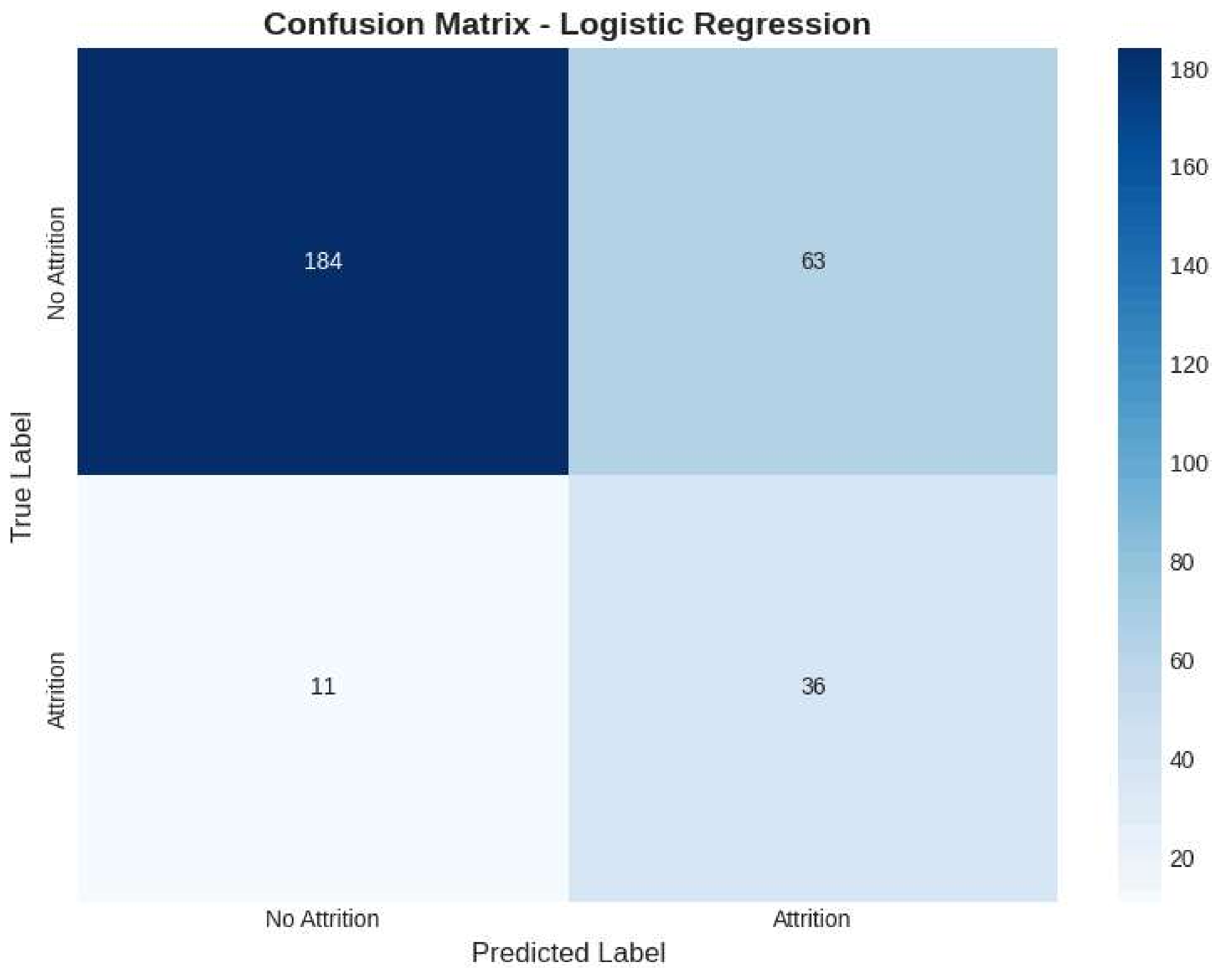
```
            'F1-Score': f1_score(y_test, y_pred),
            'ROC-AUC': roc_auc_score(y_test, y_pred_proba)
        }

        evaluation_results.append(metrics)

    # Create comparison DataFrame
    results_df = pd.DataFrame(evaluation_results)

    print("\nModel Performance Comparison:")
    print(results_df.to_string(index=False))
```

```
==================================================
MODEL EVALUATION
==================================================

Model Performance Comparison:
              Model  Accuracy  Precision   Recall  F1-Score  ROC-AUC
Logistic Regression  0.748299   0.363636 0.765957  0.493151 0.802998
      Decision Tree  0.785714   0.326087 0.319149  0.322581 0.622104
      Random Forest  0.833333   0.375000 0.063830  0.109091 0.751400
  Gradient Boosting  0.836735   0.476190 0.212766  0.294118 0.750108
            XGBoost  0.857143   0.666667 0.212766  0.322581 0.741752
```

```
# Detailed evaluation of best model
print("\n" + "="*50)
print(f"DETAILED EVALUATION: {best_model_name}")
print("="*50)

y_pred_best = best_model.predict(X_test_scaled)
y_pred_proba_best = best_model.predict_proba(X_test_scaled)[:, 1]

print("\nClassification Report:")
print(classification_report(y_test, y_pred_best,
                           target_names=['No Attrition', 'Attrition']))
```

```
==================================================
DETAILED EVALUATION: Logistic Regression
==================================================

Classification Report:
              precision    recall  f1-score   support

No Attrition       0.94      0.74      0.83       247
   Attrition       0.36      0.77      0.49        47

    accuracy                           0.75       294
   macro avg       0.65      0.76      0.66       294
weighted avg       0.85      0.75      0.78       294
```

```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_best)

plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues',
           xticklabels=['No Attrition', 'Attrition'],
           yticklabels=['No Attrition', 'Attrition'])
plt.title(f'Confusion Matrix - {best_model_name}', fontsize=14, fontweight='bol
plt.ylabel('True Label', fontsize=12)
plt.xlabel('Predicted Label', fontsize=12)
plt.tight_layout()
plt.show()

print("\nConfusion Matrix:")
print(f"  True Negatives:  {cm[0,0]}")
print(f"  False Positives: {cm[0,1]}")
print(f"  False Negatives: {cm[1,0]}")
print(f"  True Positives:  {cm[1,1]}")
```




```
Confusion Matrix:
  True Negatives:  184
  False Positives: 63
  False Negatives: 11
  True Positives:  36
```

---

9. SHAP Explainability

```
# ============================================
# STEP 9: SHAP EXPLAINABILITY
# ============================================

print("="*50)
print("SHAP EXPLAINABILITY ANALYSIS")
print("="*50)
```

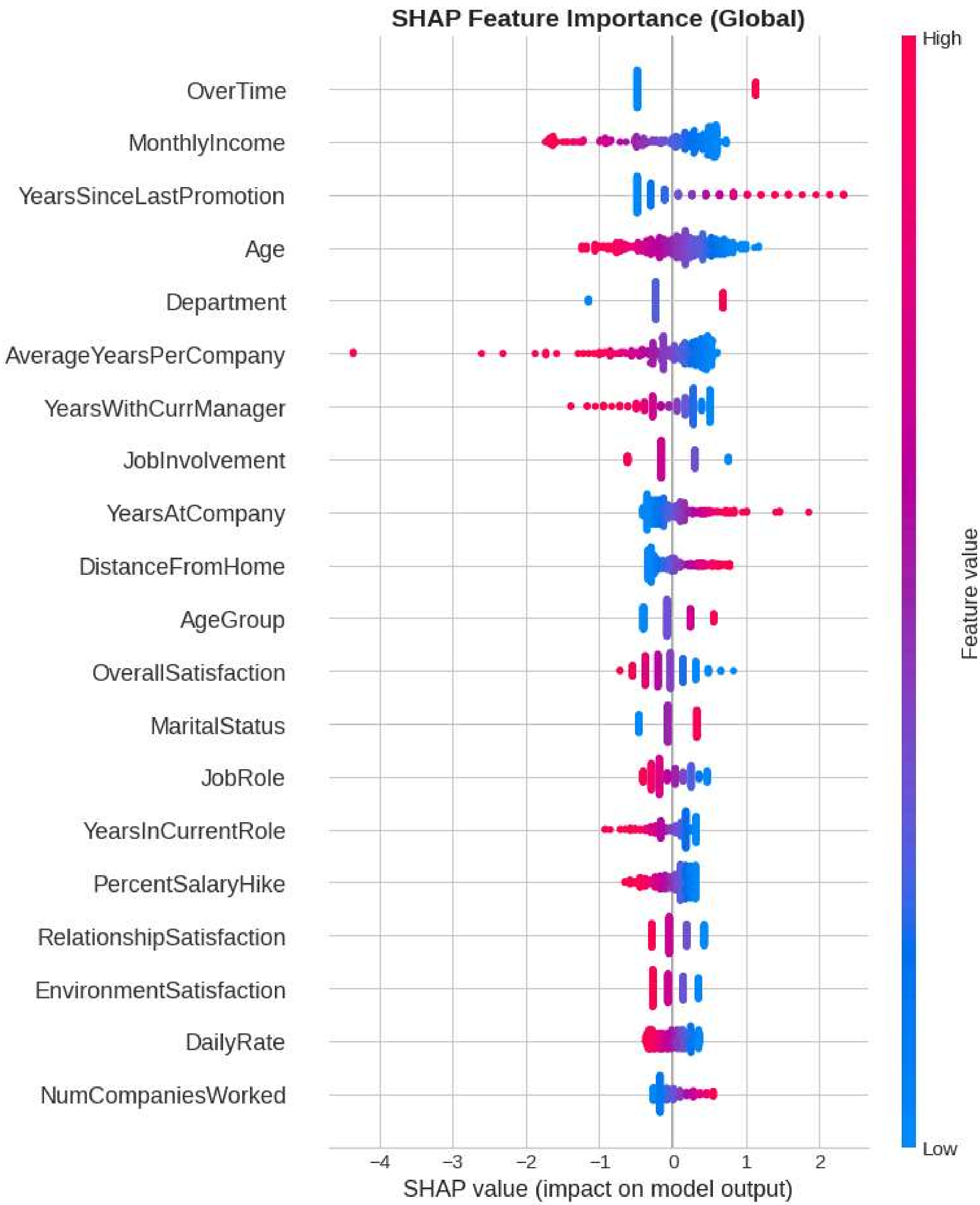
```
import shap

# Initialize SHAP explainer for linear models
explainer = shap.LinearExplainer(best_model, X_train_scaled)

# Calculate SHAP values
shap_values = explainer.shap_values(X_test_scaled)

# For binary classification, use values for class 1
if isinstance(shap_values, list):
    shap_values = shap_values[1]

print("✅ SHAP values calculated!")
```

```
==================================================
SHAP EXPLAINABILITY ANALYSIS
==================================================
✅ SHAP values calculated!
```

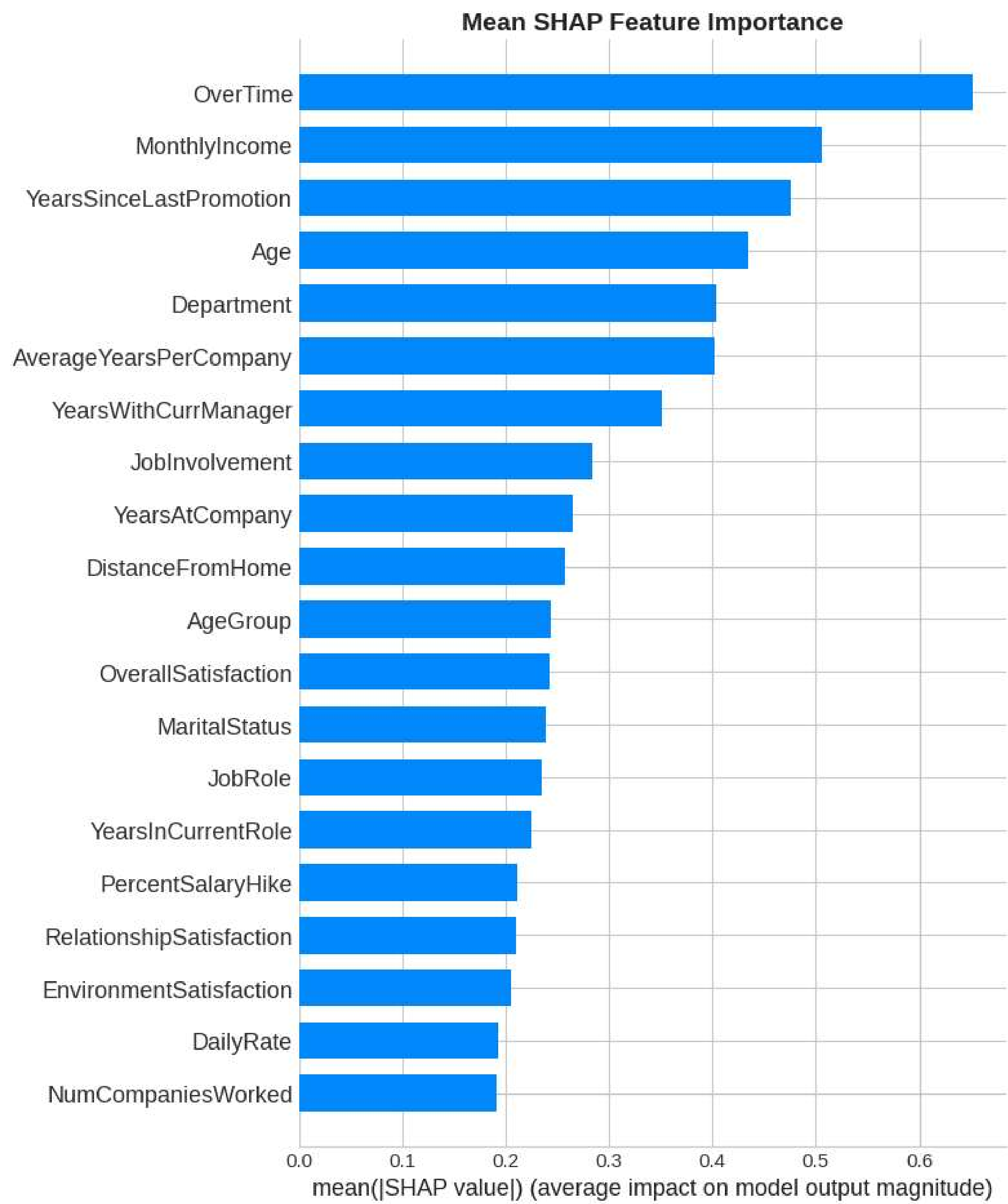
```
# Feature Importance (Mean Absolute SHAP values)
importance = np.abs(shap_values).mean(axis=0)

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

print("\nTop 10 Most Important Features:")
print(feature_importance.head(10).to_string(index=False))
```

```

Top 10 Most Important Features:
                Feature  Importance
               OverTime    0.651626
          MonthlyIncome    0.505159
YearsSinceLastPromotion    0.475348
                    Age    0.434405
             Department    0.403781
 AverageYearsPerCompany    0.401640
   YearsWithCurrManager    0.350982
         JobInvolvement    0.283521
         YearsAtCompany    0.265264
       DistanceFromHome    0.257136
```

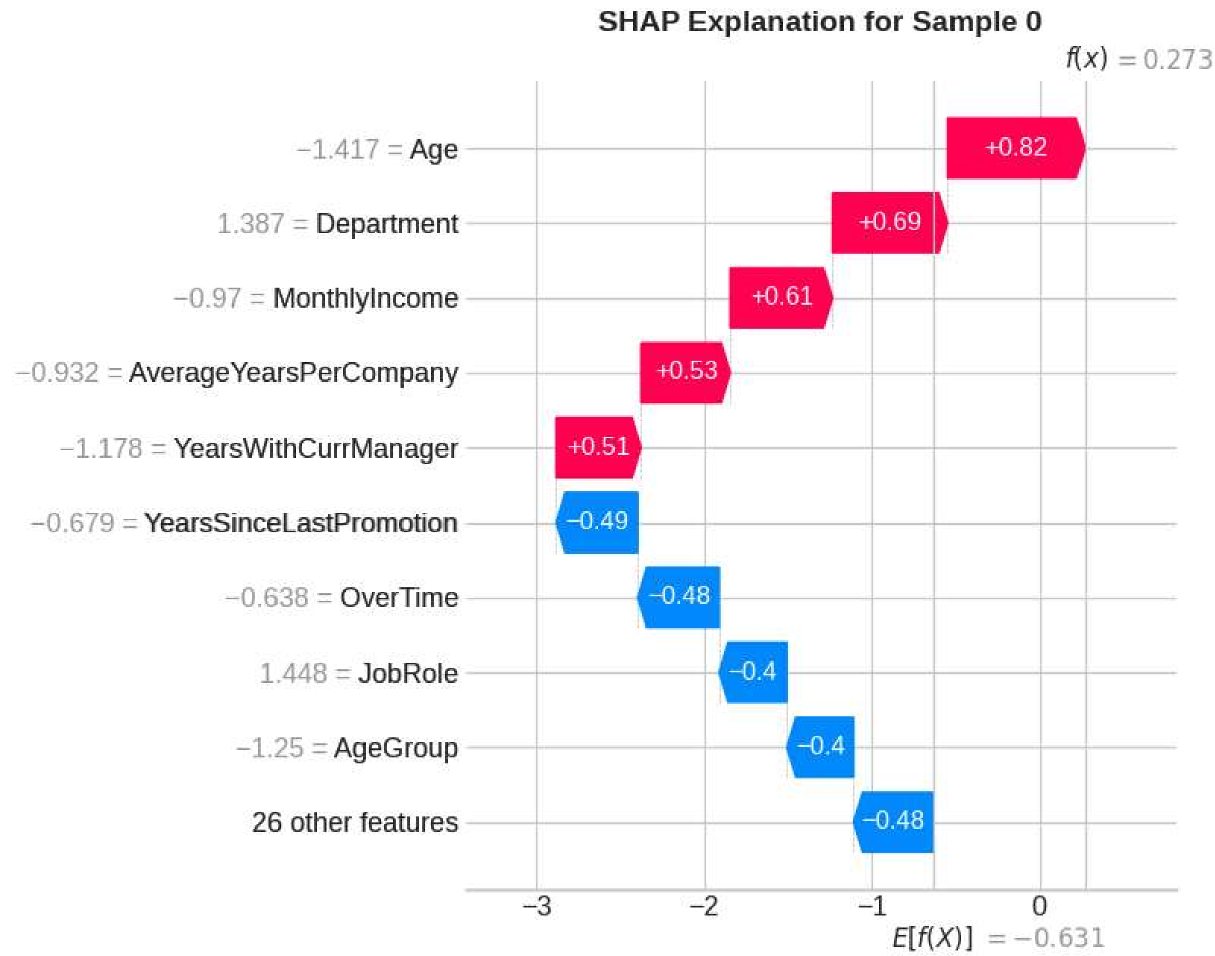
```
# SHAP Summary Plot (Global Feature Importance)
plt.figure(figsize=(10, 8))
shap.summary_plot(shap_values, X_test_scaled, show=False)
plt.title('SHAP Feature Importance (Global)', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```


SHAP Feature Importance (Global)
OverTime
MonthlyIncome
YearsSinceLastPromotion
Age
Department
AverageYearsPerCompany
YearsWithCurrManager
JobInvolvement
YearsAtCompany
DistanceFromHome
AgeGroup
OverallSatisfaction
MaritalStatus
JobRole
YearsInCurrentRole
PercentSalaryHike
RelationshipSatisfaction
EnvironmentSatisfaction
DailyRate
NumCompaniesWorked
−4
−3
−2
−1
0
1
2
SHAP value (impact on model output)
High
Feature value
Low

```python
# SHAP Bar Plot (Mean Absolute Importance)
plt.figure(figsize=(10, 8))
shap.summary_plot(shap_values, X_test_scaled, plot_type="bar", show=False)
plt.title('Mean SHAP Feature Importance', fontsize=14, fontweight='bold')
plt.tight_layout()
plt.show()
```


Mean SHAP Feature Importance
OverTime
MonthlyIncome
YearsSinceLastPromotion
Age
Department
AverageYearsPerCompany
YearsWithCurrManager
JobInvolvement
YearsAtCompany
DistanceFromHome
AgeGroup
OverallSatisfaction
MaritalStatus
JobRole
YearsInCurrentRole
PercentSalaryHike
RelationshipSatisfaction
EnvironmentSatisfaction
DailyRate
NumCompaniesWorked
0.0
0.1
0.2
0.3
0.4
0.5
0.6
mean(|SHAP value|) (average impact on model output magnitude)

```
# Explain a single prediction (Waterfall Plot)
sample_idx = 0  # Change this to explore different samples

explanation = shap.Explanation(
    values=shap_values[sample_idx],
    base_values=explainer.expected_value,
    data=X_test_scaled.iloc[sample_idx],
    feature_names=X.columns
)

plt.figure(figsize=(12, 8))
shap.waterfall_plot(explanation, show=False)
plt.title(f'SHAP Explanation for Sample {sample_idx}', fontsize=14, fontweight=
plt.tight_layout()
plt.show()

actual = y_test.iloc[sample_idx]
predicted = y_pred_best[sample_idx]
print(f"\nActual: {'Attrition' if actual == 1 else 'No Attrition'}")
print(f"Predicted: {'Attrition' if predicted == 1 else 'No Attrition'}")
```



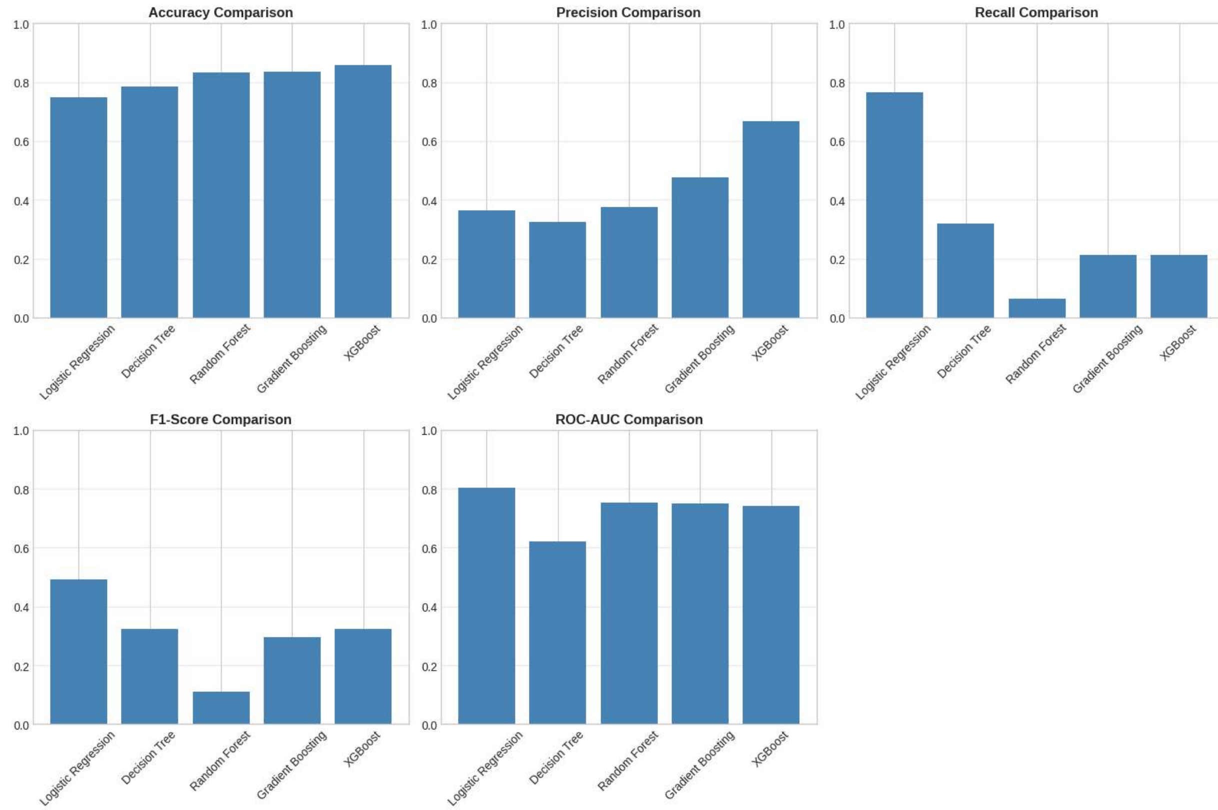

```
Actual: No Attrition
Predicted: Attrition
```

10. Visualization

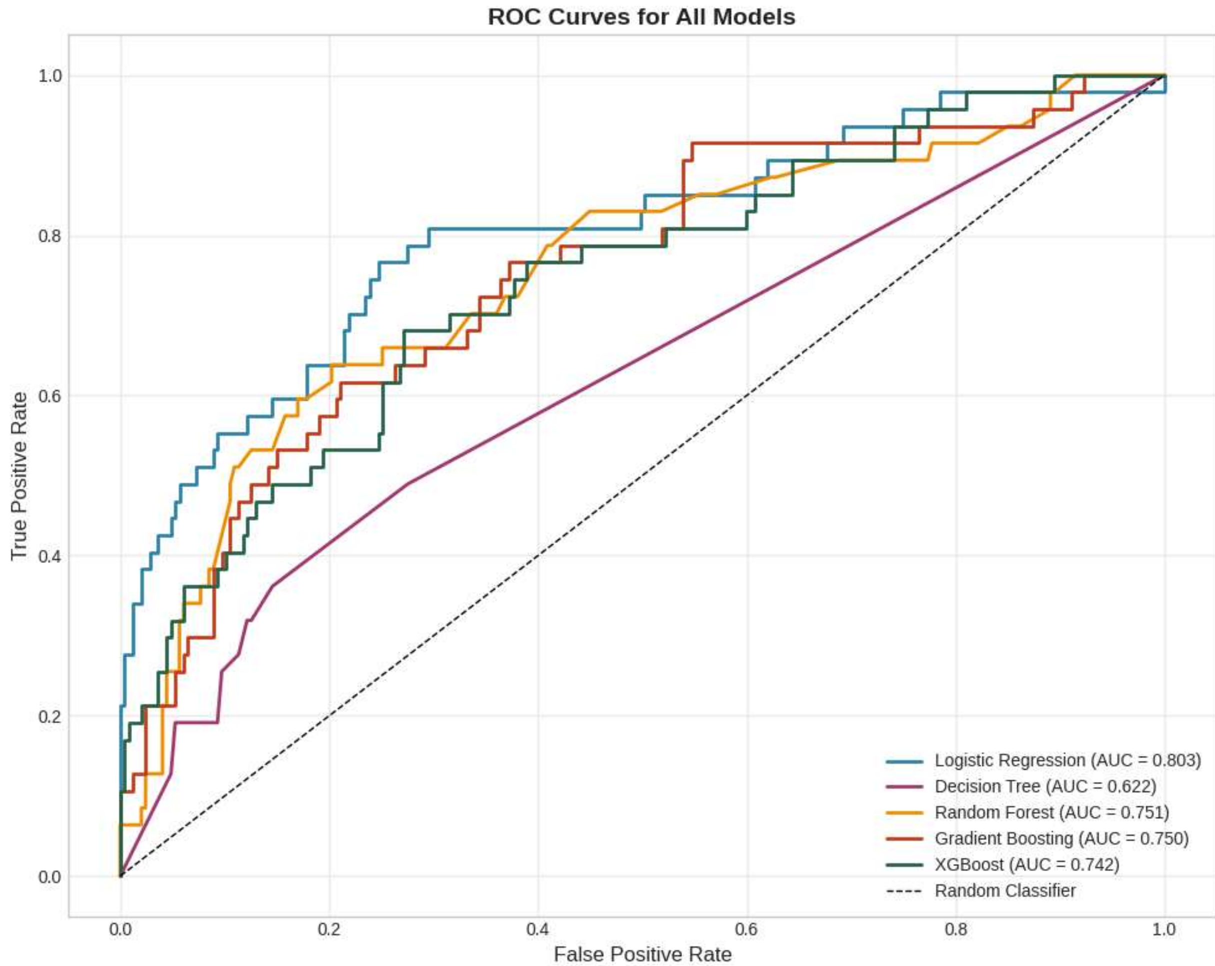
```
# ==========================================
# STEP 10: CREATE VISUALIZATIONS
# ==========================================

print("="*50)
print("CREATING VISUALIZATIONS")
print("="*50)
```

```
# 10.1: Model Performance Comparison
fig, axes = plt.subplots(2, 3, figsize=(15, 10))
axes = axes.flatten()

metrics = ['Accuracy', 'Precision', 'Recall', 'F1-Score', 'ROC-AUC']

for i, metric in enumerate(metrics):
    axes[i].bar(results_df['Model'], results_df[metric], color='steelblue')
    axes[i].set_title(f'{metric} Comparison', fontsize=12, fontweight='bold')
    axes[i].set_ylim([0, 1])
    axes[i].tick_params(axis='x', rotation=45)
    axes[i].grid(axis='y', alpha=0.3)

axes[5].axis('off')
plt.tight_layout()
plt.show()
```

```
============================================================
CREATING VISUALIZATIONS
============================================================
```

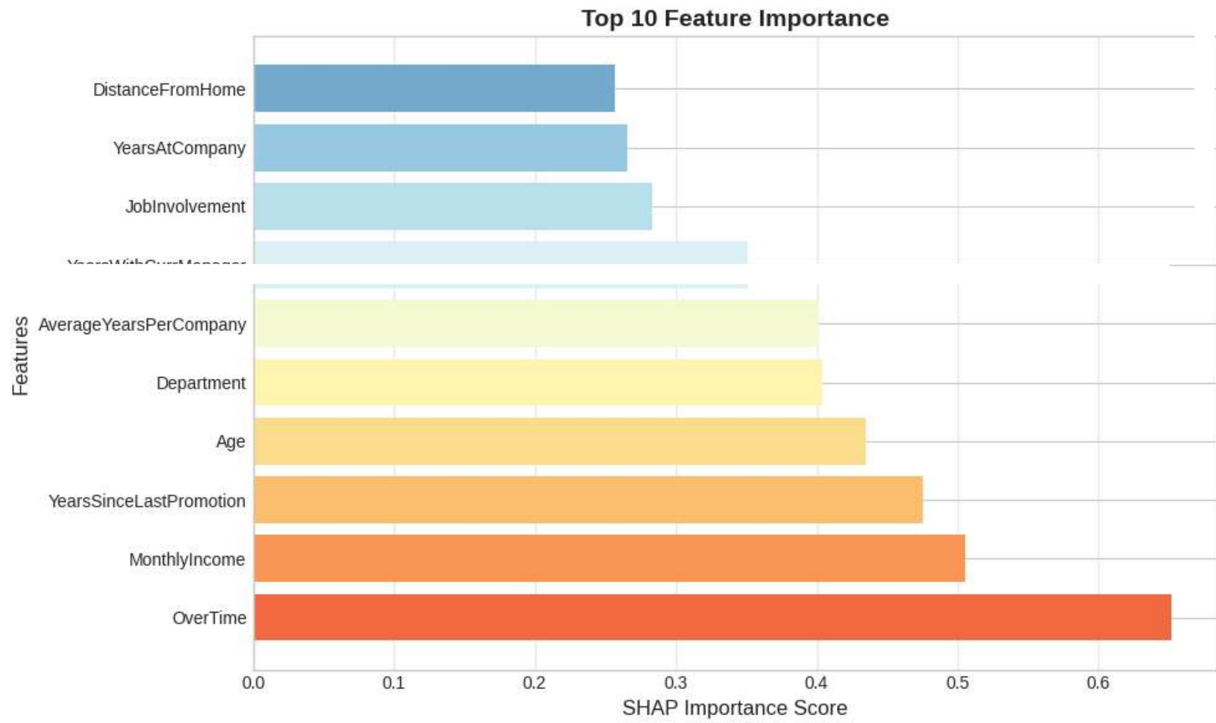


```
# 10.2: ROC Curves for All Models
plt.figure(figsize=(10, 8))

colors = ['#2E86AB', '#A23B72', '#F18F01', '#C73E1D', '#276749']

for i, (name, model) in enumerate(models.items()):
    y_pred_proba = model.predict_proba(X_test_scaled)[:, 1]
    fpr, tpr, _ = roc_curve(y_test, y_pred_proba)
    auc = roc_auc_score(y_test, y_pred_proba)
    plt.plot(fpr, tpr, linewidth=2, label=f'{name} (AUC = {auc:.3f})', color=cc

plt.plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')
plt.xlabel('False Positive Rate', fontsize=12)
plt.ylabel('True Positive Rate', fontsize=12)
plt.title('ROC Curves for All Models', fontsize=14, fontweight='bold')
plt.legend(loc='lower right')
plt.grid(alpha=0.3)
plt.tight_layout()
plt.show()
```




```
# 10.3: Feature Importance Bar Chart
plt.figure(figsize=(10, 6))

top_features = feature_importance.head(10)
colors = plt.cm.RdYlBu(np.linspace(0.2, 0.8, len(top_features)))

plt.barh(top_features['Feature'], top_features['Importance'], color=colors)
```

```
plt.xlabel('SHAP Importance Score', fontsize=12)
plt.ylabel('Features', fontsize=12)
plt.title('Top 10 Feature Importance', fontsize=14, fontweight='bold')
plt.grid(axis='x', alpha=0.3)
plt.tight_layout()
```



11. Save Model

```
# ==========================================
# STEP 11: SAVE MODEL AND PREPROCESSOR
# ==========================================
```