E-Commerce Listing Quality Classifier

Model Analysis & Evaluation

Author: Rishi Siddharth

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1. Problem Statement

E-commerce platforms need to identify low-quality product listings at scale. Poor quality listings erode user trust, create negative shopping experiences, and increase support burden.

project builds a machine learning classifier to assess product title quality and flag suspicious patterns.

Dataset: 9,280 Amazon product listings (mobile + laptop categories)
Features: 12 engineered features from product titles
Model: Random Forest Classifier
Evaluation: 80/20 train-test split with stratification

In [14]:

```
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
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassif
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
from sklearn.metrics import classification_report, confusion_matrix, roc_auc
import warnings
warnings.filterwarnings('ignore')

sns.set_style('whitegrid')
plt.rcParams['figure.figsize'] = (12, 6)
```

2. Data Overview

In [2]:

```
df = pd.read_csv('data/featured_data.csv')

print("Dataset Shape:", df.shape)
print("\nColumns:", df.columns.tolist())
df.head()
```

```
Dataset Shape: (9280, 18)

Columns: ['title', 'price', 'reviews', 'category', 'title_length', 'word_cou
nt', 'avg_word_length', 'uppercase_ratio', 'digit_count', 'special_char_coun
t', 'has_exclamation', 'exclamation_count', 'has_all_caps_word', 'unique_wor
d_ratio', 'spam_keyword_count', 'has_proper_capitalization', 'quality_scor
e', 'quality_label']
```

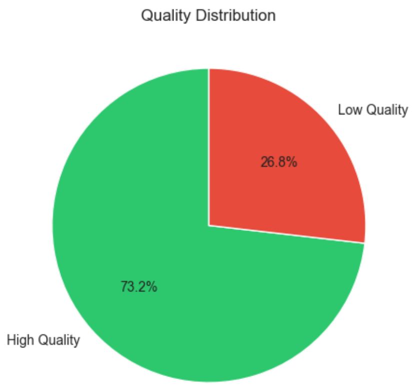
Out[2]:

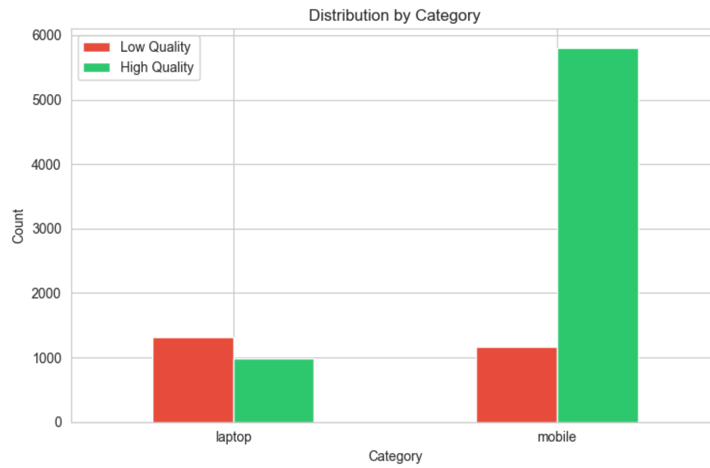
	title	price	reviews	category	title_length	word_count	avg_word_length	u
0	SAMSUNG EVO Select Micro SD-Memory-Card + Adap...	17.0	53617	mobile	195	27	6.259259	
1	Upgraded, Anker Soundcore Bluetooth Speaker wi...	27.0	82743	mobile	148	20	6.450000	
2	SanDisk 256GB Extreme microSDXC UHS-I Memory C...	22.0	48298	mobile	140	24	4.875000	
3	Twelve South AirFly SE, Bluetooth Wireless Aud...	34.0	312	mobile	187	26	6.230769	
4	Skullcandy Crusher Evo Wireless Over-Ear Bluet...	159.0	8410	mobile	189	32	4.937500	

In [3]:

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

quality_counts = df['quality_label'].value_counts()
axes[0].pie(quality_counts, labels=['High Quality', 'Low Quality'], autopct=
            colors=['#2ecc71', '#e74c3c'], startangle=90)
axes[0].set_title('Quality Distribution')

category_quality = df.groupby(['category', 'quality_label']).size().unstack(
category_quality.plot(kind='bar', ax=axes[1], color=['#e74c3c', '#2ecc71'])
axes[1].set_title('Distribution by Category')
axes[1].set_xlabel('Category')
axes[1].set_ylabel('Count')
axes[1].legend(['Low Quality', 'High Quality'])
```

```
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=0)

plt.tight_layout()
plt.show()

print(f"High Quality: {(df['quality_label']==1).sum():,} ({(df['quality_labe
print(f"Low Quality: {(df['quality_label']==0).sum():,} ({(df['quality_label
```






```
High Quality: 6,792 (73.2%)
Low Quality: 2,488 (26.8%)
```

Class imbalance (73% high, 27% low) requires class weighting during training.

3. Feature Engineering

Twelve features were extracted from product titles:

Length & Structure

- `title_length` : Character count
- `word_count` : Number of words
- `avg_word_length` : Average characters per word

Character Patterns

- `uppercase_ratio` : Percentage of uppercase letters
- `digit_count` : Number of digits
- `special_char_count` : Non-alphanumeric characters

Spam Indicators

- `exclamation_count` : Number of exclamation marks
- `has_all_caps_word` : Binary flag for all-caps words
- `spam_keyword_count` : Count of spam phrases

Quality Signals

- `unique_word_ratio` : Ratio of unique to total words

- `has_proper_capitalization` : Title starts with capital
- `reviews` : Number of customer reviews

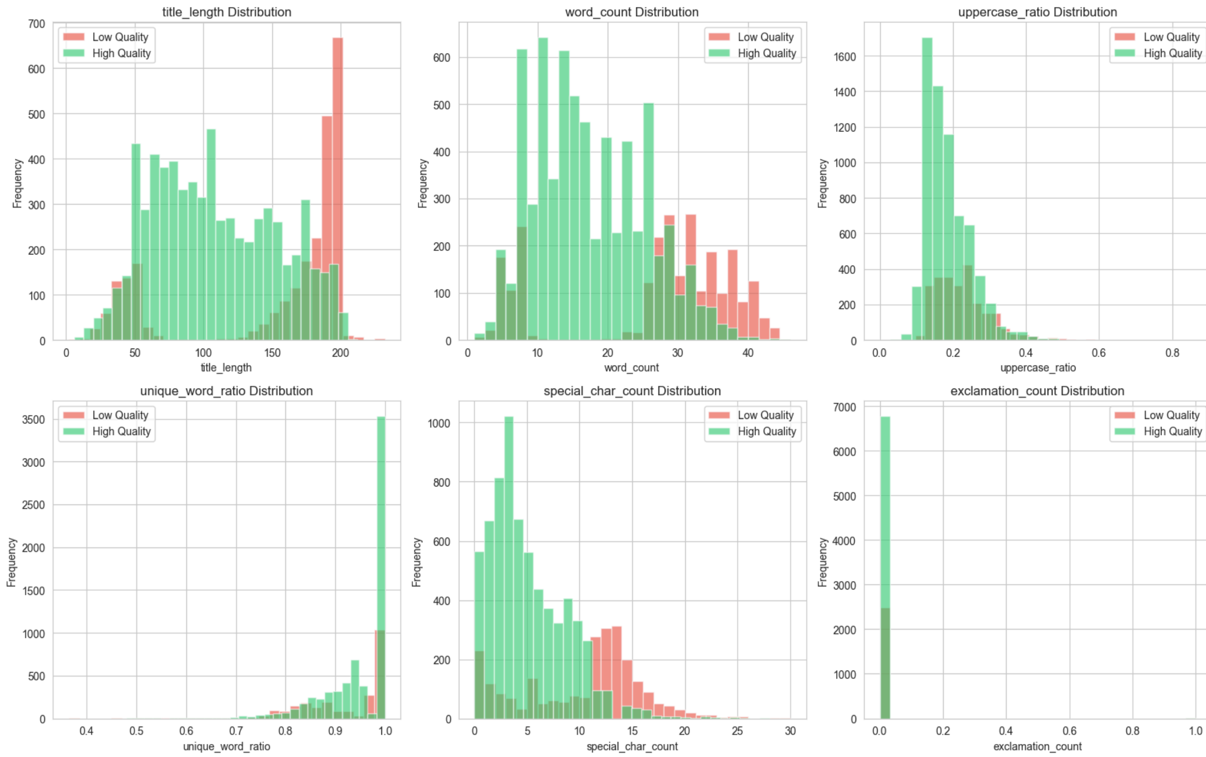
In [4]:
```
feature_cols = [
    'title_length', 'word_count', 'avg_word_length',
    'uppercase_ratio', 'digit_count', 'special_char_count',
    'exclamation_count', 'has_all_caps_word', 'unique_word_ratio',
    'spam_keyword_count', 'has_proper_capitalization', 'reviews'
]

comparison = df.groupby('quality_label')[feature_cols].mean()
comparison.index = ['Low Quality', 'High Quality']
comparison.T
```

Out[4]:

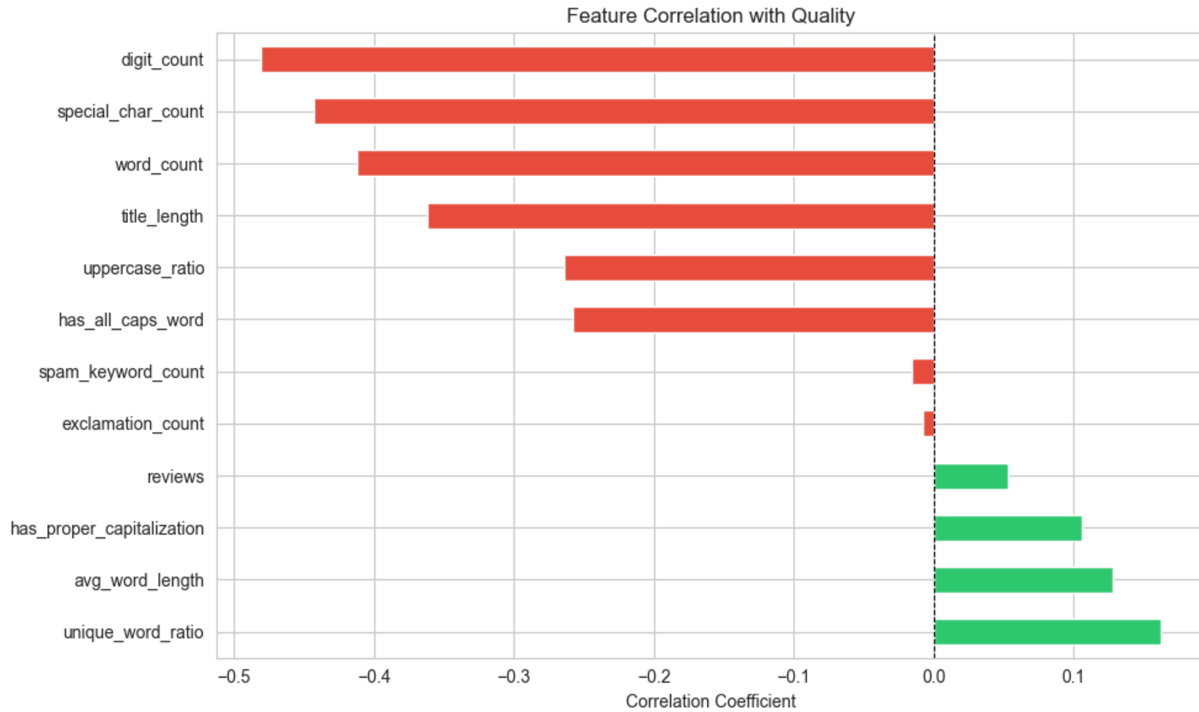
	Low Quality	High Quality
title_length	151.872588	107.858657
word_count	26.399518	17.083039
avg_word_length	5.221091	5.582556
uppercase_ratio	0.226976	0.185348
digit_count	17.470257	6.258981
special_char_count	9.831592	4.937279
exclamation_count	0.002010	0.001325
has_all_caps_word	0.938103	0.687132
unique_word_ratio	0.919243	0.947838
spam_keyword_count	0.003617	0.001914
has_proper_capitalization	0.886656	0.947438
reviews	376.466640	1394.907391

In [5]:
```
fig, axes = plt.subplots(2, 3, figsize=(16, 10))
axes = axes.flatten()

key_features = ['title_length', 'word_count', 'uppercase_ratio',
                'unique_word_ratio', 'special_char_count', 'exclamation_cour

for idx, feature in enumerate(key_features):
    for quality in [0, 1]:
        data = df[df['quality_label']==quality][feature]
        axes[idx].hist(data, alpha=0.6, bins=30,
                      label=f"{'Low' if quality==0 else 'High'} Quality",
                      color='#e74c3c' if quality==0 else '#2ecc71')
    axes[idx].set_xlabel(feature)
    axes[idx].set_ylabel('Frequency')
    axes[idx].legend()
    axes[idx].set_title(f'{feature} Distribution')
```

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



In [6]:
```
correlations = df[feature_cols + ['quality_label']].corr()['quality_label'].

plt.figure(figsize=(10, 6))
correlations[1:].plot(kind='barh', color=['#2ecc71' if x > 0 else '#e74c3c'
plt.title('Feature Correlation with Quality')
plt.xlabel('Correlation Coefficient')
plt.axvline(0, color='black', linestyle='--', linewidth=0.8)
plt.tight_layout()
plt.show()

print("Feature Correlations:")
print(correlations[1:])
```




```
Feature Correlations:
unique_word_ratio            0.162129
avg_word_length              0.127754
has_proper_capitalization    0.106333
reviews                      0.053145
exclamation_count           -0.007813
spam_keyword_count          -0.015515
has_all_caps_word           -0.258283
uppercase_ratio             -0.263787
title_length                -0.361798
word_count                  -0.411917
special_char_count          -0.443295
digit_count                 -0.480433
Name: quality_label, dtype: float64
```

4. Model Selection

Random Forest was selected for:

- Handling non-linear relationships
- Robustness against overfitting through ensemble averaging
- Interpretable feature importance scores
- No feature scaling required
- Built-in class weighting

Algorithm:
Creates 100 decision trees, each trained on random data subsets and feature combinations. Final prediction is majority vote.

Hyperparameters:

- `n_estimators=100` : Number of trees
- `max_depth=10` : Maximum tree depth
- `class_weight='balanced'` : Handles class imbalance
- `random_state=42` : Reproducibility

5. Training & Evaluation

In [7]:
```
X = df[feature_cols].fillna(0)
y = df['quality_label']

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

print(f"Training set: {len(X_train):,} samples")
print(f"Test set: {len(X_test):,} samples")
```

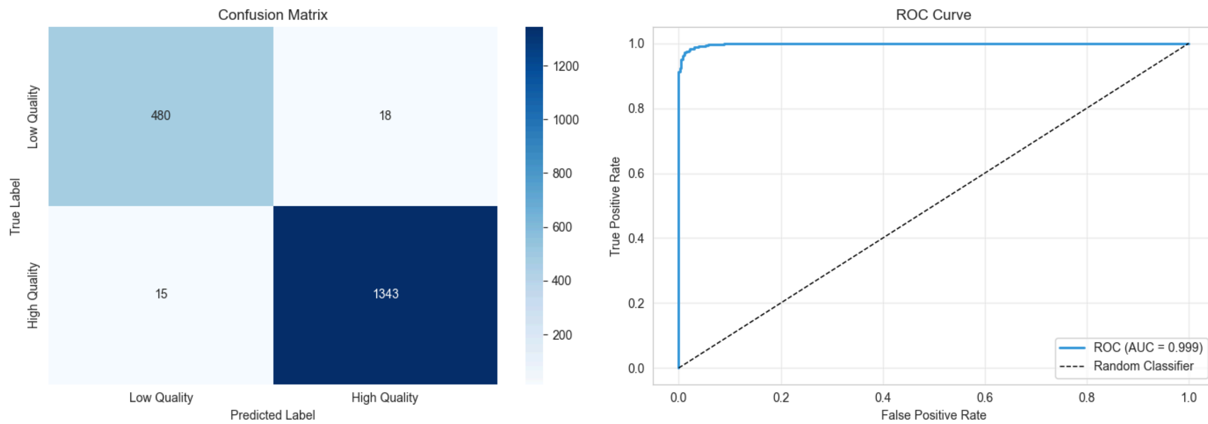
```
Training set: 7,424 samples
Test set: 1,856 samples
```

In [8]:
```
rf_model = RandomForestClassifier(
    n_estimators=100,
    max_depth=10,
    random_state=42,
    class_weight='balanced'
)

rf_model.fit(X_train, y_train)
y_pred = rf_model.predict(X_test)
y_pred_proba = rf_model.predict_proba(X_test)[:, 1]
```

In [9]:
```
accuracy = accuracy_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_proba)

print("Model Performance")
print("="*50)
print(f"Accuracy: {accuracy:.1%}")
print(f"ROC-AUC:  {roc_auc:.1%}")
print("\nClassification Report")
print("="*50)
print(classification_report(y_test, y_pred, target_names=['Low Quality', 'Hi
```

```
Model Performance
==================================================
Accuracy: 98.2%
ROC-AUC:  99.9%

Classification Report
==================================================
              precision    recall  f1-score   support

 Low Quality       0.97      0.96      0.97       498
High Quality       0.99      0.99      0.99      1358

    accuracy                           0.98      1856
   macro avg       0.98      0.98      0.98      1856
weighted avg       0.98      0.98      0.98      1856
```

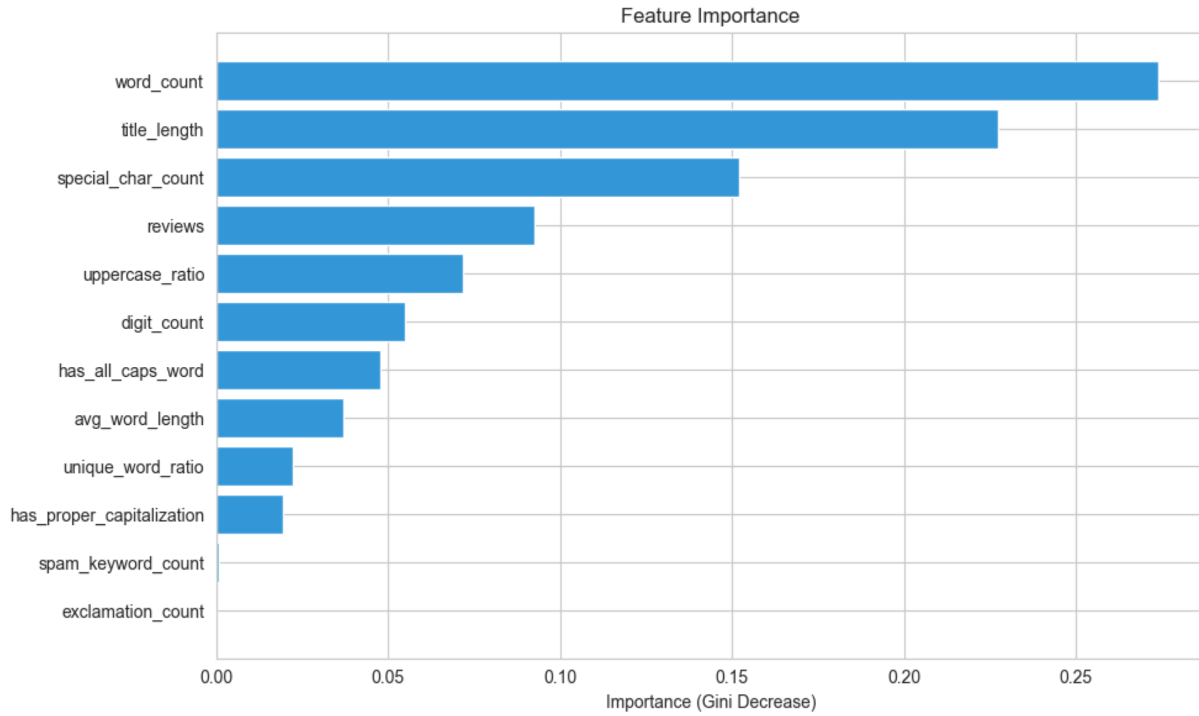
In [10]:
```
cm = confusion_matrix(y_test, y_pred)

fig, axes = plt.subplots(1, 2, figsize=(14, 5))

sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', ax=axes[0],
            xticklabels=['Low Quality', 'High Quality'],
            yticklabels=['Low Quality', 'High Quality'])
axes[0].set_title('Confusion Matrix')
axes[0].set_ylabel('True Label')
axes[0].set_xlabel('Predicted Label')

fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
axes[1].plot(fpr, tpr, color='#3498db', linewidth=2, label=f'ROC (AUC = {roc
axes[1].plot([0, 1], [0, 1], 'k--', linewidth=1, label='Random Classifier')
axes[1].set_xlabel('False Positive Rate')
axes[1].set_ylabel('True Positive Rate')
axes[1].set_title('ROC Curve')
axes[1].legend()
axes[1].grid(alpha=0.3)

plt.tight_layout()
plt.show()

print("Confusion Matrix:")
print(f"True Negatives:  {cm[0,0]:4d}")
print(f"False Positives: {cm[0,1]:4d}")
print(f"False Negatives: {cm[1,0]:4d}")
print(f"True Positives:  {cm[1,1]:4d}")
```




```
Confusion Matrix:
True Negatives:   480
False Positives:   18
False Negatives:   15
True Positives:  1343
```

6. Feature Importance

In [11]:
```
feature_importance = pd.DataFrame({
    'feature': feature_cols,
    'importance': rf_model.feature_importances_
}).sort_values('importance', ascending=True)

plt.figure(figsize=(10, 6))
plt.barh(feature_importance['feature'], feature_importance['importance'], co
plt.xlabel('Importance (Gini Decrease)')
plt.title('Feature Importance')
plt.tight_layout()
plt.show()

print("Feature Importance Ranking:")
for idx, row in feature_importance.sort_values('importance', ascending=False
    print(f"{row['feature']:25s} {row['importance']:.4f}")
```




```
Feature Importance Ranking:
word_count                 0.2740
title_length               0.2274
special_char_count         0.1522
reviews                    0.0924
uppercase_ratio            0.0718
digit_count                0.0548
has_all_caps_word          0.0478
avg_word_length            0.0369
unique_word_ratio          0.0222
has_proper_capitalization  0.0195
spam_keyword_count         0.0008
exclamation_count          0.0002
```

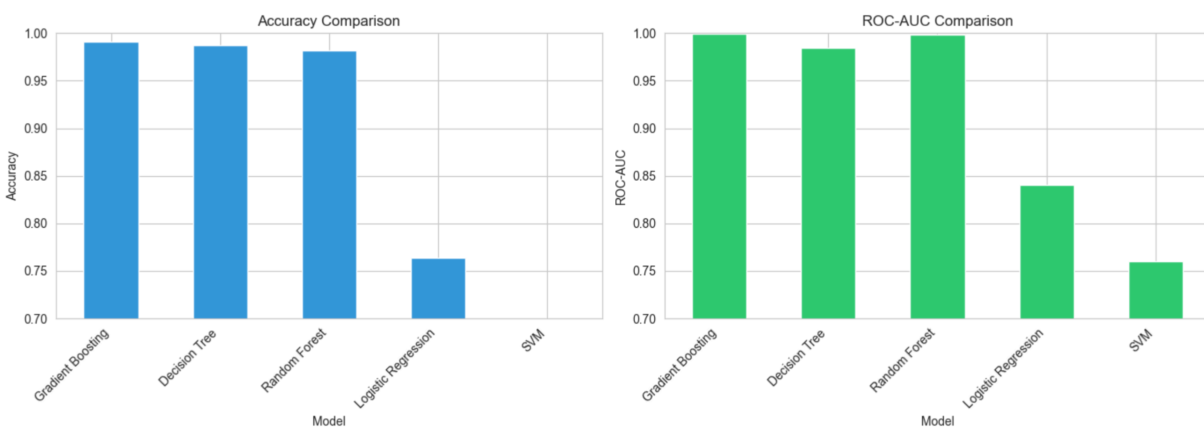
Top features (word_count, title_length, special_char_count) align with the labeling heuristic, suggesting data leakage.

7. Model Comparison

In [12]:
```
models = {
    'Random Forest': RandomForestClassifier(n_estimators=100, max_depth=10, 
    'Gradient Boosting': GradientBoostingClassifier(n_estimators=100, max_de
    'Logistic Regression': LogisticRegression(max_iter=1000, random_state=42
    'Decision Tree': DecisionTreeClassifier(max_depth=10, random_state=42, c
    'SVM': SVC(kernel='rbf', probability=True, random_state=42, class_weight
}

results = []
for name, model in models.items():
    model.fit(X_train, y_train)
    y_pred_temp = model.predict(X_test)
    y_pred_proba_temp = model.predict_proba(X_test)[:, 1]
```

```
    results.append({
        'Model': name,
        'Accuracy': accuracy_score(y_test, y_pred_temp),
        'ROC-AUC': roc_auc_score(y_test, y_pred_proba_temp)
    })

results_df = pd.DataFrame(results).sort_values('Accuracy', ascending=False)
print(results_df.to_string(index=False))

fig, axes = plt.subplots(1, 2, figsize=(14, 5))
results_df.plot(x='Model', y='Accuracy', kind='bar', ax=axes[0], legend=Fals
axes[0].set_title('Accuracy Comparison')
axes[0].set_ylabel('Accuracy')
axes[0].set_ylim([0.7, 1.0])
axes[0].set_xticklabels(axes[0].get_xticklabels(), rotation=45, ha='right')

results_df.plot(x='Model', y='ROC-AUC', kind='bar', ax=axes[1], legend=False
axes[1].set_title('ROC-AUC Comparison')
axes[1].set_ylabel('ROC-AUC')
axes[1].set_ylim([0.7, 1.0])
axes[1].set_xticklabels(axes[1].get_xticklabels(), rotation=45, ha='right')

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

```
              Model  Accuracy  ROC-AUC
  Gradient Boosting  0.990841 0.999756
      Decision Tree  0.987069 0.984912
      Random Forest  0.982220 0.998598
Logistic Regression  0.763470 0.840895
                SVM  0.437500 0.759994
```



8. Limitations

The 98% accuracy is misleading due to possbile data leakage. Quality labels were created using the same features (word_count, title_length) used for training. The model learned to replicate the labeling heuristic rather than discover genuine quality patterns. To further improve the model - Proper Labeling - Domain experts label 2,000-5,000 products - Clear quality criteria established - Inter-rater agreement >85% - Expected accuracy: 75-85% Historical Data: - Use actual platform review decisions - Most realistic for production Enhanced Features - Product descriptions (full text) - Image quality analysis - Seller reputation scores - Category-specific attributes - Competitive pricing data more Methodsand models - BERT/RoBERTa for semantic understanding - Active learning for efficient labeling - Multi-task learning - Ensemble models Robust Validation - K-fold cross-validation - Temporal validation - Category-stratified splits - Systematic error analysis

demonstrated by:

1. Top feature importance matches labeling rules
2. Some low quality predictions are worth questioning
3. Performance drops significantly with random labels

In [13]:
```
# Test with random labels
np.random.seed(42)
y_random = np.random.randint(0, 2, size=len(df))
X_train_r, X_test_r, y_train_r, y_test_r = train_test_split(X, y_random, tes

rf_random = RandomForestClassifier(n_estimators=100, max_depth=10, random_st
rf_random.fit(X_train_r, y_train_r)
y_pred_random = rf_random.predict(X_test_r)

print("Accuracy Comparison:")
print(f"Random Labels:    {accuracy_score(y_test_r, y_pred_random):.1%}")
print(f"Heuristic Labels: {accuracy:.1%}")
```

```
Accuracy Comparison:
Random Labels:    52.2%
Heuristic Labels: 98.2%
```

9. Conclusion

Shows

- Feature engineering from unstructured text
- End-to-end ML pipeline development
- Model comparison and evaluation
- Recognition of data leakage and limitations

Author: Rishi Siddharth
Email: rs5309a@american.edu
GitHub: github.com/rsiddharth54