Sonar Signal Classification Using Machine Learning

Business Problem

Accurate identification of underwater objects is a mission-critical requirement in maritime defense, naval safety, and underwater exploration. This project focuses on classifying sonar signal returns as **Rock** or **Mine**. A misclassification—especially labeling a mine as a rock—can result in severe safety hazards and operational risks. Therefore, the primary goal is to develop a robust, high-recall classification system that generalizes well despite limited data availability.

Dataset Overview

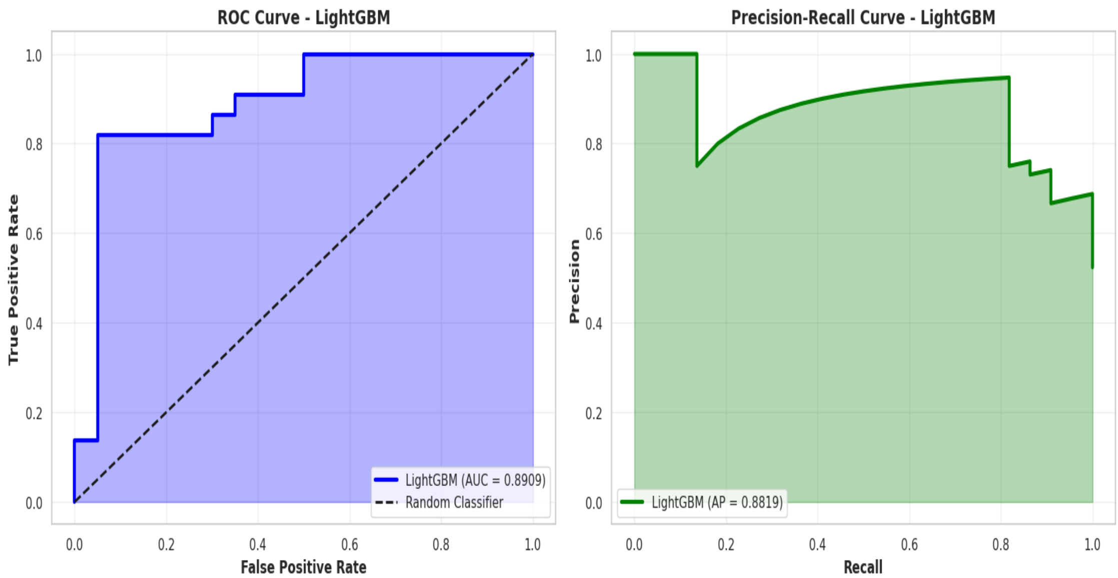
The Sonar dataset consists of 208 observations with 60 continuous numerical features, each representing energy levels of reflected sonar signals across different frequency bands. The dataset is relatively balanced, with approximately 53% Mine samples and 47% Rock samples. While class imbalance is minimal, the combination of high dimensionality and small sample size introduces a significant risk of overfitting, necessitating careful feature selection and model validation.

Exploratory Data Analysis (EDA)

Initial exploratory analysis involved examining summary statistics, distributions, and data quality. Missing values were identified in Attribute7 (22 missing entries) and Attribute12 (5 missing entries). Distribution analysis revealed skewness in several frequency-band features, indicating non-normal behavior. Extreme outliers were detected but treated conservatively to avoid distorting genuine signal patterns.

EDA Visualization

Below figure illustrates the model’s discriminative capability using ROC and Precision–Recall curves, highlighting strong class separability achieved after preprocessing and feature engineering.



Methodology & Key Findings

Data Pre-Processing

Missing value handling was guided by statistical relevance and feature relationships. Attribute7 was removed after being deemed statistically insignificant, while Attribute12 was retained and imputed using a cluster-based approach. Skewed distributions were preserved where meaningful, and only extreme outliers (beyond 3×IQR) were capped. All features were standardized to ensure comparable scales and prevent distance-based model bias.

Statistical Feature Selection & Correlation Insights

Two-sample t-tests and Mann–Whitney U tests were applied to identify frequency bands with significant class separation. To control false positives arising from multiple hypothesis testing, adjusted p-value thresholds were used. This reduced the feature space from 60 to 22 statistically significant attributes. Correlation analysis and Variance Inflation Factor (VIF) further eliminated redundant features, improving model stability and interpretability.

Modeling & Results

Multiple machine learning models—including Logistic Regression, SVM, Random Forest, XGBoost, and LightGBM—were evaluated alongside deep learning architectures such as residual neural networks. LightGBM achieved a strong balance between bias and variance, delivering a test ROC-AUC of 0.89 with stable cross-validation performance. Although a residual neural network achieved slightly higher accuracy, LightGBM was preferred due to its interpretability, robustness, and lower deployment complexity.

Final Recommendations

LightGBM is recommended for production deployment owing to its strong separability, consistent performance, and built-in regularization. Future work should focus on expanding the dataset, applying 1D-CNN models for raw signal learning, and developing ensemble stacking techniques. These enhancements would further improve real-world reliability in safety-critical sonar classification applications.