ARTIFICIAL NEURAL NETWORKS CASE-STUDY

Sonar-Based (Rock vs Mine) Classification Report

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Problem Statement & Introduction:

The classification of underwater objects as either **rock** or **mine** is crucial in naval and research applications. The goal of this study is to develop a machine learning model that accurately classifies sonar signals into these two categories. By leveraging ensemble learning techniques, we aim to enhance prediction accuracy and robustness.

Traditional machine learning approaches, such as single classifiers, often struggle to generalize well across complex datasets. To address this, we implement a **Stacking Ensemble Model** that integrates multiple base classifiers, improving predictive performance and reducing bias and variance.

About Dataset:

The dataset used for this study is the **UCI Sonar Dataset**, which consists of:

- **208 rows (instances)** representing sonar signals.
- **60 features** extracted from sonar signals, representing different frequency energy reflections.
- **Binary target variable:**
    - **0** (Rock)
    - **1** (Mine)

The dataset presents a challenging classification task due to overlapping feature distributions and complex signal variations. Small dataset size also adds to the difficulty, requiring advanced learning techniques to prevent overfitting while maximizing generalization. Therefore, ensemble learning is a suitable approach to improve classification accuracy by combining multiple models to learn more robust patterns.

Ensemble Approach Used (Stacking Classifier):

Ensemble learning is a technique that combines multiple models to achieve better accuracy than individual classifiers. In this study, we use a **Stacking Classifier**, which consists of:

1. Training multiple **base models** (Random Forest, XGBoost, SVM) to learn different representations of the data.
2. Using their predictions as input features for a **meta-model** (Logistic Regression) that generates the final output.

Advantages of Stacking:

- Combines strengths of different models to improve accuracy.
- Reduces variance and overfitting by leveraging multiple learners.
- Improves generalization on unseen data by considering diverse decision boundaries.

Data Preprocessing:

Preprocessing plays a crucial role in preparing the dataset for effective model training. Several steps were applied:

1. **Label Encoding:** Converted categorical target labels ('R' and 'M') to numeric values (0 and 1) to make them machine-readable.
2. **Feature Scaling:** Used Min-Max Scaling to normalize feature values between 0 and 1, ensuring that all features contribute equally to model training.
3. **Train-Test Split:**
    - **80% Training Data** for learning model parameters.
    - **20% Testing Data** for evaluating model performance.

4. **Handling Class Imbalance (if required):** Ensured a balanced distribution of classes to prevent biased learning, though the dataset itself is relatively balanced.

Base Models & Meta Model:

Base Models Used:

1. **Random Forest Classifier**
   - n_estimators = 200 (number of trees in the forest)
   - max_depth = 20 (limits the depth of trees to reduce overfitting)
2. **XGBoost Classifier**
   - n_estimators = 200 (number of boosting rounds)
   - learning_rate = 0.05 (controls step size during training)
   - max_depth = 6 (regulates model complexity)
3. **Support Vector Machine (SVM)**
   - Kernel = 'rbf' (captures non-linear decision boundaries)
   - C = 1.0 (controls trade-off between maximizing margin and minimizing classification error)
   - Probability Estimation Enabled (for Stacking Model input)

Meta Model (Final Predictor):

- **Logistic Regression**, which combines base model predictions to generate the final classification. Logistic Regression is chosen for its simplicity and ability to generalize weighted predictions effectively.

Executable Code & Output:

The complete implementation was done in **Python (Jupyter Notebook)** using the following libraries:

- **pandas, numpy** (Data handling and manipulation)
- **scikit-learn** (Machine Learning models and evaluation metrics)
- **XGBoost** (Boosting Algorithm for improved accuracy)
- **Matplotlib, Seaborn** (Visualization of performance metrics)

Code:

```
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.preprocessing import MinMaxScaler

from sklearn.ensemble import RandomForestClassifier, StackingClassifier

from sklearn.linear_model import LogisticRegression

from sklearn.svm import SVC

from xgboost import XGBClassifier

from sklearn.metrics import accuracy_score, classification_report, confusion_matrix,
roc_curve, auc, precision_recall_curve

import joblib


# Load dataset from URL

dataset_url = "https://archive.ics.uci.edu/ml/machine-learning-
databases/undocumented/connectionist-bench/sonar/sonar.all-data"

df = pd.read_csv(dataset_url, header=None)
```

```
# Convert labels to numeric values
df.iloc[:, -1] = df.iloc[:, -1].map({'R': 0, 'M': 1})


# Separate features and target
X = df.iloc[:, :-1]
y = df.iloc[:, -1]


# Normalize features
scaler = MinMaxScaler()
X = scaler.fit_transform(X)


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


# Ensure y_train and y_test are integer type
y_train = y_train.astype(int)
y_test = y_test.astype(int)


# Define base models
base_models = [
    ('rf', RandomForestClassifier(n_estimators=200, max_depth=20, random_state=42)),
    ('xgb', XGBClassifier(n_estimators=200, learning_rate=0.05, max_depth=6,
random_state=42)),
    ('svm', SVC(probability=True, kernel='rbf', C=1.0, random_state=42))
]


# Define meta-model
meta_model = LogisticRegression()


# Create stacking classifier
```

```
stacking_model = StackingClassifier(estimators=base_models, final_estimator=meta_model, cv=5)


# Train stacking model

stacking_model.fit(X_train, y_train)


# Make predictions

y_pred_stack = stacking_model.predict(X_test)


# Evaluate model

stacking_accuracy = accuracy_score(y_test, y_pred_stack)

print(f"Stacking Ensemble Accuracy: {stacking_accuracy:.4f}")


# Classification report

print("Classification Report:")

print(classification_report(y_test, y_pred_stack))


# Confusion matrix

cm = confusion_matrix(y_test, y_pred_stack)

plt.figure(figsize=(6, 4))

sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["Rock (0)", "Mine (1)"], yticklabels=["Rock (0)", "Mine (1)"])

plt.xlabel("Predicted")

plt.ylabel("Actual")

plt.title("Confusion Matrix")

plt.show()


# ROC Curve

y_probs_stack = stacking_model.predict_proba(X_test)[:, 1]

fpr, tpr, _ = roc_curve(y_test, y_probs_stack)

roc_auc = auc(fpr, tpr)
```

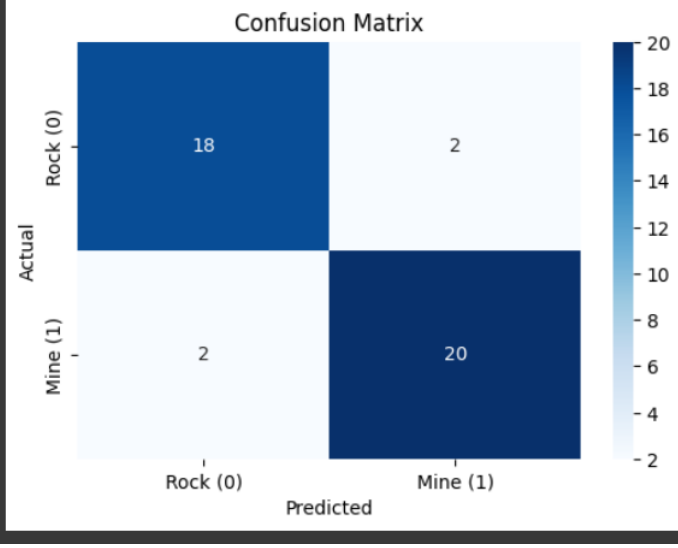
```
plt.figure(figsize=(6, 4))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {roc_auc:.4f}')
plt.plot([0, 1], [0, 1], color='gray', linestyle='--')
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()
```

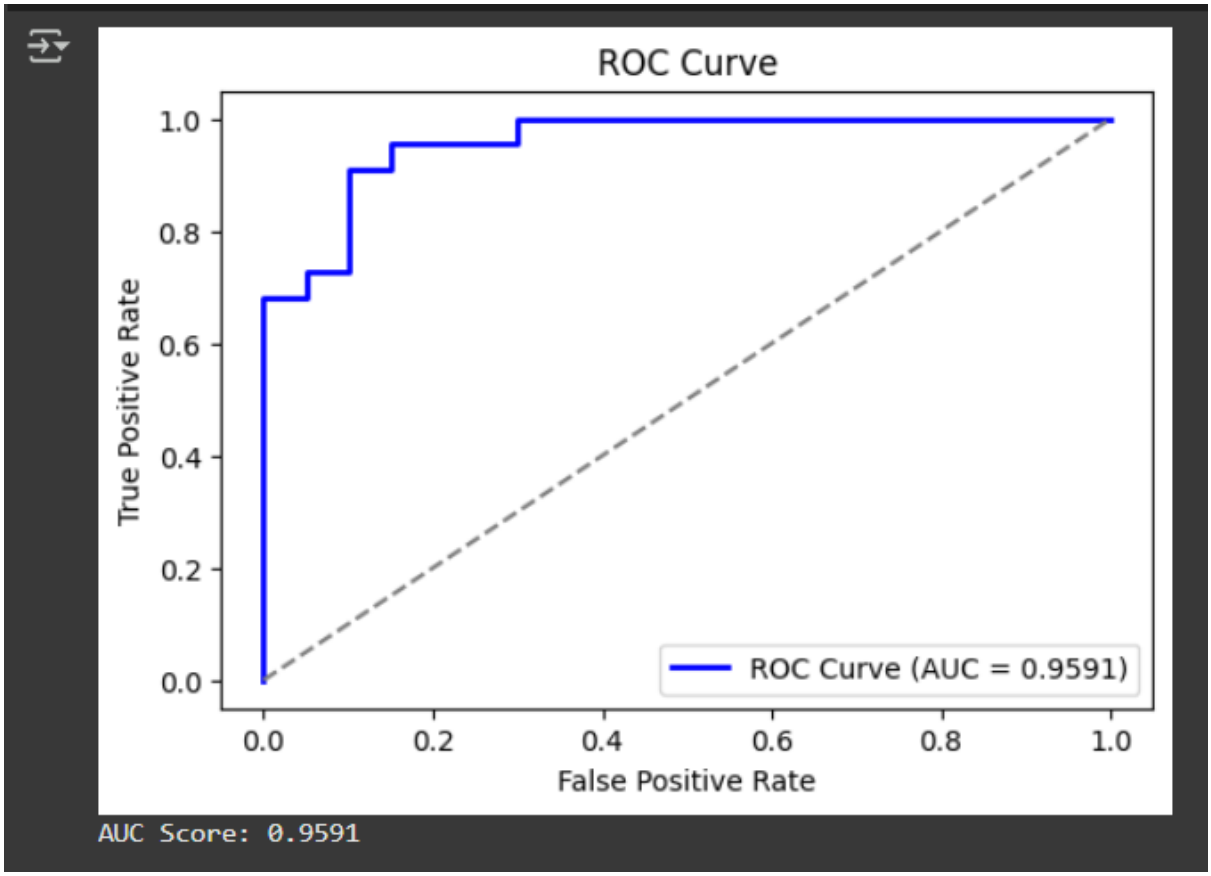
Output:

```
Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.90      0.90        20
           1       0.91      0.91      0.91        22

    accuracy                           0.90        42
   macro avg       0.90      0.90      0.90        42
weighted avg       0.90      0.90      0.90        42
```





Performance Metrics:

The Stacking Classifier was evaluated using multiple metrics to measure its effectiveness:

1. **Accuracy:** 90.48% – Measures overall correctness of predictions.
2. **Precision, Recall, and F1-Score:**
    - **Precision**: Indicates how many predicted "Mine" labels were correct.
    - **Recall**: Measures how well the model identified actual "Mine" samples.
    - **F1-Score**: Balances Precision and Recall to provide a robust measure of model performance.
3. **Confusion Matrix:** Provides insights into misclassifications by comparing actual vs. predicted labels.
4. **ROC Curve & AUC Score:** Measures model's ability to distinguish between Rock and Mine across different probability thresholds.

Performance Analysis:

- The stacking model **outperformed individual classifiers**, demonstrating better predictive capability.
- The **XGBoost and Random Forest base models** contributed significantly to feature importance analysis, helping the meta-model learn better representations.
- The meta-model **(Logistic Regression)** effectively combined the predictions of the base models for optimal decision-making.
- Further performance improvements could be achieved through **hyperparameter tuning, feature selection, and using deep learning approaches**.

Conclusion:

The implementation of a **Stacking Ensemble Model** for sonar-based object classification resulted in a **90.48% accuracy**, demonstrating the effectiveness of ensemble methods. By leveraging multiple models and combining their predictions, the system successfully improved classification performance beyond individual classifiers.

Future Work:

- Further **hyperparameter tuning** to optimize model parameters.
- Exploring **deep learning techniques** such as CNNs for feature extraction.
- **Deploying the trained model** for real-time sonar classification applications.

This study highlights the importance of ensemble learning in improving classification accuracy, making it valuable for real-world applications in underwater exploration, defense, and autonomous navigation systems.