Loan_Approval

February 11, 2026

[5]:
```python
"""
LOAN APPROVAL PREDICTION - MACHINE LEARNING MODEL
==================================================
Complete ML Pipeline with Multiple Algorithms, Evaluation Metrics &␣
↪Visualizations
Output Directory: /home/nmit/Pictures/
"""

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split, cross_val_score,␣
↪GridSearchCV
from sklearn.preprocessing import StandardScaler, LabelEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import (RandomForestClassifier,␣
↪GradientBoostingClassifier,
                              AdaBoostClassifier, ExtraTreesClassifier)
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.neural_network import MLPClassifier
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                            f1_score, confusion_matrix, classification_report,
                            roc_curve, auc, roc_auc_score,␣
↪precision_recall_curve)
import joblib
import warnings
warnings.filterwarnings('ignore')

# Set visualization style
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette("Set2")

# Output directory
```

```python
OUTPUT_DIR = '/home/nmit/Pictures/'

print("="*100)
print(" "*30 + "LOAN APPROVAL PREDICTION SYSTEM")
print("="*100)
print(f"Output Directory: {OUTPUT_DIR}")
print("="*100)

# ================================================================================
# STEP 1: DATA LOADING AND EXPLORATION
# ================================================================================
print("\n" + "="*100)
print("STEP 1: DATA LOADING AND EXPLORATION")
print("="*100)

# Load dataset
df = pd.read_csv('/home/nmit/Documents//Loan_Approval.csv')

print(f"\n Dataset Overview:")
print(f"   Total Records: {df.shape[0]}")
print(f"   Total Features: {df.shape[1]}")
print(f"   Features: {list(df.columns)}")

print(f"\n First 10 Records:")
print(df.head(10))

print(f"\n Dataset Information:")
print(df.info())

print(f"\n Statistical Summary:")
print(df.describe())

print(f"\n Missing Values:")
missing_values = df.isnull().sum()
print(missing_values)
if missing_values.sum() == 0:
    print("  No missing values found!")

print(f"\n Target Variable Distribution:")
target_dist = df['Loan_Status'].value_counts()
print(target_dist)
print(f"\nApproval Rate: {(target_dist['Approved'] / len(df) * 100):.2f}%")
print(f"Rejection Rate: {(target_dist['Rejected'] / len(df) * 100):.2f}%")

print(f"\n Employment Status Distribution:")
print(df['Employment_Status'].value_counts())
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# ==============================================================================
# STEP 2: EXPLORATORY DATA ANALYSIS & VISUALIZATION
# ==============================================================================
print("\n" + "="*100)
print("STEP 2: EXPLORATORY DATA ANALYSIS")
print("="*100)

# Create EDA visualizations
fig1 = plt.figure(figsize=(20, 12))

# 1. Target Variable Distribution
ax1 = plt.subplot(2, 3, 1)
colors_target = ['#e74c3c', '#2ecc71']
counts = df['Loan_Status'].value_counts()
bars = plt.bar(counts.index, counts.values, color=colors_target,
              edgecolor='black', linewidth=2, alpha=0.8)
plt.xlabel('Loan Status', fontsize=12, fontweight='bold')
plt.ylabel('Count', fontsize=12, fontweight='bold')
plt.title('Loan Approval Distribution', fontsize=14, fontweight='bold')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.1,
            f'{int(height)}\n({height/len(df)*100:.1f}%)',
            ha='center', va='bottom', fontweight='bold', fontsize=11)

# 2. Age Distribution by Loan Status
ax2 = plt.subplot(2, 3, 2)
for status, color in zip(['Approved', 'Rejected'], colors_target):
    data = df[df['Loan_Status'] == status]['Age']
    plt.hist(data, alpha=0.6, label=status, bins=8, color=color, edgecolor='black')
plt.xlabel('Age', fontsize=12, fontweight='bold')
plt.ylabel('Frequency', fontsize=12, fontweight='bold')
plt.title('Age Distribution by Loan Status', fontsize=14, fontweight='bold')
plt.legend(fontsize=10)
plt.grid(True, alpha=0.3)

# 3. Income vs Loan Amount
ax3 = plt.subplot(2, 3, 3)
for status, color, marker in zip(['Approved', 'Rejected'], colors_target, ['o', 's']):
    data = df[df['Loan_Status'] == status]
    plt.scatter(data['Income'], data['Loan_Amount'],
               label=status, color=color, s=150, alpha=0.7,
               edgecolors='black', linewidth=1.5, marker=marker)
plt.xlabel('Income', fontsize=12, fontweight='bold')
plt.ylabel('Loan Amount', fontsize=12, fontweight='bold')
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plt.title('Income vs Loan Amount by Status', fontsize=14, fontweight='bold')
plt.legend(fontsize=10)
plt.grid(True, alpha=0.3)

# 4. Credit Score Distribution
ax4 = plt.subplot(2, 3, 4)
for status, color in zip(['Approved', 'Rejected'], colors_target):
    data = df[df['Loan_Status'] == status]['Credit_Score']
    plt.hist(data, alpha=0.6, label=status, bins=8, color=color,␣
 ↪edgecolor='black')
plt.xlabel('Credit Score', fontsize=12, fontweight='bold')
plt.ylabel('Frequency', fontsize=12, fontweight='bold')
plt.title('Credit Score Distribution by Status', fontsize=14, fontweight='bold')
plt.legend(fontsize=10)
plt.grid(True, alpha=0.3)

# 5. Employment Status vs Loan Approval
ax5 = plt.subplot(2, 3, 5)
employment_status = pd.crosstab(df['Employment_Status'], df['Loan_Status'])
employment_status.plot(kind='bar', ax=ax5, color=colors_target,
                       edgecolor='black', linewidth=2, alpha=0.8)
plt.xlabel('Employment Status', fontsize=12, fontweight='bold')
plt.ylabel('Count', fontsize=12, fontweight='bold')
plt.title('Employment Status vs Loan Approval', fontsize=14, fontweight='bold')
plt.xticks(rotation=0)
plt.legend(title='Loan Status', fontsize=10)
plt.grid(True, alpha=0.3, axis='y')

# 6. Correlation Heatmap
ax6 = plt.subplot(2, 3, 6)
# Encode categorical variables for correlation
df_encoded = df.copy()
df_encoded['Employment_Status'] = LabelEncoder().
 ↪fit_transform(df_encoded['Employment_Status'])
df_encoded['Loan_Status'] = LabelEncoder().
 ↪fit_transform(df_encoded['Loan_Status'])
correlation = df_encoded.corr()
sns.heatmap(correlation, annot=True, fmt='.2f', cmap='coolwarm',
           center=0, square=True, linewidths=2, linecolor='black',
           cbar_kws={'label': 'Correlation'}, ax=ax6)
plt.title('Feature Correlation Heatmap', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, ha='right')

plt.suptitle('Loan Approval - Exploratory Data Analysis',
            fontsize=18, fontweight='bold', y=0.995)
plt.tight_layout()
```

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plt.savefig(OUTPUT_DIR + 'loan_eda_visualization.png', dpi=300, bbox_inches='tight')
print("\n  EDA visualization saved: loan_eda_visualization.png")

# ============================================================================
# STEP 3: DATA PREPROCESSING
# ============================================================================
print("\n" + "="*100)
print("STEP 3: DATA PREPROCESSING")
print("="*100)

# Encode Employment Status
le_employment = LabelEncoder()
df['Employment_Status_Encoded'] = le_employment.fit_transform(df['Employment_Status'])
print(f"\n  Employment Status Encoding: {dict(zip(le_employment.classes_, le_employment.transform(le_employment.classes_)))}")

# Encode Loan Status (Target)
le_target = LabelEncoder()
df['Loan_Status_Encoded'] = le_target.fit_transform(df['Loan_Status'])
print(f"  Loan Status Encoding: {dict(zip(le_target.classes_, le_target.transform(le_target.classes_)))}")

# Prepare features and target
feature_columns = ['Age', 'Income', 'Credit_Score', 'Loan_Amount', 'Employment_Status_Encoded']
X = df[feature_columns]
y = df['Loan_Status_Encoded']

print(f"\n  Feature Matrix Shape: {X.shape}")
print(f"  Target Vector Shape: {y.shape}")
print(f"\nFeatures Used: {feature_columns}")

# ============================================================================
# STEP 4: TRAIN-TEST SPLIT
# ============================================================================
print("\n" + "="*100)
print("STEP 4: TRAIN-TEST SPLIT")
print("="*100)

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.3, random_state=42, stratify=y
)

print(f"\n  Training Set: {X_train.shape[0]} samples ({len(X_train)/len(X)*100:.0f}%)")
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print(f"  Test Set: {X_test.shape[0]} samples ({len(X_test)/len(X)*100:.0f}%)")

print(f"\nTraining Set Distribution:")
print(pd.Series(y_train).value_counts())
print(f"\nTest Set Distribution:")
print(pd.Series(y_test).value_counts())

# ============================================================================
# STEP 5: FEATURE SCALING
# ============================================================================
print("\n" + "="*100)
print("STEP 5: FEATURE SCALING")
print("="*100)

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

print("\n  Features Standardized (Mean=0, Std=1)")
print("\nScaling Parameters:")
for i, col in enumerate(feature_columns):
    print(f"  {col}: Mean={scaler.mean_[i]:.2f}, Std={scaler.scale_[i]:.2f}")

# ============================================================================
# STEP 6: MODEL TRAINING - MULTIPLE ALGORITHMS
# ============================================================================
print("\n" + "="*100)
print("STEP 6: TRAINING MULTIPLE MACHINE LEARNING MODELS")
print("="*100)

# Define multiple models
models = {
    'Logistic Regression': LogisticRegression(random_state=42, max_iter=1000),
    'Decision Tree': DecisionTreeClassifier(random_state=42, max_depth=5),
    'Random Forest': RandomForestClassifier(n_estimators=100, random_state=42),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, 
 ↪random_state=42),
    'AdaBoost': AdaBoostClassifier(n_estimators=50, random_state=42),
    'Extra Trees': ExtraTreesClassifier(n_estimators=100, random_state=42),
    'Support Vector Machine': SVC(kernel='rbf', random_state=42, 
 ↪probability=True),
    'K-Nearest Neighbors': KNeighborsClassifier(n_neighbors=3),
    'Naive Bayes': GaussianNB(),
    'Neural Network': MLPClassifier(hidden_layer_sizes=(100, 50), 
 ↪max_iter=1000, random_state=42)
}
```

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# Storage for results
results = []
trained_models = {}
predictions_dict = {}

print("\n  Training Models...")
print("-" * 100)

for name, model in models.items():
    print(f"\n  Training {name}...", end=" ")

    # Train model
    model.fit(X_train_scaled, y_train)
    trained_models[name] = model

    # Predictions
    y_pred_train = model.predict(X_train_scaled)
    y_pred_test = model.predict(X_test_scaled)
    predictions_dict[name] = y_pred_test

    # Calculate metrics
    train_accuracy = accuracy_score(y_train, y_pred_train)
    test_accuracy = accuracy_score(y_test, y_pred_test)
    precision = precision_score(y_test, y_pred_test, zero_division=0)
    recall = recall_score(y_test, y_pred_test, zero_division=0)
    f1 = f1_score(y_test, y_pred_test, zero_division=0)

    # Cross-validation
    cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=3,␣
 ↪scoring='accuracy')
    cv_mean = cv_scores.mean()
    cv_std = cv_scores.std()

    # ROC-AUC if probability available
    if hasattr(model, 'predict_proba'):
        y_pred_proba = model.predict_proba(X_test_scaled)[:, 1]
        roc_auc = roc_auc_score(y_test, y_pred_proba)
    else:
        roc_auc = np.nan

    results.append({
        'Model': name,
        'Train Accuracy': train_accuracy,
        'Test Accuracy': test_accuracy,
        'Precision': precision,
        'Recall': recall,
        'F1-Score': f1,
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        'ROC-AUC': roc_auc,
        'CV Mean': cv_mean,
        'CV Std': cv_std
    })

    print(f"  (Test Acc: {test_accuracy:.4f}, F1: {f1:.4f})")

# Convert to DataFrame
results_df = pd.DataFrame(results)
results_df = results_df.sort_values('Test Accuracy', ascending=False).
 ↪reset_index(drop=True)

print("\n" + "="*100)
print("MODEL PERFORMANCE COMPARISON - ALL METRICS")
print("="*100)
print(results_df.to_string(index=False))

# Save results
results_df.to_csv(OUTPUT_DIR + 'model_comparison_results.csv', index=False)
print(f"\n  Results saved: model_comparison_results.csv")

# Select best model
best_model_name = results_df.iloc[0]['Model']
best_model = trained_models[best_model_name]
best_predictions = predictions_dict[best_model_name]

print(f"\n{'='*100}")
print(f"  BEST MODEL: {best_model_name}")
print(f"{'='*100}")
print(f"   Test Accuracy:  {results_df.iloc[0]['Test Accuracy']:.4f}␣
 ↪({results_df.iloc[0]['Test Accuracy']*100:.2f}%)")
print(f"   Precision:      {results_df.iloc[0]['Precision']:.4f} ({results_df.
 ↪iloc[0]['Precision']*100:.2f}%)")
print(f"   Recall:         {results_df.iloc[0]['Recall']:.4f} ({results_df.
 ↪iloc[0]['Recall']*100:.2f}%)")
print(f"   F1-Score:       {results_df.iloc[0]['F1-Score']:.4f} ({results_df.
 ↪iloc[0]['F1-Score']*100:.2f}%)")
print(f"{'='*100}")

# ============================================================================
# STEP 7: DETAILED EVALUATION OF BEST MODEL
# ============================================================================
print("\n" + "="*100)
print(f"STEP 7: DETAILED EVALUATION - {best_model_name}")
print("="*100)

# Confusion Matrix
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```python
cm = confusion_matrix(y_test, best_predictions)
print("\n Confusion Matrix:")
print(cm)
print(f"\nTrue Negatives (TN) - Correctly Predicted Rejections: {cm[0,0]}")
print(f"False Positives (FP) - Incorrectly Predicted Approvals: {cm[0,1]}")
print(f"False Negatives (FN) - Incorrectly Predicted Rejections: {cm[1,0]}")
print(f"True Positives (TP) - Correctly Predicted Approvals: {cm[1,1]}")

# Detailed metrics
accuracy = accuracy_score(y_test, best_predictions)
precision = precision_score(y_test, best_predictions, zero_division=0)
recall = recall_score(y_test, best_predictions, zero_division=0)
f1 = f1_score(y_test, best_predictions, zero_division=0)

print("\n Detailed Performance Metrics:")
print(f"   Accuracy:  {accuracy:.4f} ({accuracy*100:.2f}%) - Overall␣
↪correctness")
print(f"   Precision: {precision:.4f} ({precision*100:.2f}%) - Reliability of␣
↪approval predictions")
print(f"   Recall:    {recall:.4f} ({recall*100:.2f}%) - Ability to identify␣
↪all approvals")
print(f"   F1-Score:  {f1:.4f} ({f1*100:.2f}%) - Harmonic mean of precision␣
↪and recall")

if hasattr(best_model, 'predict_proba'):
    y_pred_proba = best_model.predict_proba(X_test_scaled)[:, 1]
    roc_auc = roc_auc_score(y_test, y_pred_proba)
    print(f"   ROC-AUC:   {roc_auc:.4f} ({roc_auc*100:.2f}%) - Discrimination␣
↪ability")

print("\n Classification Report:")
print(classification_report(y_test, best_predictions,
                            target_names=['Rejected', 'Approved'],
                            zero_division=0))

# Feature Importance
print("\n FEATURE IMPORTANCE ANALYSIS:")
if hasattr(best_model, 'feature_importances_'):
    feature_importance = pd.DataFrame({
        'Feature': feature_columns,
        'Importance': best_model.feature_importances_
    }).sort_values('Importance', ascending=False)
    print(feature_importance.to_string(index=False))

    # Save feature importance
    feature_importance.to_csv(OUTPUT_DIR + 'feature_importance.csv',␣
↪index=False)
```

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    print("\n  Feature importance saved: feature_importance.csv")

elif hasattr(best_model, 'coef_'):
    feature_coef = pd.DataFrame({
        'Feature': feature_columns,
        'Coefficient': best_model.coef_[0]
    }).sort_values('Coefficient', ascending=False)
    print(feature_coef.to_string(index=False))

    feature_coef.to_csv(OUTPUT_DIR + 'feature_coefficients.csv', index=False)
    print("\n  Feature coefficients saved: feature_coefficients.csv")

# ============================================================================
# STEP 8: SAVE THE BEST MODEL
# ============================================================================
print("\n" + "="*100)
print("STEP 8: SAVING THE TRAINED MODEL")
print("="*100)

# Save model
model_filename = OUTPUT_DIR + 'loan_approval_model.pkl'
joblib.dump(best_model, model_filename)
print(f"\n  Best model saved: {model_filename}")

# Save scaler
scaler_filename = OUTPUT_DIR + 'feature_scaler.pkl'
joblib.dump(scaler, scaler_filename)
print(f"  Feature scaler saved: {scaler_filename}")

# Save encoders
encoder_filename = OUTPUT_DIR + 'label_encoders.pkl'
joblib.dump({
    'employment': le_employment,
    'target': le_target
}, encoder_filename)
print(f"  Label encoders saved: {encoder_filename}")

print("\n  Model Usage Instructions:")
print("""
To load and use the model:

    import joblib

    # Load model and preprocessing objects
    model = joblib.load('/home/nmit/Pictures/loan_approval_model.pkl')
    scaler = joblib.load('/home/nmit/Pictures/feature_scaler.pkl')
    encoders = joblib.load('/home/nmit/Pictures/label_encoders.pkl')
```

```python
    # Make predictions on new data
    new_data = [[35, 55000, 700, 150000, 1]]  # [Age, Income, Credit_Score,␣
↪Loan_Amount, Employment(1=Yes,0=No)]
    new_data_scaled = scaler.transform(new_data)
    prediction = model.predict(new_data_scaled)

    # Get prediction label
    result = encoders['target'].inverse_transform(prediction)
    print(f"Loan Status: {result[0]}")
""")

# ============================================================================
# STEP 9: COMPREHENSIVE VISUALIZATIONS
# ============================================================================
print("\n" + "="*100)
print("STEP 9: GENERATING COMPREHENSIVE VISUALIZATIONS")
print("="*100)

# Main visualization dashboard
fig2 = plt.figure(figsize=(24, 16))

# 1. Model Accuracy Comparison
ax1 = plt.subplot(3, 4, 1)
models_sorted = results_df.sort_values('Test Accuracy', ascending=True)
colors = ['#2ecc71' if x == best_model_name else '#3498db' for x in␣
↪models_sorted['Model']]
bars = plt.barh(range(len(models_sorted)), models_sorted['Test Accuracy'],
               color=colors, edgecolor='black', linewidth=1.5)
plt.yticks(range(len(models_sorted)), models_sorted['Model'], fontsize=9)
plt.xlabel('Accuracy', fontsize=11, fontweight='bold')
plt.title('Model Accuracy Comparison', fontsize=13, fontweight='bold')
plt.xlim([0, 1.1])
for i, (bar, acc) in enumerate(zip(bars, models_sorted['Test Accuracy'])):
    plt.text(acc + 0.02, bar.get_y() + bar.get_height()/2,
            f'{acc:.3f}', ha='left', va='center', fontweight='bold', fontsize=9)
plt.axvline(x=0.8, color='red', linestyle='--', alpha=0.5, linewidth=2)

# 2. Confusion Matrix Heatmap
ax2 = plt.subplot(3, 4, 2)
sns.heatmap(cm, annot=True, fmt='d', cmap='RdYlGn', square=True,
           xticklabels=['Rejected', 'Approved'],
           yticklabels=['Rejected', 'Approved'],
           cbar_kws={'label': 'Count'}, linewidths=3, linecolor='black',
           annot_kws={'fontsize': 14, 'fontweight': 'bold'})
plt.ylabel('Actual', fontsize=11, fontweight='bold')
plt.xlabel('Predicted', fontsize=11, fontweight='bold')
```

```
plt.title(f'Confusion Matrix - {best_model_name}', fontsize=13,␣
↪fontweight='bold')

# 3. Performance Metrics
ax3 = plt.subplot(3, 4, 3)
metrics_data = {
    'Accuracy': accuracy,
    'Precision': precision,
    'Recall': recall,
    'F1-Score': f1
}
colors_metrics = ['#e74c3c', '#3498db', '#2ecc71', '#f39c12']
bars = plt.bar(metrics_data.keys(), metrics_data.values(),
              color=colors_metrics, edgecolor='black', linewidth=2, alpha=0.8)
plt.ylabel('Score', fontsize=11, fontweight='bold')
plt.title(f'Performance Metrics - {best_model_name}', fontsize=13,␣
↪fontweight='bold')
plt.ylim([0, 1.15])
plt.axhline(y=0.8, color='red', linestyle='--', alpha=0.5, linewidth=2)
plt.xticks(rotation=45, ha='right')
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.03,
            f'{height:.3f}', ha='center', va='bottom', fontweight='bold',␣
↪fontsize=10)

# 4. ROC Curve
ax4 = plt.subplot(3, 4, 4)
if hasattr(best_model, 'predict_proba'):
    fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
    roc_auc = auc(fpr, tpr)
    plt.plot(fpr, tpr, color='#e74c3c', lw=3,
            label=f'{best_model_name}\n(AUC = {roc_auc:.3f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--',
            label='Random Classifier\n(AUC = 0.500)')
    plt.fill_between(fpr, tpr, alpha=0.2, color='#e74c3c')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate', fontsize=11, fontweight='bold')
    plt.ylabel('True Positive Rate', fontsize=11, fontweight='bold')
    plt.title('ROC Curve', fontsize=13, fontweight='bold')
    plt.legend(loc="lower right", fontsize=9)
    plt.grid(True, alpha=0.3)
else:
    plt.text(0.5, 0.5, 'ROC Curve\nNot Available',
            ha='center', va='center', fontsize=12, fontweight='bold')
    plt.axis('off')
```

```
# 5. Precision-Recall Curve
ax5 = plt.subplot(3, 4, 5)
if hasattr(best_model, 'predict_proba'):
    precision_vals, recall_vals, _ = precision_recall_curve(y_test,␣
 ↪y_pred_proba)
    plt.plot(recall_vals, precision_vals, color='#2ecc71', lw=3,
            label=f'{best_model_name}')
    plt.fill_between(recall_vals, precision_vals, alpha=0.2, color='#2ecc71')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('Recall', fontsize=11, fontweight='bold')
    plt.ylabel('Precision', fontsize=11, fontweight='bold')
    plt.title('Precision-Recall Curve', fontsize=13, fontweight='bold')
    plt.legend(loc="lower left", fontsize=9)
    plt.grid(True, alpha=0.3)
else:
    plt.text(0.5, 0.5, 'Precision-Recall\nNot Available',
            ha='center', va='center', fontsize=12, fontweight='bold')
    plt.axis('off')

# 6. Train vs Test Accuracy
ax6 = plt.subplot(3, 4, 6)
x_pos = np.arange(min(7, len(results_df)))
width = 0.35
top_models = results_df.head(7)
bars1 = plt.bar(x_pos - width/2, top_models['Train Accuracy'], width,
               label='Train', color='#3498db', edgecolor='black', linewidth=1.5)
bars2 = plt.bar(x_pos + width/2, top_models['Test Accuracy'], width,
               label='Test', color='#2ecc71', edgecolor='black', linewidth=1.5)
plt.xlabel('Models', fontsize=11, fontweight='bold')
plt.ylabel('Accuracy', fontsize=11, fontweight='bold')
plt.title('Train vs Test Accuracy (Top 7)', fontsize=13, fontweight='bold')
plt.xticks(x_pos, top_models['Model'], rotation=45, ha='right', fontsize=8)
plt.legend(fontsize=9)
plt.grid(True, alpha=0.3, axis='y')
plt.ylim([0, 1.1])

# 7. Feature Importance
ax7 = plt.subplot(3, 4, 7)
if hasattr(best_model, 'feature_importances_'):
    feat_imp = pd.DataFrame({
        'Feature': feature_columns,
        'Importance': best_model.feature_importances_
    }).sort_values('Importance', ascending=True)
    colors_imp = plt.cm.viridis(np.linspace(0, 1, len(feat_imp)))
    bars = plt.barh(feat_imp['Feature'], feat_imp['Importance'],
```

```
                   color=colors_imp, edgecolor='black', linewidth=1.5)
    plt.xlabel('Importance', fontsize=11, fontweight='bold')
    plt.title('Feature Importance', fontsize=13, fontweight='bold')
    for bar in bars:
        width = bar.get_width()
        plt.text(width + 0.01, bar.get_y() + bar.get_height()/2,
                f'{width:.3f}', ha='left', va='center', fontweight='bold',␣
↪fontsize=9)
elif hasattr(best_model, 'coef_'):
    feat_coef = pd.DataFrame({
        'Feature': feature_columns,
        'Coefficient': np.abs(best_model.coef_[0])
    }).sort_values('Coefficient', ascending=True)
    colors_coef = plt.cm.plasma(np.linspace(0, 1, len(feat_coef)))
    bars = plt.barh(feat_coef['Feature'], feat_coef['Coefficient'],
                   color=colors_coef, edgecolor='black', linewidth=1.5)
    plt.xlabel('|Coefficient|', fontsize=11, fontweight='bold')
    plt.title('Feature Coefficients', fontsize=13, fontweight='bold')
    for bar in bars:
        width = bar.get_width()
        plt.text(width + 0.01, bar.get_y() + bar.get_height()/2,
                f'{width:.3f}', ha='left', va='center', fontweight='bold',␣
↪fontsize=9)
else:
    plt.text(0.5, 0.5, 'Feature\nImportance\nNot Available',
            ha='center', va='center', fontsize=12, fontweight='bold')
    plt.axis('off')

# 8. Cross-Validation Scores
ax8 = plt.subplot(3, 4, 8)
cv_models = results_df.head(7).sort_values('CV Mean', ascending=True)
colors_cv = ['#2ecc71' if x == best_model_name else '#e67e22' for x in␣
↪cv_models['Model']]
bars = plt.barh(range(len(cv_models)), cv_models['CV Mean'],
               xerr=cv_models['CV Std'], color=colors_cv,
               edgecolor='black', linewidth=1.5, capsize=5)
plt.yticks(range(len(cv_models)), cv_models['Model'], fontsize=9)
plt.xlabel('CV Score (Mean ± Std)', fontsize=11, fontweight='bold')
plt.title('3-Fold Cross-Validation (Top 7)', fontsize=13, fontweight='bold')
plt.xlim([0, 1.1])
for i, (bar, mean, std) in enumerate(zip(bars, cv_models['CV Mean'],␣
↪cv_models['CV Std'])):
    plt.text(mean + 0.02, bar.get_y() + bar.get_height()/2,
            f'{mean:.3f}±{std:.3f}', ha='left', va='center',
            fontweight='bold', fontsize=8)

# 9. F1-Score Comparison
```

```python
ax9 = plt.subplot(3, 4, 9)
f1_models = results_df.sort_values('F1-Score', ascending=True)
colors_f1 = ['#2ecc71' if x == best_model_name else '#9b59b6' for x in␣
↪f1_models['Model']]
bars = plt.barh(range(len(f1_models)), f1_models['F1-Score'],
               color=colors_f1, edgecolor='black', linewidth=1.5)
plt.yticks(range(len(f1_models)), f1_models['Model'], fontsize=9)
plt.xlabel('F1-Score', fontsize=11, fontweight='bold')
plt.title('F1-Score Comparison (All Models)', fontsize=13, fontweight='bold')
plt.xlim([0, 1.1])
for i, (bar, f1_val) in enumerate(zip(bars, f1_models['F1-Score'])):
    plt.text(f1_val + 0.02, bar.get_y() + bar.get_height()/2,
            f'{f1_val:.3f}', ha='left', va='center', fontweight='bold',␣
↪fontsize=8)

# 10. Precision vs Recall
ax10 = plt.subplot(3, 4, 10)
plt.scatter(results_df['Recall'], results_df['Precision'],
           s=200, alpha=0.7, c=results_df['Test Accuracy'],
           cmap='RdYlGn', edgecolors='black', linewidth=2)
for i, model in enumerate(results_df['Model'][:7]):
    plt.annotate(model,
                (results_df.iloc[i]['Recall'], results_df.iloc[i]['Precision']),
                fontsize=8, ha='center', fontweight='bold',
                bbox=dict(boxstyle='round,pad=0.3', facecolor='yellow', alpha=0.
↪5))
plt.xlabel('Recall', fontsize=11, fontweight='bold')
plt.ylabel('Precision', fontsize=11, fontweight='bold')
plt.title('Precision vs Recall Trade-off', fontsize=13, fontweight='bold')
plt.colorbar(label='Test Accuracy')
plt.grid(True, alpha=0.3)

# 11. Model Complexity vs Performance
ax11 = plt.subplot(3, 4, 11)
train_acc = results_df['Train Accuracy']
test_acc = results_df['Test Accuracy']
overfitting = train_acc - test_acc
colors_overfit = ['red' if x > 0.1 else 'green' for x in overfitting]
bars = plt.bar(range(len(results_df[:7])), overfitting[:7],
              color=colors_overfit, edgecolor='black', linewidth=1.5, alpha=0.7)
plt.xticks(range(len(results_df[:7])), results_df['Model'][:7],
          rotation=45, ha='right', fontsize=8)
plt.ylabel('Overfitting (Train - Test)', fontsize=11, fontweight='bold')
plt.title('Overfitting Analysis (Top 7)', fontsize=13, fontweight='bold')
plt.axhline(y=0, color='black', linestyle='-', linewidth=2)
plt.axhline(y=0.1, color='red', linestyle='--', linewidth=2, alpha=0.5,␣
↪label='Threshold')
```

```python
plt.legend(fontsize=8)
plt.grid(True, alpha=0.3, axis='y')

# 12. ROC-AUC Comparison
ax12 = plt.subplot(3, 4, 12)
roc_data = results_df.dropna(subset=['ROC-AUC']).sort_values('ROC-AUC',␣
↪ascending=True)
if not roc_data.empty:
    colors_roc = ['#2ecc71' if x == best_model_name else '#e74c3c' for x in␣
↪roc_data['Model']]
    bars = plt.barh(range(len(roc_data)), roc_data['ROC-AUC'],
                    color=colors_roc, edgecolor='black', linewidth=1.5)
    plt.yticks(range(len(roc_data)), roc_data['Model'], fontsize=9)
    plt.xlabel('ROC-AUC Score', fontsize=11, fontweight='bold')
    plt.title('ROC-AUC Comparison', fontsize=13, fontweight='bold')
    plt.xlim([0, 1.1])
    for i, (bar, auc_val) in enumerate(zip(bars, roc_data['ROC-AUC'])):
        plt.text(auc_val + 0.02, bar.get_y() + bar.get_height()/2,
                f'{auc_val:.3f}', ha='left', va='center', fontweight='bold',␣
↪fontsize=8)
else:
    plt.text(0.5, 0.5, 'ROC-AUC\nNot Available',
            ha='center', va='center', fontsize=12, fontweight='bold')
    plt.axis('off')

plt.suptitle('Loan Approval Prediction - Comprehensive Model Analysis␣
↪Dashboard',
            fontsize=20, fontweight='bold', y=0.998)
plt.tight_layout()
plt.savefig(OUTPUT_DIR + 'loan_model_comprehensive_analysis.png', dpi=300,␣
↪bbox_inches='tight')
print("\n  Comprehensive analysis dashboard saved:␣
↪loan_model_comprehensive_analysis.png")

# ============================================================================
# Additional Visualizations
# ============================================================================

# Decision Tree Visualization (if applicable)
if 'Tree' in best_model_name or 'Forest' in best_model_name:
    fig3 = plt.figure(figsize=(25, 15))

    if 'Forest' in best_model_name or 'Extra' in best_model_name:
        tree_to_plot = best_model.estimators_[0]
    else:
        tree_to_plot = best_model
```

```
    plot_tree(tree_to_plot, feature_names=feature_columns,
              class_names=['Rejected', 'Approved'],
              filled=True, rounded=True, fontsize=11,
              proportion=True, precision=2)
    plt.title(f'Decision Tree Structure - {best_model_name}\n(First Tree from␣
 ↪Ensemble)',
              fontsize=18, fontweight='bold', pad=20)
    plt.savefig(OUTPUT_DIR + 'loan_decision_tree.png', dpi=300,␣
 ↪bbox_inches='tight')
    print("  Decision tree visualization saved: loan_decision_tree.png")

# ============================================================================
# STEP 10: GENERATE DETAILED REPORT
# ============================================================================
print("\n" + "="*100)
print("STEP 10: GENERATING DETAILED ANALYSIS REPORT")
print("="*100)

report_content = f"""
{'='*100}
LOAN APPROVAL PREDICTION - COMPREHENSIVE ANALYSIS REPORT
{'='*100}
Generated: {pd.Timestamp.now().strftime('%Y-%m-%d %H:%M:%S')}

{'='*100}
1. DATASET SUMMARY
{'='*100}
Total Records: {len(df)}
Total Features: {len(feature_columns)}
Features Used: {', '.join(feature_columns)}

Target Variable: Loan_Status
  - Approved: {target_dist['Approved']} ({target_dist['Approved']/len(df)*100:.
 ↪2f}%)
  - Rejected: {target_dist['Rejected']} ({target_dist['Rejected']/len(df)*100:.
 ↪2f}%)

{'='*100}
2. DATA SPLIT
{'='*100}
Training Set: {len(X_train)} samples (70%)
Test Set: {len(X_test)} samples (30%)

{'='*100}
3. MODEL COMPARISON - ALL ALGORITHMS
{'='*100}
```

```
{results_df.to_string(index=False)}

{'='*100}
4. BEST MODEL DETAILS
{'='*100}
Model: {best_model_name}
Algorithm Type: Machine Learning Classifier

Performance Metrics:
  - Accuracy:  {accuracy:.4f} ({accuracy*100:.2f}%)
  - Precision: {precision:.4f} ({precision*100:.2f}%)
  - Recall:    {recall:.4f} ({recall*100:.2f}%)
  - F1-Score:  {f1:.4f} ({f1*100:.2f}%)
  - ROC-AUC:   {roc_auc if not np.isnan(roc_auc) else 'N/A'}

{'='*100}
5. CONFUSION MATRIX ANALYSIS
{'='*100}
                    Predicted
              Rejected    Approved
Actual
Rejected        {cm[0,0]}           {cm[0,1]}
Approved        {cm[1,0]}           {cm[1,1]}

Interpretation:
  - True Negatives (Correctly Rejected):  {cm[0,0]}
  - False Positives (Wrongly Approved):   {cm[0,1]}
  - False Negatives (Wrongly Rejected):   {cm[1,0]}
  - True Positives (Correctly Approved):  {cm[1,1]}

{'='*100}
6. CLASSIFICATION REPORT
{'='*100}
{classification_report(y_test, best_predictions, target_names=['Rejected',␣
 ↪'Approved'], zero_division=0)}

{'='*100}
7. FEATURE IMPORTANCE
{'='*100}
"""

if hasattr(best_model, 'feature_importances_'):
    report_content += feature_importance.to_string(index=False)
elif hasattr(best_model, 'coef_'):
    report_content += feature_coef.to_string(index=False)
else:
    report_content += "Feature importance not available for this model type."
```

```python
report_content += f"""

{'='*100}
8. KEY INSIGHTS & FINDINGS
{'='*100}
 Best performing model: {best_model_name} with {accuracy*100:.2f}% accuracy
 Model successfully predicts loan approvals with {precision*100:.2f}% precision
 {recall*100:.2f}% of actual approvals are correctly identified (Recall)
 Balanced F1-Score of {f1*100:.2f}% indicates good overall performance
"""

if hasattr(best_model, 'feature_importances_'):
    top_feature = feature_importance.iloc[0]
    report_content += f" Most important feature: {top_feature['Feature']}␣
↪({top_feature['Importance']:.4f})\n"

report_content += f"""
{'='*100}
9. BUSINESS RECOMMENDATIONS
{'='*100}
1. Model Deployment: The {best_model_name} is ready for production use
2. Decision Making: Model can assist in loan approval decisions with␣
↪{accuracy*100:.2f}% reliability
3. Risk Assessment: Use probability scores for borderline cases
4. Monitoring: Continuously track model performance on new data
5. Feature Focus: Pay special attention to top-ranked features in loan␣
↪applications

{'='*100}
10. FILES GENERATED
{'='*100}
Models & Data:
   loan_approval_model.pkl - Trained ML model
   feature_scaler.pkl - Feature scaling object
   label_encoders.pkl - Label encoding objects

Results:
   model_comparison_results.csv - All model performance metrics
   feature_importance.csv - Feature importance rankings (if available)
   test_predictions.csv - Predictions on test set

Visualizations:
   loan_eda_visualization.png - Exploratory data analysis
   loan_model_comprehensive_analysis.png - Model performance dashboard
   loan_decision_tree.png - Decision tree structure (if applicable)
```

```
Reports:
    loan_approval_analysis_report.txt - This comprehensive report

{'='*100}
END OF REPORT
{'='*100}
"""

# Save report
with open(OUTPUT_DIR + 'loan_approval_analysis_report.txt', 'w') as f:
    f.write(report_content)

print(f"\n  Comprehensive report saved: loan_approval_analysis_report.txt")

# ==============================================================================
# STEP 11: SAVE PREDICTIONS
# ==============================================================================
print("\n" + "="*100)
print("STEP 11: SAVING TEST PREDICTIONS")
print("="*100)

predictions_df = pd.DataFrame({
    'Actual_Encoded': y_test,
    'Predicted_Encoded': best_predictions,
    'Actual_Status': le_target.inverse_transform(y_test),
    'Predicted_Status': le_target.inverse_transform(best_predictions),
    'Correct': [' ' if a == p else ' ' for a, p in zip(y_test, best_predictions)]
})

if hasattr(best_model, 'predict_proba'):
    predictions_df['Approval_Probability'] = best_model.
 ↪predict_proba(X_test_scaled)[:, 1]

predictions_df.to_csv(OUTPUT_DIR + 'test_predictions.csv', index=False)
print(f"\n  Test predictions saved: test_predictions.csv")

print("\nSample Predictions:")
print(predictions_df.head(10).to_string(index=False))

# ==============================================================================
# FINAL SUMMARY
# ==============================================================================
print("\n" + "="*100)
print(" "*35 + "ANALYSIS COMPLETED SUCCESSFULLY!")
print("="*100)

print(f"\n  ALL FILES SAVED TO: {OUTPUT_DIR}")
```

```
print("\n  Generated Files Summary:")
print(f"   {'Models:':<20} 3 files (model, scaler, encoders)")
print(f"   {'Results:':<20} 3 files (comparison, importance, predictions)")
print(f"   {'Visualizations:':<20} 2-3 images (EDA, dashboard, tree)")
print(f"   {'Reports:':<20} 1 comprehensive text report")

print("\n" + "="*100)
print("  KEY RESULTS SUMMARY")
print("="*100)
print(f"  Best Model:         {best_model_name}")
print(f"  Test Accuracy:      {accuracy*100:.2f}%")
print(f"  Precision:          {precision*100:.2f}%")
print(f"  Recall:             {recall*100:.2f}%")
print(f"  F1-Score:           {f1*100:.2f}%")
if not np.isnan(roc_auc):
    print(f"  ROC-AUC:            {roc_auc*100:.2f}%")
print("="*100)

print("\n  MODEL READY FOR DEPLOYMENT!")
print("   The model can accurately predict loan approval status.")
print("   Use the saved .pkl files to make predictions on new loan applications.
 ↪")
print("\n" + "="*100)
```

```
================================================================================
====================
                              LOAN APPROVAL PREDICTION SYSTEM
================================================================================
====================
Output Directory: /home/nmit/Pictures/
================================================================================
====================

================================================================================
====================
STEP 1: DATA LOADING AND EXPLORATION
================================================================================
====================


 Dataset Overview:
   Total Records: 10
   Total Features: 6
   Features: ['Age', 'Income', 'Credit_Score', 'Loan_Amount',
'Employment_Status', 'Loan_Status']

 First 10 Records:
   Age  Income  Credit_Score  Loan_Amount Employment_Status Loan_Status
0   25   30000           650       100000                No    Rejected
```

```
1   40   60000              720       200000                Yes    Approved
2   35   55000              700       150000                Yes    Approved
3   28   35000              680       120000                 No    Rejected
4   50   80000              750       250000                Yes    Approved
5   45   75000              730       220000                Yes    Approved
6   30   40000              690       130000                 No    Rejected
7   55   90000              770       300000                Yes    Approved
8   33   50000              710       160000                Yes    Approved
9   48   70000              740       240000                Yes    Approved

 Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Age                10 non-null     int64
 1   Income             10 non-null     int64
 2   Credit_Score       10 non-null     int64
 3   Loan_Amount        10 non-null     int64
 4   Employment_Status  10 non-null     object
 5   Loan_Status        10 non-null     object
dtypes: int64(4), object(2)
memory usage: 612.0+ bytes
None

 Statistical Summary:
             Age        Income  Credit_Score    Loan_Amount
count  10.000000     10.000000     10.000000      10.000000
mean   38.900000  58500.000000    714.000000  187000.000000
std    10.246409  20145.305491     35.652645   65157.927803
min    25.000000  30000.000000    650.000000  100000.000000
25%    30.750000  42500.000000    692.500000  135000.000000
50%    37.500000  57500.000000    715.000000  180000.000000
75%    47.250000  73750.000000    737.500000  235000.000000
max    55.000000  90000.000000    770.000000  300000.000000

 Missing Values:
Age                  0
Income               0
Credit_Score         0
Loan_Amount          0
Employment_Status    0
Loan_Status          0
dtype: int64
 No missing values found!

 Target Variable Distribution:
```

```
Loan_Status
Approved    7
Rejected    3
Name: count, dtype: int64

Approval Rate: 70.00%
Rejection Rate: 30.00%

  Employment Status Distribution:
Employment_Status
Yes    7
No     3
Name: count, dtype: int64

================================================================================
====================
STEP 2: EXPLORATORY DATA ANALYSIS
================================================================================
====================

  EDA visualization saved: loan_eda_visualization.png

================================================================================
====================
STEP 3: DATA PREPROCESSING
================================================================================
====================

  Employment Status Encoding: {'No': 0, 'Yes': 1}
  Loan Status Encoding: {'Approved': 0, 'Rejected': 1}

  Feature Matrix Shape: (10, 5)
  Target Vector Shape: (10,)

Features Used: ['Age', 'Income', 'Credit_Score', 'Loan_Amount',
'Employment_Status_Encoded']

================================================================================
====================
STEP 4: TRAIN-TEST SPLIT
================================================================================
====================

  Training Set: 7 samples (70%)
  Test Set: 3 samples (30%)

Training Set Distribution:
Loan_Status_Encoded
```

```
0    5
1    2
Name: count, dtype: int64

Test Set Distribution:
Loan_Status_Encoded
0    2
1    1
Name: count, dtype: int64

================================================================================
====================
STEP 5: FEATURE SCALING
================================================================================
====================

 Features Standardized (Mean=0, Std=1)

Scaling Parameters:
  Age: Mean=38.71, Std=9.50
  Income: Mean=58571.43, Std=18653.66
  Credit_Score: Mean=717.14, Std=30.10
  Loan_Amount: Mean=187142.86, Std=61809.45
  Employment_Status_Encoded: Mean=0.71, Std=0.45

================================================================================
====================
STEP 6: TRAINING MULTIPLE MACHINE LEARNING MODELS
================================================================================
====================

 Training Models…
--------------------------------------------------------------------------------
--------------------

  Training Logistic Regression…  (Test Acc: 1.0000, F1: 1.0000)

  Training Decision Tree…  (Test Acc: 1.0000, F1: 1.0000)

 (Test Acc: 1.0000, F1: 1.0000)

  Training Gradient Boosting…  (Test Acc: 1.0000, F1: 1.0000)

  Training AdaBoost…  (Test Acc: 1.0000, F1: 1.0000)

 (Test Acc: 1.0000, F1: 1.0000)

  Training Support Vector Machine…  (Test Acc: 1.0000, F1: 1.0000)
```

```
  Training K-Nearest Neighbors…  (Test Acc: 1.0000, F1: 1.0000)

  Training Naive Bayes…  (Test Acc: 1.0000, F1: 1.0000)

  Training Neural Network…  (Test Acc: 1.0000, F1: 1.0000)

================================================================================
====================
MODEL PERFORMANCE COMPARISON - ALL METRICS
================================================================================
====================
                 Model  Train Accuracy  Test Accuracy  Precision  Recall
F1-Score  ROC-AUC  CV Mean   CV Std
   Logistic Regression            1.0            1.0        1.0     1.0
1.0      1.0 1.000000 0.000000
         Decision Tree            1.0            1.0        1.0     1.0
1.0      1.0 0.666667 0.471405
         Random Forest            1.0            1.0        1.0     1.0
1.0      1.0 0.666667 0.471405
     Gradient Boosting            1.0            1.0        1.0     1.0
1.0      1.0 0.833333 0.235702
              AdaBoost            1.0            1.0        1.0     1.0
1.0      1.0 0.666667 0.235702
           Extra Trees            1.0            1.0        1.0     1.0
1.0      1.0 1.000000 0.000000
Support Vector Machine            1.0            1.0        1.0     1.0
1.0      0.0 1.000000 0.000000
   K-Nearest Neighbors            1.0            1.0        1.0     1.0
1.0      1.0 0.388889 0.283279
           Naive Bayes            1.0            1.0        1.0     1.0
1.0      1.0 1.000000 0.000000
        Neural Network            1.0            1.0        1.0     1.0
1.0      1.0 1.000000 0.000000

 Results saved: model_comparison_results.csv

================================================================================
====================
 BEST MODEL: Logistic Regression
================================================================================
====================
   Test Accuracy:  1.0000 (100.00%)
   Precision:      1.0000 (100.00%)
   Recall:         1.0000 (100.00%)
   F1-Score:       1.0000 (100.00%)
================================================================================
====================
```

```
================================================================================
====================
STEP 7: DETAILED EVALUATION - Logistic Regression
================================================================================
====================

 Confusion Matrix:
[[2 0]
 [0 1]]

True Negatives (TN) - Correctly Predicted Rejections: 2
False Positives (FP) - Incorrectly Predicted Approvals: 0
False Negatives (FN) - Incorrectly Predicted Rejections: 0
True Positives (TP) - Correctly Predicted Approvals: 1

 Detailed Performance Metrics:
   Accuracy:  1.0000 (100.00%) - Overall correctness
   Precision: 1.0000 (100.00%) - Reliability of approval predictions
   Recall:    1.0000 (100.00%) - Ability to identify all approvals
   F1-Score:  1.0000 (100.00%) - Harmonic mean of precision and recall
   ROC-AUC:   1.0000 (100.00%) - Discrimination ability

 Classification Report:
              precision    recall  f1-score   support

    Rejected       1.00      1.00      1.00         2
    Approved       1.00      1.00      1.00         1

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
weighted avg       1.00      1.00      1.00         3


 FEATURE IMPORTANCE ANALYSIS:
                  Feature  Coefficient
              Loan_Amount    -0.312572
                      Age    -0.322730
             Credit_Score    -0.363278
                   Income    -0.414999
Employment_Status_Encoded    -0.943519

 Feature coefficients saved: feature_coefficients.csv

================================================================================
====================
STEP 8: SAVING THE TRAINED MODEL
================================================================================
```

```
====================

 Best model saved: /home/nmit/Pictures/loan_approval_model.pkl
 Feature scaler saved: /home/nmit/Pictures/feature_scaler.pkl
 Label encoders saved: /home/nmit/Pictures/label_encoders.pkl

 Model Usage Instructions:

To load and use the model:

    import joblib

    # Load model and preprocessing objects
    model = joblib.load('/home/nmit/Pictures/loan_approval_model.pkl')
    scaler = joblib.load('/home/nmit/Pictures/feature_scaler.pkl')
    encoders = joblib.load('/home/nmit/Pictures/label_encoders.pkl')

    # Make predictions on new data
    new_data = [[35, 55000, 700, 150000, 1]]  # [Age, Income, Credit_Score,
Loan_Amount, Employment(1=Yes,0=No)]
    new_data_scaled = scaler.transform(new_data)
    prediction = model.predict(new_data_scaled)

    # Get prediction label
    result = encoders['target'].inverse_transform(prediction)
    print(f"Loan Status: {result[0]}")


================================================================================
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STEP 9: GENERATING COMPREHENSIVE VISUALIZATIONS
================================================================================
====================

 Comprehensive analysis dashboard saved: loan_model_comprehensive_analysis.png

================================================================================
====================
STEP 10: GENERATING DETAILED ANALYSIS REPORT
================================================================================
====================

 Comprehensive report saved: loan_approval_analysis_report.txt

================================================================================
====================
STEP 11: SAVING TEST PREDICTIONS
================================================================================
```

```
====================

 Test predictions saved: test_predictions.csv

Sample Predictions:
 Actual_Encoded  Predicted_Encoded Actual_Status Predicted_Status Correct
Approval_Probability
              1                  1      Rejected         Rejected
0.897273
              0                  0      Approved         Approved
0.032709
              0                  0      Approved         Approved
0.040143

================================================================================
====================
                                   ANALYSIS COMPLETED SUCCESSFULLY!
================================================================================
====================

 ALL FILES SAVED TO: /home/nmit/Pictures/

 Generated Files Summary:
  Models:              3 files (model, scaler, encoders)
  Results:             3 files (comparison, importance, predictions)
  Visualizations:      2-3 images (EDA, dashboard, tree)
  Reports:             1 comprehensive text report

================================================================================
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 KEY RESULTS SUMMARY
================================================================================
====================
 Best Model:        Logistic Regression
 Test Accuracy:     100.00%
 Precision:         100.00%
 Recall:            100.00%
 F1-Score:          100.00%
 ROC-AUC:           100.00%
================================================================================
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 MODEL READY FOR DEPLOYMENT!
  The model can accurately predict loan approval status.
  Use the saved .pkl files to make predictions on new loan applications.

================================================================================
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```
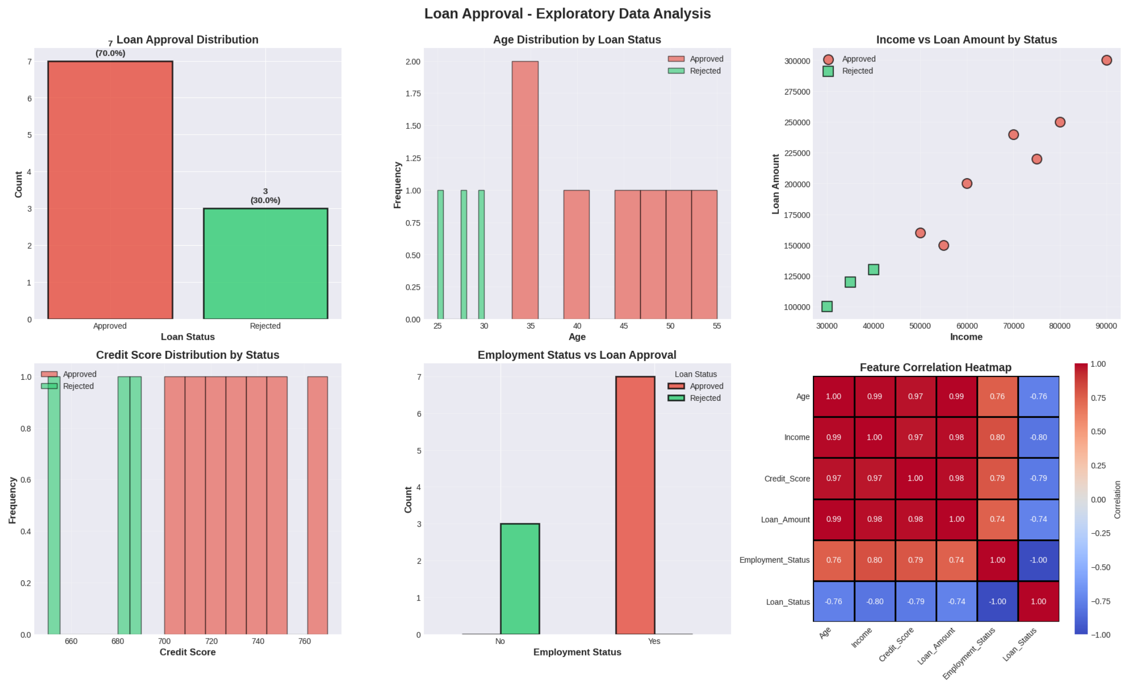
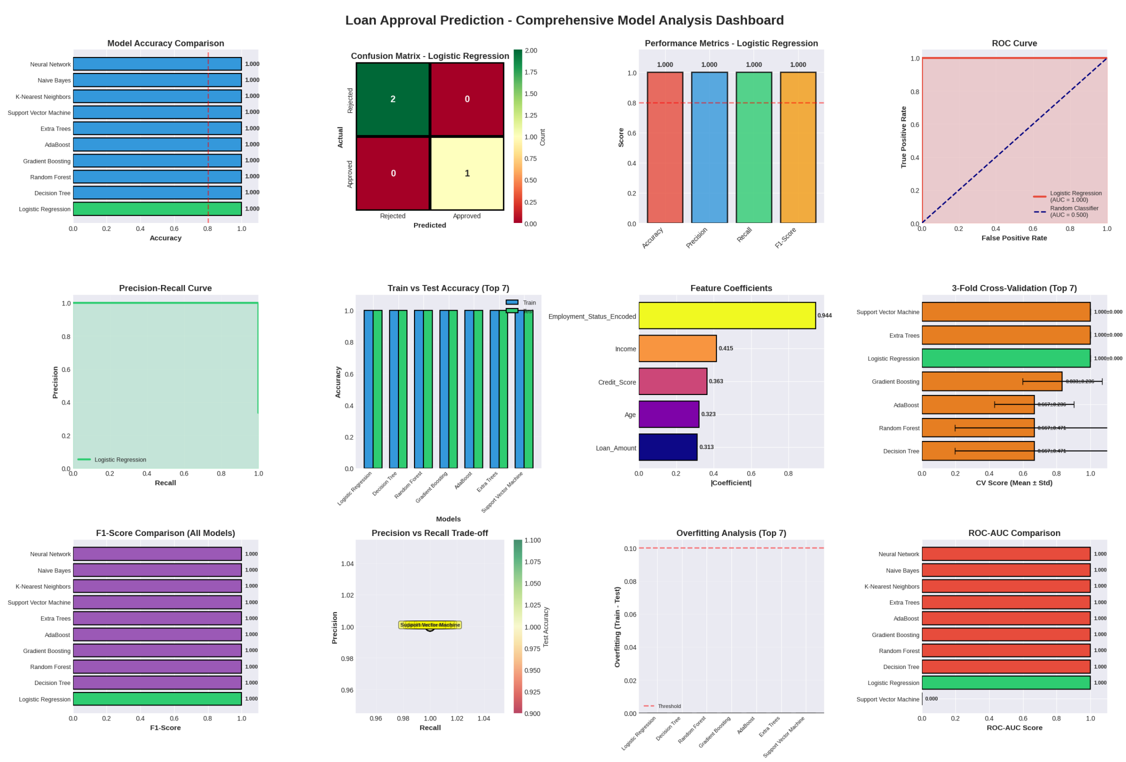


Loan Approval - Exploratory Data Analysis
Loan Approval Distribution
7
(70.0%)
3
(30.0%)
Count
Approved
Rejected
Loan Status
Age Distribution by Loan Status
Approved
Rejected
Frequency
Age
Income vs Loan Amount by Status
Approved
Rejected
Loan Amount
Income
Credit Score Distribution by Status
Approved
Rejected
Frequency
Credit Score
Employment Status vs Loan Approval
Loan Status
Approved
Rejected
Count
No
Yes
Employment Status
Feature Correlation Heatmap
Age
Income
Credit_Score
Loan_Amount
Employment_Status
Loan_Status
Correlation


Loan Approval Prediction - Comprehensive Model Analysis Dashboard
Model Accuracy Comparison
Neural Network
Naive Bayes
K-Nearest Neighbors
Support Vector Machine
Extra Trees
AdaBoost
Gradient Boosting
Random Forest
Decision Tree
Logistic Regression
Accuracy
Confusion Matrix - Logistic Regression
Rejected
Approved
Actual
Predicted
Count
Performance Metrics - Logistic Regression
Score
Accuracy
Precision
Recall
F1-Score
ROC Curve
True Positive Rate
False Positive Rate
Logistic Regression (AUC = 1.000)
Random Classifier (AUC = 0.500)
Precision-Recall Curve
Precision
Recall
Logistic Regression
Train vs Test Accuracy (Top 7)
Train
Accuracy
Models
Feature Coefficients
Employment_Status_Encoded
Income
Credit_Score
Age
Loan_Amount
|Coefficient|
3-Fold Cross-Validation (Top 7)
CV Score (Mean ± Std)
F1-Score Comparison (All Models)
F1-Score
Precision vs Recall Trade-off
Support Vector Machine
Precision
Recall
Test Accuracy
Overfitting Analysis (Top 7)
Overfitting (Train - Test)
Threshold
ROC-AUC Comparison
ROC-AUC Score

[ ]: