Student_Prediction

February 10, 2026

[4]:
```python
"""
Student Placement Prediction - Machine Learning Classification Model
Complete Pipeline: Data Analysis, Model Training, Evaluation & Visualization
"""

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
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import (accuracy_score, precision_score, recall_score,
                             f1_score, confusion_matrix, classification_report,
                             roc_curve, auc, roc_auc_score)
import warnings
warnings.filterwarnings('ignore')

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

print("="*90)
print("STUDENT PLACEMENT PREDICTION - MACHINE LEARNING CLASSIFICATION")
print("="*90)

# ========================================================================
# 1. DATA LOADING AND EXPLORATION
# ========================================================================
print("\n" + "="*90)
print("STEP 1: DATA LOADING AND EXPLORATION")
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print("="*90)

df = pd.read_csv('/home/nmit/Documents/Student_Placement.csv')

print(f"\n  Dataset Shape: {df.shape}")
print(f"   - Total Students: {df.shape[0]}")
print(f"   - Total Features: {df.shape[1]}")

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

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

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

print("\n  Missing Values:")
print(df.isnull().sum())

print("\n  Target Variable Distribution:")
print(df['Placement_Status'].value_counts())
print(f"\nPlacement Rate: {(df['Placement_Status'].str.contains('Placed', case=False).sum() / len(df) * 100):.2f}%")

# ============================================================================
# 2. DATA PREPROCESSING
# ============================================================================
print("\n" + "="*90)
print("STEP 2: DATA PREPROCESSING")
print("="*90)

# Handle the target variable (fix inconsistency in data)
df['Placement_Status'] = df['Placement_Status'].str.strip()
df['Placement_Status'] = df['Placement_Status'].replace('Not Place', 'Not Placed')

print("\n  Cleaned Placement Status")
print(f"Unique values: {df['Placement_Status'].unique()}")

# Encode target variable
le = LabelEncoder()
df['Placement_Encoded'] = le.fit_transform(df['Placement_Status'])
print(f"\n  Label Encoding: {dict(zip(le.classes_, le.transform(le.classes_)))}")

# Separate features and target
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X = df.drop(['Placement_Status', 'Placement_Encoded'], axis=1)
y = df['Placement_Encoded']

print(f"\n  Feature Matrix Shape: {X.shape}")
print(f"  Target Vector Shape: {y.shape}")
print(f"\nFeature Names: {list(X.columns)}")

# ============================================================================
# 3. TRAIN-TEST SPLIT
# ============================================================================
print("\n" + "="*90)
print("STEP 3: TRAIN-TEST SPLIT")
print("="*90)

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 Size: {X_train.shape[0]} samples ({(len(X_train)/
 ↪len(X)*100):.0f}%)")
print(f"  Test Set Size: {X_test.shape[0]} samples ({(len(X_test)/len(X)*100):.
 ↪0f}%)")
print(f"\nTraining set class distribution:")
print(pd.Series(y_train).value_counts())
print(f"\nTest set class distribution:")
print(pd.Series(y_test).value_counts())

# ============================================================================
# 4. FEATURE SCALING
# ============================================================================
print("\n" + "="*90)
print("STEP 4: FEATURE SCALING")
print("="*90)

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(X.columns):
    print(f"  {col}: Mean={scaler.mean_[i]:.2f}, Std={scaler.scale_[i]:.2f}")

# ============================================================================
# 5. MODEL TRAINING - MULTIPLE ALGORITHMS
# ============================================================================
print("\n" + "="*90)
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```python
print("STEP 5: TRAINING MULTIPLE CLASSIFICATION MODELS")
print("="*90)

# Define 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),
    'Support Vector Machine': SVC(kernel='rbf', random_state=42,␣
 ↪probability=True),
    'K-Nearest Neighbors': KNeighborsClassifier(n_neighbors=3),
    'Naive Bayes': GaussianNB(),
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100,␣
 ↪random_state=42)
}

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

print("\n  Training Models...")
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

    # Make predictions
    y_pred_train = model.predict(X_train_scaled)
    y_pred_test = model.predict(X_test_scaled)

    # 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 score
    cv_scores = cross_val_score(model, X_train_scaled, y_train, cv=3,␣
 ↪scoring='accuracy')
    cv_mean = cv_scores.mean()

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

    print(f"  (Accuracy: {test_accuracy:.4f})")

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

print("\n" + "="*90)
print("MODEL PERFORMANCE COMPARISON")
print("="*90)
print(results_df.to_string(index=False))

# Select best model
best_model_name = results_df.iloc[0]['Model']
best_model = trained_models[best_model_name]
print(f"\n  BEST MODEL: {best_model_name}")
print(f"   Test Accuracy: {results_df.iloc[0]['Test Accuracy']:.4f}")

# ============================================================================
# 6. DETAILED EVALUATION OF BEST MODEL
# ============================================================================
print("\n" + "="*90)
print(f"STEP 6: DETAILED EVALUATION - {best_model_name}")
print("="*90)

# Predictions
y_pred = best_model.predict(X_test_scaled)
y_pred_proba = best_model.predict_proba(X_test_scaled)[:, 1] if hasattr(best_model, 'predict_proba') else None

# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
print("\n  Confusion Matrix:")
print(cm)
print(f"\nTrue Negatives (TN): {cm[0,0]}")
print(f"False Positives (FP): {cm[0,1]}")
print(f"False Negatives (FN): {cm[1,0]}")
print(f"True Positives (TP): {cm[1,1]}")

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

print("\n  Performance Metrics:")
print(f"    Accuracy:  {accuracy:.4f} ({accuracy*100:.2f}%)")
print(f"    Precision: {precision:.4f} ({precision*100:.2f}%)")
print(f"    Recall:    {recall:.4f} ({recall*100:.2f}%)")
print(f"    F1-Score:  {f1:.4f} ({f1*100:.2f}%)")

if y_pred_proba is not None:
    roc_auc = roc_auc_score(y_test, y_pred_proba)
    print(f"    ROC-AUC:   {roc_auc:.4f} ({roc_auc*100:.2f}%)")

print("\n  Classification Report:")
print(classification_report(y_test, y_pred,
                            target_names=['Not Placed', 'Placed'],
                            zero_division=0))

# Feature Importance (if available)
if hasattr(best_model, 'feature_importances_'):
    print("\n  Feature Importance:")
    feature_importance = pd.DataFrame({
        'Feature': X.columns,
        'Importance': best_model.feature_importances_
    }).sort_values('Importance', ascending=False)
    print(feature_importance.to_string(index=False))
elif hasattr(best_model, 'coef_'):
    print("\n  Feature Coefficients:")
    feature_coef = pd.DataFrame({
        'Feature': X.columns,
        'Coefficient': best_model.coef_[0]
    }).sort_values('Coefficient', ascending=False)
    print(feature_coef.to_string(index=False))

# ============================================================================
# 7. VISUALIZATIONS
# ============================================================================
print("\n" + "="*90)
print("STEP 7: GENERATING VISUALIZATIONS")
print("="*90)

# Create comprehensive visualization
fig = plt.figure(figsize=(20, 16))

# 1. Model Comparison - Accuracy
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```python
ax1 = plt.subplot(3, 3, 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(models_sorted['Model'], models_sorted['Test Accuracy'],␣
↪color=colors, edgecolor='black', linewidth=1.5)
plt.xlabel('Accuracy', fontsize=12, fontweight='bold')
plt.title('Model Accuracy Comparison', fontsize=14, fontweight='bold')
plt.xlim([0, 1.1])
for i, bar in enumerate(bars):
    width = bar.get_width()
    plt.text(width + 0.02, bar.get_y() + bar.get_height()/2,
            f'{width:.3f}', ha='left', va='center', fontweight='bold')
plt.axvline(x=0.8, color='red', linestyle='--', alpha=0.5, label='80%␣
↪Threshold')
plt.legend()

# 2. Confusion Matrix Heatmap
ax2 = plt.subplot(3, 3, 2)
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', square=True,
           xticklabels=['Not Placed', 'Placed'],
           yticklabels=['Not Placed', 'Placed'],
           cbar_kws={'label': 'Count'}, linewidths=2, linecolor='black')
plt.ylabel('Actual', fontsize=12, fontweight='bold')
plt.xlabel('Predicted', fontsize=12, fontweight='bold')
plt.title(f'Confusion Matrix - {best_model_name}', fontsize=14,␣
↪fontweight='bold')

# 3. Performance Metrics Bar Chart
ax3 = plt.subplot(3, 3, 3)
metrics_data = {
    'Accuracy': accuracy,
    'Precision': precision,
    'Recall': recall,
    'F1-Score': f1
}
bars = plt.bar(metrics_data.keys(), metrics_data.values(),
              color=['#e74c3c', '#3498db', '#2ecc71', '#f39c12'],
              edgecolor='black', linewidth=2, alpha=0.8)
plt.ylabel('Score', fontsize=12, fontweight='bold')
plt.title(f'Performance Metrics - {best_model_name}', fontsize=14,␣
↪fontweight='bold')
plt.ylim([0, 1.1])
plt.axhline(y=0.8, color='red', linestyle='--', alpha=0.5)
for bar in bars:
    height = bar.get_height()
    plt.text(bar.get_x() + bar.get_width()/2., height + 0.02,
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            f'{height:.3f}', ha='center', va='bottom', fontweight='bold',␣
 ↪fontsize=11)

# 4. ROC Curve (if available)
ax4 = plt.subplot(3, 3, 4)
if y_pred_proba is not None:
    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} (AUC =␣
 ↪{roc_auc:.3f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--', label='Random␣
 ↪Classifier')
    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=12, fontweight='bold')
    plt.ylabel('True Positive Rate', fontsize=12, fontweight='bold')
    plt.title('ROC Curve', fontsize=14, fontweight='bold')
    plt.legend(loc="lower right", fontsize=10)
    plt.grid(True, alpha=0.3)
else:
    plt.text(0.5, 0.5, 'ROC Curve\nNot Available\nfor this model',
            ha='center', va='center', fontsize=14)
    plt.axis('off')

# 5. Train vs Test Accuracy
ax5 = plt.subplot(3, 3, 5)
x = np.arange(len(results_df))
width = 0.35
bars1 = plt.bar(x - width/2, results_df['Train Accuracy'], width,
               label='Train', color='#3498db', edgecolor='black', linewidth=1.5)
bars2 = plt.bar(x + width/2, results_df['Test Accuracy'], width,
               label='Test', color='#2ecc71', edgecolor='black', linewidth=1.5)
plt.xlabel('Models', fontsize=12, fontweight='bold')
plt.ylabel('Accuracy', fontsize=12, fontweight='bold')
plt.title('Train vs Test Accuracy (Overfitting Check)', fontsize=14,␣
 ↪fontweight='bold')
plt.xticks(x, results_df['Model'], rotation=45, ha='right')
plt.legend()
plt.grid(True, alpha=0.3, axis='y')
plt.tight_layout()

# 6. Feature Importance (if available)
ax6 = plt.subplot(3, 3, 6)
if hasattr(best_model, 'feature_importances_'):
    feature_imp = pd.DataFrame({
        'Feature': X.columns,
```

```
        'Importance': best_model.feature_importances_
    }).sort_values('Importance', ascending=True)
    colors_imp = plt.cm.viridis(np.linspace(0, 1, len(feature_imp)))
    bars = plt.barh(feature_imp['Feature'], feature_imp['Importance'],
                   color=colors_imp, edgecolor='black', linewidth=1.5)
    plt.xlabel('Importance', fontsize=12, fontweight='bold')
    plt.title('Feature Importance', fontsize=14, fontweight='bold')
    for i, bar in enumerate(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')
elif hasattr(best_model, 'coef_'):
    feature_coef = pd.DataFrame({
        'Feature': X.columns,
        'Coefficient': np.abs(best_model.coef_[0])
    }).sort_values('Coefficient', ascending=True)
    colors_coef = plt.cm.plasma(np.linspace(0, 1, len(feature_coef)))
    bars = plt.barh(feature_coef['Feature'], feature_coef['Coefficient'],
                   color=colors_coef, edgecolor='black', linewidth=1.5)
    plt.xlabel('Absolute Coefficient Value', fontsize=12, fontweight='bold')
    plt.title('Feature Coefficients', fontsize=14, fontweight='bold')
    for i, bar in enumerate(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')
else:
    plt.text(0.5, 0.5, 'Feature Importance\nNot Available\nfor this model',
            ha='center', va='center', fontsize=14)
    plt.axis('off')

# 7. Cross-Validation Scores
ax7 = plt.subplot(3, 3, 7)
models_cv = results_df.sort_values('CV Score', ascending=True)
colors_cv = ['#2ecc71' if x == best_model_name else '#e67e22' for x in␣
 ↪models_cv['Model']]
bars = plt.barh(models_cv['Model'], models_cv['CV Score'], color=colors_cv,
               edgecolor='black', linewidth=1.5)
plt.xlabel('Cross-Validation Score', fontsize=12, fontweight='bold')
plt.title('3-Fold Cross-Validation Scores', fontsize=14, fontweight='bold')
plt.xlim([0, 1.1])
for i, bar in enumerate(bars):
    width = bar.get_width()
    plt.text(width + 0.02, bar.get_y() + bar.get_height()/2,
            f'{width:.3f}', ha='left', va='center', fontweight='bold')

# 8. Target Distribution
ax8 = plt.subplot(3, 3, 8)
```

```python
placement_counts = df['Placement_Status'].value_counts()
colors_pie = ['#e74c3c', '#2ecc71']
wedges, texts, autotexts = plt.pie(placement_counts.values,␣
↪labels=placement_counts.index,
                                    autopct='%1.1f%%', startangle=90,␣
↪colors=colors_pie,
                                    wedgeprops={'edgecolor': 'black',␣
↪'linewidth': 2},
                                    textprops={'fontsize': 12, 'fontweight':␣
↪'bold'})
plt.title('Target Variable Distribution', fontsize=14, fontweight='bold')

# 9. Correlation Heatmap
ax9 = plt.subplot(3, 3, 9)
correlation_matrix = df[list(X.columns) + ['Placement_Encoded']].corr()
sns.heatmap(correlation_matrix, annot=True, fmt='.2f', cmap='coolwarm',
           center=0, square=True, linewidths=1, linecolor='black',
           cbar_kws={'label': 'Correlation'})
plt.title('Feature Correlation Matrix', fontsize=14, fontweight='bold')
plt.xticks(rotation=45, ha='right')
plt.yticks(rotation=0)

plt.suptitle('Student Placement Prediction - Comprehensive Analysis',
            fontsize=18, fontweight='bold', y=0.995)
plt.tight_layout()
plt.savefig('/home/nmit/Pictures/placement_prediction_comprehensive.png',
           dpi=300, bbox_inches='tight')
print("\n Comprehensive visualization saved!")

# ============================================================================
# Additional Visualization: Decision Tree (if best model is tree-based)
# ============================================================================
if 'Decision Tree' in best_model_name or 'Random Forest' in best_model_name:
    fig2 = plt.figure(figsize=(20, 12))

    if 'Decision Tree' in best_model_name:
        tree_model = best_model
    else:
        tree_model = best_model.estimators_[0]

    plot_tree(tree_model, feature_names=X.columns,
             class_names=['Not Placed', 'Placed'],
             filled=True, rounded=True, fontsize=10)
    plt.title(f'Decision Tree Visualization - {best_model_name}',
             fontsize=16, fontweight='bold', pad=20)
    plt.savefig('/home/nmit/Pictures/decision_tree_visualization.png',
               dpi=300, bbox_inches='tight')
```

```
    print("  Decision tree visualization saved!")

# ============================================================================
# Prediction Examples
# ============================================================================
print("\n" + "="*90)
print("STEP 8: SAMPLE PREDICTIONS")
print("="*90)

print("\n  Sample Predictions on Test Data:")
sample_predictions = pd.DataFrame({
    'Actual': ['Placed' if y == 1 else 'Not Placed' for y in y_test[:5]],
    'Predicted': ['Placed' if y == 1 else 'Not Placed' for y in y_pred[:5]],
    'Correct': [' ' if a == p else ' ' for a, p in zip(y_test[:5], y_pred[:5])]
})
print(sample_predictions.to_string(index=False))

# ============================================================================
# Save Results
# ============================================================================
print("\n" + "="*90)
print("STEP 9: SAVING RESULTS")
print("="*90)

# Save model comparison
results_df.to_csv('/home/nmit/Pictures/model_comparison_results.csv', index=False)
print("  Model comparison results saved!")

# Save detailed metrics
with open('/home/nmit/Pictures/placement_prediction_report.txt', 'w') as f:
    f.write("="*90 + "\n")
    f.write("STUDENT PLACEMENT PREDICTION - DETAILED REPORT\n")
    f.write("="*90 + "\n\n")

    f.write("DATASET SUMMARY\n")
    f.write("-"*90 + "\n")
    f.write(f"Total Students: {df.shape[0]}\n")
    f.write(f"Features: {', '.join(X.columns)}\n")
    f.write(f"Placement Rate: {(df['Placement_Status'].str.contains('Placed', case=False).sum() / len(df) * 100):.2f}%\n\n")

    f.write("MODEL COMPARISON\n")
    f.write("-"*90 + "\n")
    f.write(results_df.to_string(index=False))
    f.write("\n\n")
```

```python
    f.write(f"BEST MODEL: {best_model_name}\n")
    f.write("-"*90 + "\n")
    f.write(f"Test Accuracy:  {accuracy:.4f} ({accuracy*100:.2f}%)\n")
    f.write(f"Precision:      {precision:.4f} ({precision*100:.2f}%)\n")
    f.write(f"Recall:         {recall:.4f} ({recall*100:.2f}%)\n")
    f.write(f"F1-Score:       {f1:.4f} ({f1*100:.2f}%)\n\n")

    f.write("CONFUSION MATRIX\n")
    f.write("-"*90 + "\n")
    f.write(f"True Negatives (TN):  {cm[0,0]}\n")
    f.write(f"False Positives (FP): {cm[0,1]}\n")
    f.write(f"False Negatives (FN): {cm[1,0]}\n")
    f.write(f"True Positives (TP):  {cm[1,1]}\n\n")

    f.write("CLASSIFICATION REPORT\n")
    f.write("-"*90 + "\n")
    f.write(classification_report(y_test, y_pred,
                                  target_names=['Not Placed', 'Placed'],
                                  zero_division=0))
    f.write("\n")

    if hasattr(best_model, 'feature_importances_'):
        f.write("FEATURE IMPORTANCE\n")
        f.write("-"*90 + "\n")
        f.write(feature_importance.to_string(index=False))
        f.write("\n")

print("  Detailed report saved!")

# Save predictions
predictions_df = pd.DataFrame({
    'Actual': y_test,
    'Predicted': y_pred,
    'Actual_Label': ['Placed' if y == 1 else 'Not Placed' for y in y_test],
    'Predicted_Label': ['Placed' if y == 1 else 'Not Placed' for y in y_pred]
})
predictions_df.to_csv('/home/nmit/Pictures/test_predictions.csv', index=False)
print("  Test predictions saved!")

print("\n" + "="*90)
print("ANALYSIS COMPLETE!")
print("="*90)
print("\n  Generated Files:")
print("   1. placement_prediction_comprehensive.png - Main visualizations")
print("   2. model_comparison_results.csv - Model performance comparison")
print("   3. placement_prediction_report.txt - Detailed analysis report")
print("   4. test_predictions.csv - Predictions on test data")
```

```python
if 'Decision Tree' in best_model_name or 'Random Forest' in best_model_name:
    print("   5. decision_tree_visualization.png - Decision tree structure")

print("\n" + "="*90)
print("  KEY FINDINGS")
print("="*90)
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}%")
print("\nThe model can predict student placement with high accuracy!")
print("="*90)
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================================================================================
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STUDENT PLACEMENT PREDICTION - MACHINE LEARNING CLASSIFICATION
================================================================================
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================================================================================
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STEP 1: DATA LOADING AND EXPLORATION
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 Dataset Shape: (10, 6)
   - Total Students: 10
   - Total Features: 6

 First 10 Rows:
   CGPA  Internships  Technical_Skills  Communication_Skills  Aptitutde_Score  \
0   6.5            0                60                    55               58
1   7.2            1                70                    65               68
2   8.1            2                85                    80               82
3   8.8            3                90                    85               90
4   5.9            0                55                    50               55
5   7.5            1                75                    70               72
6   9.0            3                95                    90               92
7   6.8            1                65                    60               62
8   8.5            2                88                    82               85
9   6.0            0                58                    52               57

  Placement_Status
0       Not Place
1          Placed
2          Placed
3          Placed
```

```
4       Not Placed
5           Placed
6           Placed
7       Not Placed
8           Placed
9       Not Placed

 Dataset Information:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10 entries, 0 to 9
Data columns (total 6 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   CGPA                  10 non-null     float64
 1   Internships           10 non-null     int64
 2   Technical_Skills      10 non-null     int64
 3   Communication_Skills  10 non-null     int64
 4   Aptitutde_Score       10 non-null     int64
 5   Placement_Status      10 non-null     object
dtypes: float64(1), int64(4), object(1)
memory usage: 612.0+ bytes
None

 Statistical Summary:
            CGPA  Internships  Technical_Skills  Communication_Skills  \
count  10.000000    10.000000         10.000000             10.000000
mean    7.430000     1.300000         74.100000             68.900000
std     1.137297     1.159502         14.624561             14.647336
min     5.900000     0.000000         55.000000             50.000000
25%     6.575000     0.250000         61.250000             56.250000
50%     7.350000     1.000000         72.500000             67.500000
75%     8.400000     2.000000         87.250000             81.500000
max     9.000000     3.000000         95.000000             90.000000

       Aptitutde_Score
count        10.000000
mean         72.100000
std          14.216188
min          55.000000
25%          59.000000
50%          70.000000
75%          84.250000
max          92.000000

 Missing Values:
CGPA                    0
Internships             0
Technical_Skills        0
```

```
Communication_Skills    0
Aptitutde_Score         0
Placement_Status        0
dtype: int64

 Target Variable Distribution:
Placement_Status
Placed        6
Not Placed    3
Not Place     1
Name: count, dtype: int64

Placement Rate: 90.00%

================================================================================
==========
STEP 2: DATA PREPROCESSING
================================================================================
==========

 Cleaned Placement Status
Unique values: ['Not Placed' 'Placed']

 Label Encoding: {'Not Placed': 0, 'Placed': 1}

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

Feature Names: ['CGPA', 'Internships', 'Technical_Skills',
'Communication_Skills', 'Aptitutde_Score']

================================================================================
==========
STEP 3: TRAIN-TEST SPLIT
================================================================================
==========

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

Training set class distribution:
Placement_Encoded
1    4
0    3
Name: count, dtype: int64

Test set class distribution:
Placement_Encoded
```

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

================================================================================
==========
STEP 4: FEATURE SCALING
================================================================================
==========

 Features Standardized (Mean=0, Std=1)

Scaling Parameters:
  CGPA: Mean=7.10, Std=0.94
  Internships: Mean=0.86, Std=0.83
  Technical_Skills: Mean=70.14, Std=12.21
  Communication_Skills: Mean=64.86, Std=12.15
  Aptitutde_Score: Mean=68.14, Std=11.28

================================================================================
==========
STEP 5: TRAINING MULTIPLE CLASSIFICATION MODELS
================================================================================
==========

 Training Models…

  Training Logistic Regression…  (Accuracy: 0.6667)

  Training Decision Tree…  (Accuracy: 0.6667)

 (Accuracy: 1.0000)rest…

  Training Support Vector Machine…  (Accuracy: 0.6667)

  Training K-Nearest Neighbors…  (Accuracy: 0.6667)

  Training Naive Bayes…  (Accuracy: 0.6667)

  Training Gradient Boosting…  (Accuracy: 0.6667)

================================================================================
==========
MODEL PERFORMANCE COMPARISON
================================================================================
==========
                 Model  Train Accuracy  Test Accuracy  Precision  Recall
F1-Score  CV Score
```

```
       Random Forest            1.0       1.000000   1.000000     1.0
1.0  1.000000
   Logistic Regression          1.0       0.666667   0.666667     1.0
0.8  1.000000
       Decision Tree            1.0       0.666667   0.666667     1.0
0.8  1.000000
Support Vector Machine          1.0       0.666667   0.666667     1.0
0.8  1.000000
   K-Nearest Neighbors          1.0       0.666667   0.666667     1.0
0.8  1.000000
         Naive Bayes            1.0       0.666667   0.666667     1.0
0.8  0.833333
     Gradient Boosting          1.0       0.666667   0.666667     1.0
0.8  1.000000

 BEST MODEL: Random Forest
   Test Accuracy: 1.0000

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==========
STEP 6: DETAILED EVALUATION - Random Forest
================================================================================
==========

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

True Negatives (TN): 1
False Positives (FP): 0
False Negatives (FN): 0
True Positives (TP): 2

 Performance Metrics:
   Accuracy:  1.0000 (100.00%)
   Precision: 1.0000 (100.00%)
   Recall:    1.0000 (100.00%)
   F1-Score:  1.0000 (100.00%)
   ROC-AUC:   1.0000 (100.00%)

 Classification Report:
             precision    recall  f1-score   support

  Not Placed       1.00      1.00      1.00         1
      Placed       1.00      1.00      1.00         2

    accuracy                           1.00         3
   macro avg       1.00      1.00      1.00         3
```

```
weighted avg       1.00      1.00      1.00         3


 Feature Importance:
            Feature  Importance
               CGPA    0.224490
Communication_Skills    0.224490
     Aptitutde_Score    0.204082
         Internships    0.193878
    Technical_Skills    0.153061

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==========
STEP 7: GENERATING VISUALIZATIONS
================================================================================
==========

 Comprehensive visualization saved!
 Decision tree visualization saved!

================================================================================
==========
STEP 8: SAMPLE PREDICTIONS
================================================================================
==========

 Sample Predictions on Test Data:
    Actual  Predicted Correct
Not Placed Not Placed
    Placed     Placed
    Placed     Placed

================================================================================
==========
STEP 9: SAVING RESULTS
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==========
 Model comparison results saved!
 Detailed report saved!
 Test predictions saved!

================================================================================
==========
ANALYSIS COMPLETE!
================================================================================
==========

 Generated Files:
```

```
1. placement_prediction_comprehensive.png - Main visualizations
2. model_comparison_results.csv - Model performance comparison
3. placement_prediction_report.txt - Detailed analysis report
4. test_predictions.csv - Predictions on test data
5. decision_tree_visualization.png - Decision tree structure

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==========
 KEY FINDINGS
================================================================================
==========
 Best Model: Random Forest
 Test Accuracy: 100.00%
 Precision: 100.00%
 Recall: 100.00%
 F1-Score: 100.00%

The model can predict student placement with high accuracy!
================================================================================
==========
```

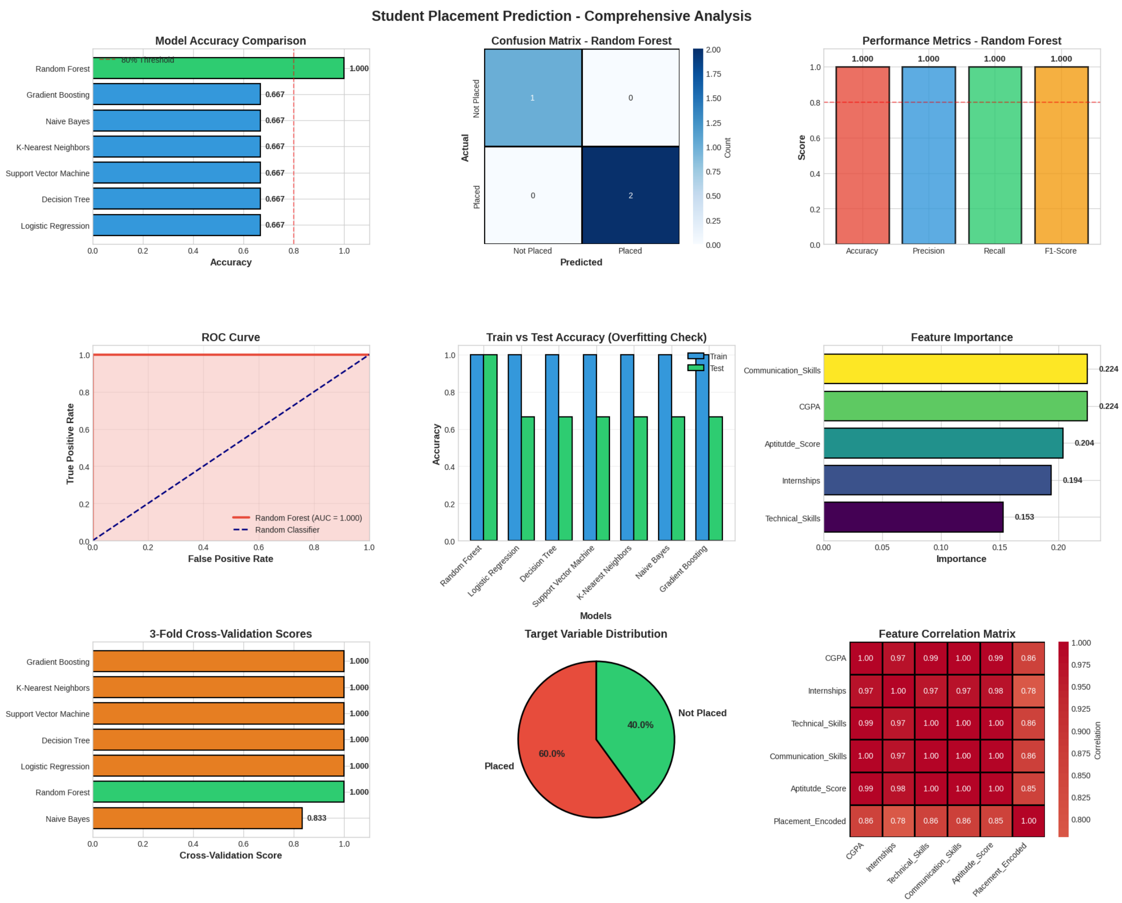

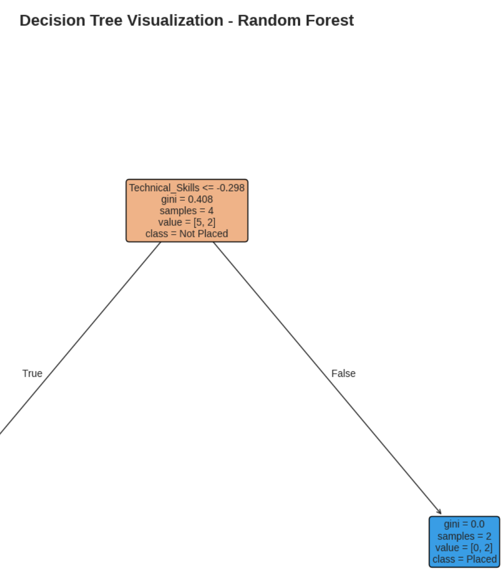
Decision Tree Visualization - Random Forest
Technical_Skills <= -0.298
gini = 0.408
samples = 4
value = [5, 2]
class = Not Placed
True
False
gini = 0.0
samples = 2
value = [5, 0]
class = Not Placed
gini = 0.0
samples = 2
value = [0, 2]
class = Placed

```
[ ]:
```