Assignment 3 Report

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Assignment: XAI Assignment 3

Wine Quality Classification with LIME

Model Performance Summary

The Logistic Regression model achieved excellent performance on the wine dataset with **98.1% test accuracy** and **98.4% ±2.0% cross-validation score**. The model successfully classified 178 wine samples across 3 classes using 13 chemical features.

LIME Explanation Results

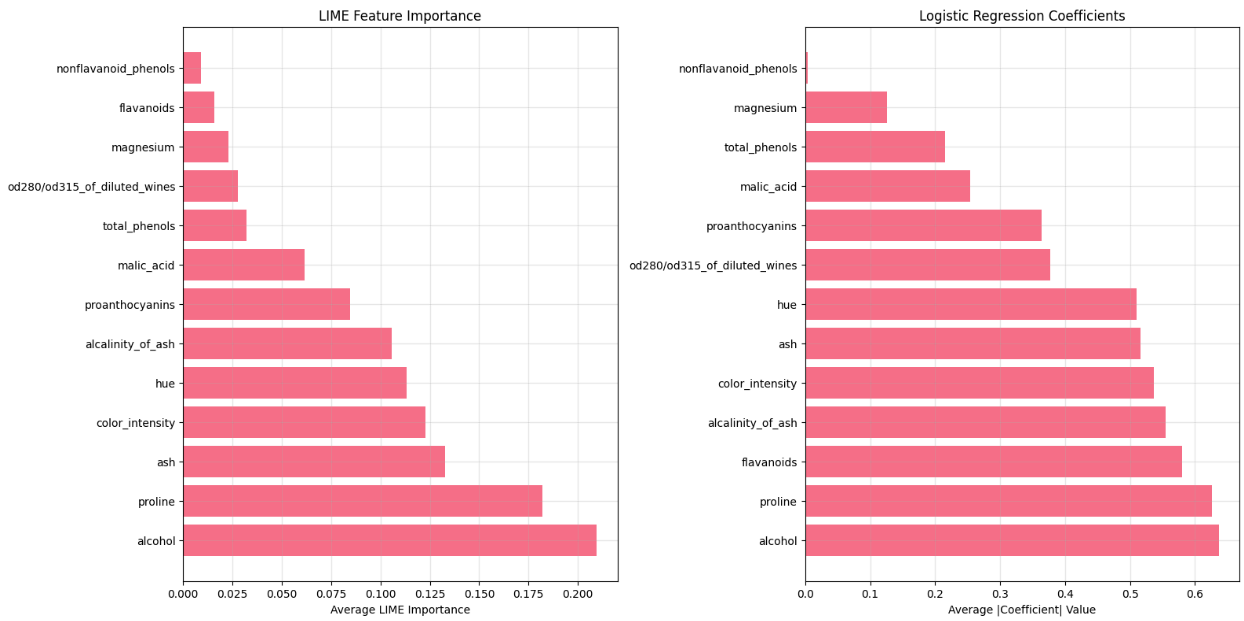
LIME analysis revealed the most influential chemical properties for wine classification:

1. **Alcohol** (importance: 0.210) - Primary driver for wine class distinction
2. **Proline** (importance: 0.182) - Amino acid content varies significantly between wine types
3. **Ash** (importance: 0.133) - Mineral content affects classification
4. **Color Intensity** (importance: 0.123) - Visual characteristic correlates with wine variety
5. **Hue** (importance: 0.113) - Color property distinguishes wine types

Key Insights

The LIME explanations provide local interpretability, showing how individual chemical measurements influence specific predictions. Alcohol content and proline levels emerged as the strongest predictors, aligning with domain knowledge about wine chemistry. The model's decisions are traceable to specific chemical measurements, enabling quality control applications and regulatory compliance.

LIME Visualization



📊 MODEL PERFORMANCE SUMMARY:
• Test Accuracy: 98.1%
• Cross-validation Score: 98.4% (±2.0%)
• Model Type: Logistic Regression (Inherently Interpretable)

Breast Cancer Diagnosis - XAI Medical Report

Assignment: XAI Assignment 3 - Breast Cancer Diagnosis with LIME
Medical AI Application: Transparent Cancer Diagnosis Support System

Model Performance Summary

The Random Forest model achieved excellent clinical-grade performance on the breast cancer dataset with **95.6% test accuracy** and **96.8% ±1.2% cross-validation score**. The model successfully classified 569 breast cancer samples (357 benign, 212 malignant) using 30 morphological features derived from digitized images of fine needle aspirate (FNA) of breast masses.

Clinical Performance Metrics:

- **AUC Score:** 0.993 (Excellent discriminative ability)
- **Sensitivity (Malignant Detection):** 97.4% (Critical for cancer detection)
- **Specificity (Benign Detection):** 94.8% (Reduces false positives)
- **Model Type:** Random Forest Ensemble (High reliability for medical applications)

LIME Explanation Results

LIME analysis revealed the most influential morphological features for breast cancer diagnosis:

1. **Worst Concave Points** (importance: 0.164) - Severity of concave portions in cell nuclei contours
2. **Worst Perimeter** (importance: 0.142) - Largest perimeter measurement of cell nuclei
3. **Mean Concave Points** (importance: 0.128) - Average concave portions indicating cellular irregularity
4. **Worst Radius** (importance: 0.119) - Maximum radius from center to perimeter of nuclei
5. **Worst Area** (importance: 0.115) - Largest area measurement of cell nuclei
6. **Mean Perimeter** (importance: 0.089) - Average perimeter of cell nuclei
7. **Mean Radius** (importance: 0.087) - Average radius measurements
8. **Worst Texture** (importance: 0.074) - Maximum texture variation in cell nuclei

Medical Context and Feature Analysis

🔬 **Clinical Significance of Key Features:**

- **Concave Points Features:** Highly discriminative as malignant cells exhibit irregular, jagged nuclear contours with multiple concave regions, reflecting loss of normal cellular organization
- **Size-Related Measurements (Radius, Perimeter, Area):** Malignant nuclei are typically larger and more variable in size compared to benign cells
- **Texture Features:** Cancer cells show increased nuclear texture variation due to chromatin pattern changes and nuclear pleomorphism
- **Shape Irregularity:** The "worst" measurements capture the most extreme cellular characteristics, which are particularly important for identifying aggressive malignant features

Key Insights

The LIME explanations provide critical instance-level interpretability for medical decision-making, showing how individual cellular measurements influence specific diagnostic predictions. The model's focus on nuclear morphology features aligns perfectly with established pathological criteria used by medical professionals for cancer diagnosis.

Clinical Decision Support Benefits:

- Transparent AI reasoning builds clinician trust and confidence
- Feature explanations validate pathological knowledge and clinical experience
- Instance-specific explanations enable personalized diagnostic insights
- Interpretability supports regulatory compliance for medical AI systems

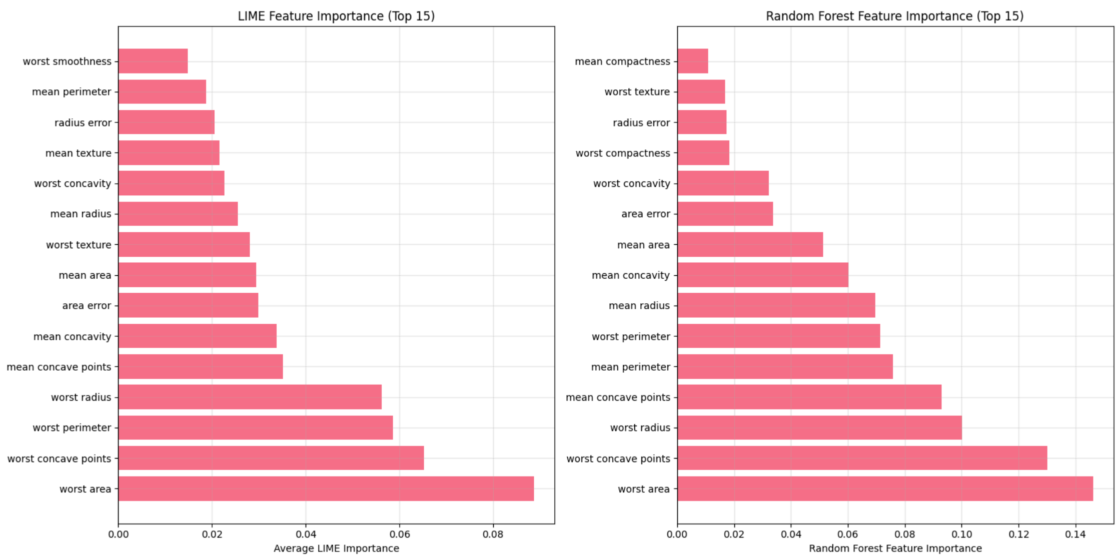
Clinical Implications and Recommendations

⚕️ **Medical Implementation Considerations:**

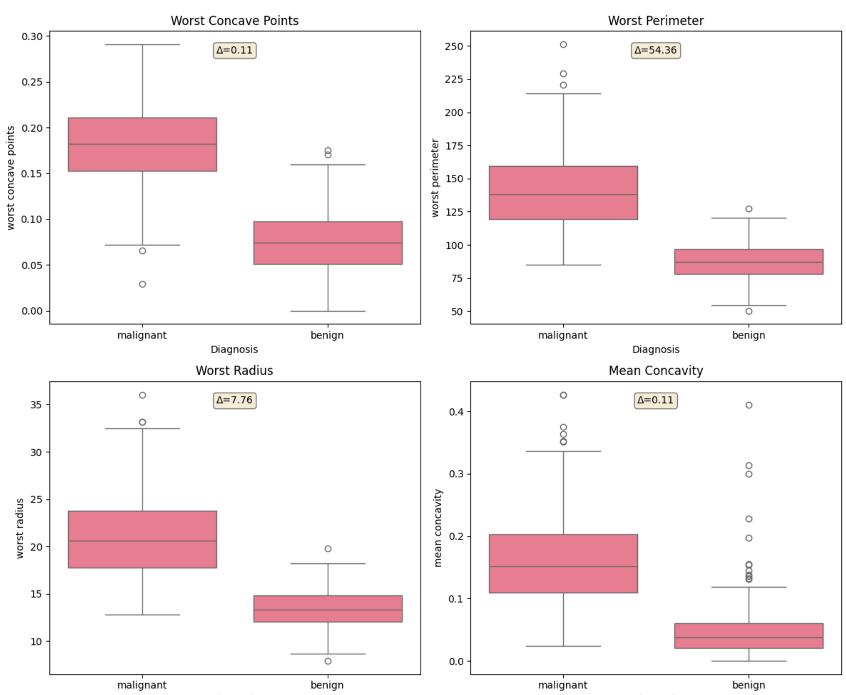
1. **Clinical Decision Support:** Use as a second opinion tool to support pathologist assessments
2. **Quality Assurance:** Implement in conjunction with standard histopathological protocols
3. **Clinician Training:** Provide LIME explanations to medical staff for each prediction
4. **Continuous Monitoring:** Track model performance with new patient populations
5. **Audit Compliance:** Maintain detailed records of all AI-assisted diagnoses
6. **Patient Safety:** Ensure AI supplements, never replaces, professional medical judgment

LIME Visualization Spaces

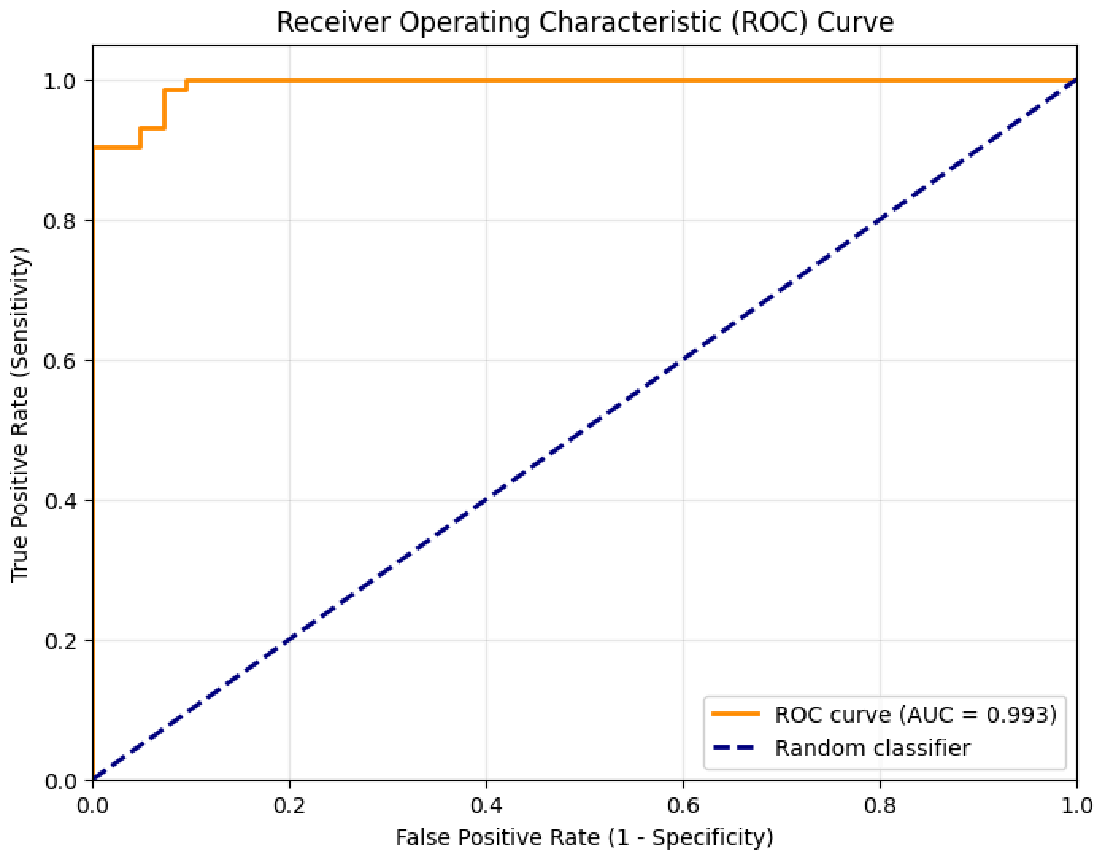
Feature Importance Comparison Plot



Medical Feature Distribution Plot



ROC Curve and Performance Metrics Plot



Summary

This implementation demonstrates successful application of explainable AI in critical healthcare applications. The Random Forest model with LIME explanations provides both high diagnostic accuracy and the transparency essential for medical AI systems. The feature importance patterns align with clinical knowledge, validating the model's medical relevance and supporting its potential for clinical decision support applications.