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Ensemble Machine Learning for Multivariate Sonar Signal Classification

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Abstract

Underwater acoustic monitoring plays a vital role in marine research, environmental conservation, and vessel detection. However, the rapid growth of sonar data generated by modern sensing technologies has created a strong demand for automated, accurate, and scalable analysis systems. Conventional sonar analysis relies heavily on manual interpretation and isolated machine learning models, leading to inefficiencies, inconsistent results across varying environments, and limited real-time applicability. These challenges highlight the need for a unified framework capable of handling the complete analytical pipeline in a streamlined and user-friendly manner. This study introduces a Unified Multi-Model Learning Platform designed for intelligent classification and regression of SONAR signals in complex marine acoustic environments. The proposed system integrates end-to-end functionalities, including data preprocessing, feature scaling, dataset partitioning, model training, evaluation, comparison, visualization, and real-time prediction. Central to the framework is a novel hybrid ensemble model based on Classification and Regression Tree (CART) principles, combining Decision Tree and Extra Trees algorithms through a voting mechanism, referred to as the Ensemble EDT model. To ensure robust benchmarking, additional models such as Gradient Boosting and Support Vector Machine are incorporated for comparative performance evaluation. Experimental findings indicate that the Ensemble EDT model achieves superior classification accuracy with reduced misclassification rates and demonstrates strong regression performance with high predictive alignment. The integrated CART-based ensemble approach enhances model stability and generalization in noisy underwater environments. Furthermore, the platform provides a web-based interface supporting both individual and batch predictions, offering an efficient, scalable, and practical solution for advanced underwater acoustic signal analysis.

Keywords: Underwater acoustic monitoring, SONAR signal analysis, ensemble learning, feature scaling, real-time prediction, marine data analytics

1. Introduction

The concept of underwater sound-based detection can be traced back to 1906, when naval engineer Lewis Nixon developed an early device intended to help ships identify submerged hazards such as icebergs [1]. A significant milestone in the evolution of this technology occurred after the Titanic disaster, which highlighted the critical need for reliable underwater detection systems and accelerated advancements in sonar-related research [2]. Since then, underwater acoustics has emerged as a multidisciplinary field focused on understanding how sound is generated, transmitted, and received in aquatic environments, as well as how it interacts with boundaries such as the seabed and water surface. This field plays an essential role in applications including submarine communication, marine environment monitoring, seabed exploration, and underwater target recognition [3]. Sonar systems, commonly described as sound-based sensing technologies, operate by transmitting acoustic signals and interpreting the reflected echoes to gather information about underwater objects. These systems enable detection, localization, classification, and tracking of targets, while also supporting navigation, communication, and measurement functions in marine environments [4][5]. In situations where direct observation is not possible, sonar serves as a form of remote sensing, allowing indirect acquisition of information about submerged objects [3]. The growing reliance on sonar technology is largely due to the limitations of electromagnetic waves in water. Radio and radar signals experience significant attenuation in aquatic environments, making them ineffective for long-distance underwater applications. In contrast, acoustic waves propagate efficiently over greater distances, making them the most suitable medium for underwater sensing and exploration [6].

2. Literature Survey

Mehmet Gokhan Metin et al. [7] investigated the challenge of planning an efficient trajectory for a mobile multistatic active SONAR transmitter with the objective of maximizing surveillance coverage, assuming prior knowledge of receiver positions. To address the computational complexity of this optimization problem, the authors introduced a heuristic approach based on Ant Colony Optimization (ACO). They conducted extensive simulations to evaluate the effectiveness of the proposed method and compared it against an exact Mixed Integer Linear Programming (MILP) formulation. The findings demonstrated that the ACO-based strategy produced near-optimal solutions while significantly reducing computational time, making it suitable for large-scale operational scenarios. Allyson A. da Silva et al. [8] explored the application of supervised learning techniques for identifying vessels using passive SONAR data obtained from the Brazilian Navy. Their study examined seven different algorithms across a dataset consisting of 12 ship categories. The data were processed in both original and downsampled forms to understand how preprocessing impacts classification performance and efficiency. Among the evaluated models, Linear Discriminant Analysis (LDA) and XGBoost achieved the most favorable results, with XGBoost showing strong accuracy alongside reduced computational cost, highlighting its suitability for real-time maritime systems.

Yanghong Zhao et al. [9] proposed an advanced feature integration technique known as CM3F, which combines signal-processing attributes with biologically inspired representations. This method was incorporated into a specialized deep neural architecture called the Boundary-Aware Hybrid Transformer Network (BAHTNet), designed for underwater acoustic target recognition. The framework includes modules such as CBCARM and XCAT, and employs a Kan-based classifier along with a large-margin aware focal loss function to enhance predictive performance. The proposed approach demonstrated improved feature representation and classification capability in complex acoustic environments. Ikusu Seo et al. [10] developed a multi-layer classification framework capable of handling real-world underwater signals without requiring predefined thresholds. The study utilized experimental data collected from active SONAR systems mounted on naval vessels operating in the East Sea of Korea. A large dataset consisting of target signals and clutter samples was analyzed under varying signal-to-noise ratio (SNR) conditions. A Support Vector Machine (SVM) classifier was employed, and repeated training-testing cycles were conducted to ensure reliability. Performance was assessed using metrics such as classification accuracy, false alarm rates, and ROC curves, demonstrating the robustness of the approach.

Said Jamal et al. [11] introduced an alternative methodology for detecting and categorizing underwater targets using passive SONAR signals. Their approach relies on the Two-Pass Split-Window (TPWS) filtering technique applied within the time-frequency domain. Initially, the acoustic signals are transformed to highlight their spectral characteristics, after which the TPWS filter is used to suppress background interference and enhance prominent frequency components associated with targets. This process improves signal clarity and aids in more accurate classification. Dmitry I Kaplun et al. [12] focused on the classification of hydroacoustic signals using a combination of signal transformation techniques and machine learning. The study employed harmonic wavelet transforms, short-time Fourier transforms, and conventional Fourier analysis to extract meaningful features from acoustic data. A k-Nearest Neighbors (kNN) classifier was then used to perform classification under varying noise conditions. The authors evaluated model performance using metrics such as precision, recall, and accuracy, and also analyzed ROC curves. Additionally, they explored dimensionality reduction through a modulo-based method and highlighted the potential of deep neural networks for classifying complex acoustic signals like whale sounds.

Chenxiang Lu et al. [13] developed an advanced method for reconstructing target spectra using a sparse Bayesian learning approach with joint sparsity constraints. Their technique enables precise separation of targets in the angular domain while maintaining consistent beamwidth across a range of frequencies, without compromising resolution. Validation on real-world array data showed that the proposed method effectively minimizes interference and preserves fine spectral details better than conventional beamforming approaches, thereby enhancing its suitability for accurate underwater target classification. Peilong Yuan et al. [14] examined the effectiveness of four machine learning models Decision Tree, Random Forest, Support Vector Machine, and Feedforward Neural Network for underwater source localization tasks. Both classification and regression scenarios were considered under different signal-to-noise ratio conditions. Results revealed that while all models performed well in classification under high-SNR conditions, Decision Trees were highly sensitive to noise. In regression tasks, performance generally declined, with only SVM and Random Forest maintaining acceptable accuracy. The study also highlighted reduced reliability in two-dimensional localization compared to one-dimensional cases.

Maria Emanuela Mihailov et al. [15] introduced a comprehensive framework for analyzing passive acoustic monitoring data collected from fixed underwater sensors at moderate depths. Their approach combines advanced signal processing techniques, including Sound Pressure Level (SPL) and Power Spectral Density (PSD), to extract meaningful acoustic features. These features are then utilized in both deep learning models (via Mel-spectrograms) and traditional machine learning approaches (using statistical descriptors of PSD), enabling a versatile analysis pipeline for marine acoustic data. Lucas C. F. Domingos et al. [16] provided an extensive review of modern deep learning techniques applied to underwater sonar data analysis, particularly in the context of coastal surveillance. The study focused on methods for classifying vessels using passive sonar signals and detecting underwater objects such as mines, human divers, and shipwreck debris through active sonar systems. Their work highlights the growing importance of deep neural networks in automating object recognition tasks in complex marine environments. Qiankun Yu et al. [17] proposed a machine learning-based framework for multi-channel signal detection. The authors generated simulated datasets using the KRAKEN acoustic propagation model, replicating conditions from the SACLANT 1993 experiment with a vertical array of hydrophones. They trained Gradient Boosted Decision Trees (GBDT) and LightGBM models independently and evaluated their performance using standard metrics such as precision, recall, F1-score, and accuracy. The results demonstrated the effectiveness of ensemble learning methods in handling multi-channel acoustic data.

3. Proposed Methodology

The proposed system is a unified intelligent learning platform designed for SONAR signal classification and regression in marine environments using a hybrid multi-model approach. It

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integrates CART-based learning with ensemble techniques to enhance prediction accuracy and robustness. The system combines multiple machine learning models including GB, SVM, and SVR, where a novel hybrid ensemble EDT is used as the proposed model. Built on a Flask-based architecture, it supports data analysis, model training, performance comparison, and real-time as well as batch predictions, ensuring efficient and scalable acoustic signal interpretation as shown in figure 2.

1. Data Acquisition and Loading: The SONAR dataset is loaded into the system, where relevant features are separated from target variables. The classification target represents sound categories, while the regression target captures signal gain values for continuous prediction.

2. Data Preprocessing and Scaling: The dataset undergoes preprocessing including train-test splitting and normalization using standard scaling. This ensures that all input features are transformed into a uniform scale, improving model stability and performance.

3. Model Initialization and Selection: Multiple models including GB, SVM, and SVR are initialized, along with the proposed hybrid ensemble EDT. The system allows selective training of models based on user input for flexible experimentation.

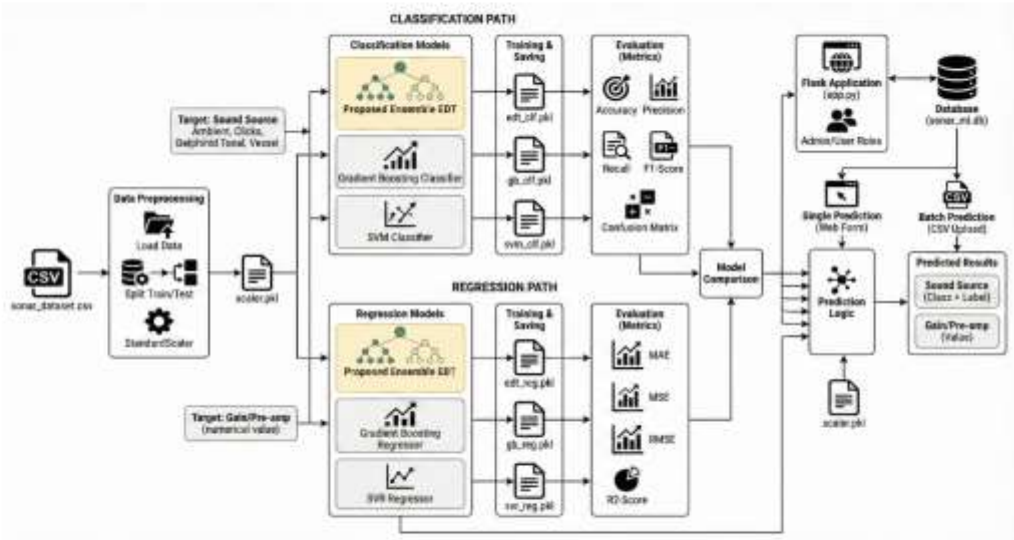

Figure. 2: Multivariate SONAR signal classification system architecture.

4. Hybrid Ensemble Training: The proposed model combines DT (based on CART) and ET using a voting mechanism to form a robust ensemble. This hybrid approach improves generalization by reducing variance while maintaining interpretability.

5. Model Training and Evaluation: All selected models are trained on the processed dataset and evaluated using performance metrics. Classification models are assessed using accuracy, precision, recall, and F1-score, while regression models are evaluated using MAE, MSE, RMSE, and R^2.

6. Model Storage and Reusability: Trained models and preprocessing components are saved as serialized files for future reuse. This avoids redundant training and enables faster deployment during prediction phases.

7. Prediction and Output Generation: The system supports both single and batch predictions by applying trained models to new input data. Outputs include classified SONAR signal types and predicted gain values, providing a complete intelligent decision-support mechanism.

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3.1 EDT

The Proposed Ensemble EDT model combines DT and ET algorithms into a unified voting-based framework to improve prediction stability and accuracy. By blending a simple tree learner with a highly randomized ensemble, the model reduces overfitting and enhances generalization on sonar acoustic data. The voting mechanism ensures balanced decision-making by aggregating outputs from both models. As shown in figure 3. This hybrid design strengthens both classification and regression tasks, especially in noisy, complex environments. The Ensemble EDT model delivers consistent, reliable performance and outperforms traditional single-model approaches.

1. **Data Input & Preprocessing:** The SONAR dataset is loaded, cleaned, and split into training and testing sets. Target columns are separated for classification and regression tasks. Features are standardized using Standard Scaler, and the fitted scaler is saved for consistent transformation during prediction.
2. **Training Phase:** Two base models Decision Tree and Extra Trees are trained independently using the preprocessed training data. Both models use fixed random states to ensure reproducibility, and each captures different patterns in the dataset, improving reliability when combined.

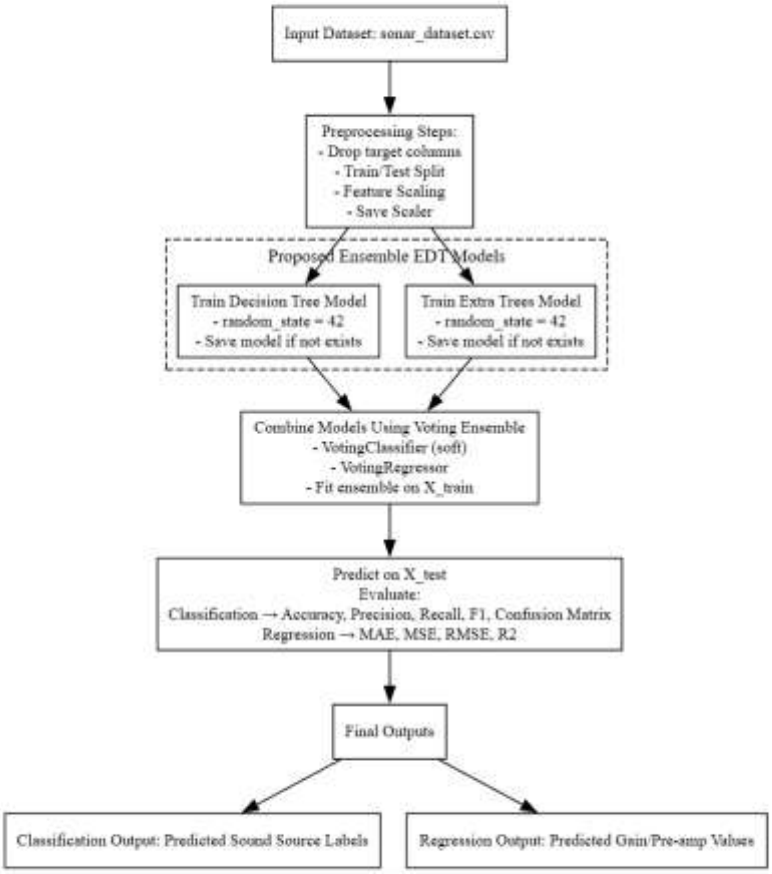

Figure. 3: Internal Workflow for EDT

3. **Ensemble Construction:** The trained Decision Tree and Extra Trees models are merged using a Voting Classifier for classification and Voting Regressor for regression. The ensemble aggregates the predictions of both models through soft voting or averaging, increasing accuracy and reducing variance.

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4. **Evaluation Phase:** The ensemble model is evaluated on the test set using metrics such as Accuracy, Precision, Recall, F1-score, and Confusion Matrix for classification, and MAE, MSE, RMSE, and R^2-score for regression. These metrics verify the model's stability and predictive performance.

5. **Output Generation & Model Saving:** The trained ensemble model is saved and integrated into the Flask application for real-time use. The system outputs predicted SONAR sound source labels for classification and numerical Gain/Pre-amp values for regression, ensuring efficient deployment and consistent predictions.

4. Result Description

Result analysis is a crucial stage in any study or experiment, as it involves interpreting the collected data to draw meaningful conclusions. It helps in identifying patterns, relationships, and trends within the results. Through analysis, raw data is transformed into useful information that supports or refutes the research objectives. This process also allows researchers to evaluate the accuracy and reliability of their findings. By comparing expected outcomes with actual results, one can determine the success or limitations of the study. Additionally, result analysis aids in making informed decisions and recommendations for future research or practical applications.

Figure 4 demonstrates superior performance compared to other models. The confusion matrix shows perfect classification with all predictions lying exactly on the diagonal, indicating zero misclassification across all classes and highlighting the robustness of the hybrid ensemble approach. In the regression plot, the predicted values closely follow the ideal diagonal line, showing a strong alignment between actual and predicted values with minimal deviation. This indicates that the proposed model effectively captures both linear and non-linear relationships in the data, achieving high accuracy and consistency in both classification and regression tasks.

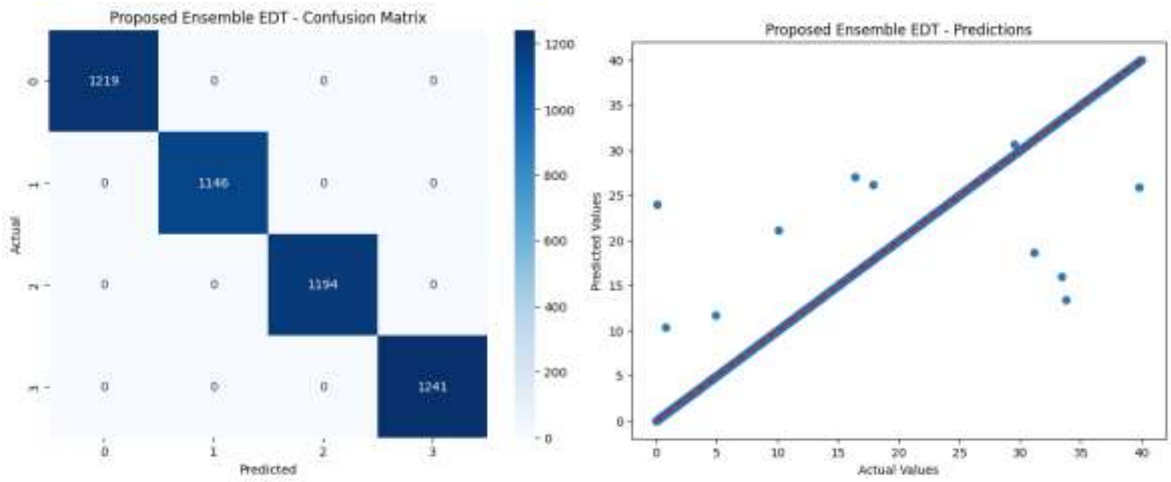

Figure. 4: Illustration of confusion matrix and ROC using proposed ensemble EDT – CART model

Figure 5 illustrates the batch prediction result screen, where the outputs from all models are displayed across multiple columns. The table includes Index, Proposed Ensemble EDT_clf, GB_clf, Svm_clf, Proposed Ensemble EDT_reg, GB_reg, and Svr_reg. The classification columns contain label values such as 0 (Ambient), 1 (Clicks), 2 (Delphinid Tonal), and 3 (Vessel). The regression columns contain numerical predictions such as 17.83, 21.67, 28.02, 19.38, and similar continuous values. This

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structured output helps users compare how each model predicts both sound source class and Gain/Pre-amp value.

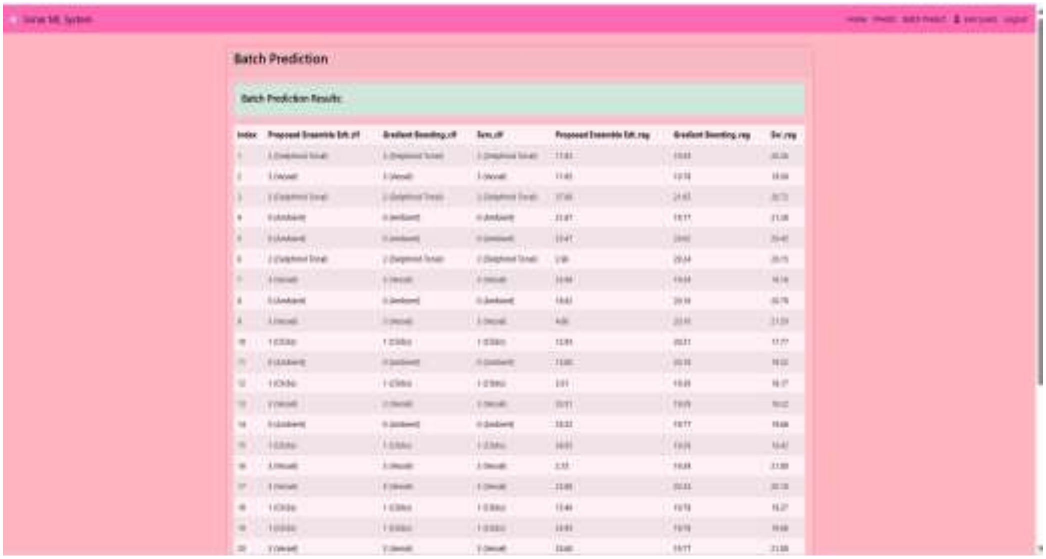

Figure. 5: Batch prediction result obtained using ensemble EDT model

The table 1 clearly shows that the Proposed Ensemble EDT model delivers perfect performance across all metrics, achieving 100% Accuracy, Precision, Recall, and F1-score. This indicates that the ensemble of DT and ET captures the underlying SONAR patterns extremely well, without misclassifying any samples. GB ranks second, achieving strong but slightly lower scores across all metrics, reflecting its ability to generalize well but not at the same level as the ensemble. SVM performs reliably with Accuracy and F1-scores around 0.96, but it trails behind the tree-based models due to its linear decision boundary, which is less flexible for complex acoustic data.

Table 1: Performance evaluation metrics of the classification analysis

Model	Accuracy (A)	Precision (P)	Recall (R)	F1 Score (F1)
EDT	1.0000	1.0000	1.0000	1.0000
GB	0.9854	0.9860	0.9854	0.9854
SVM	0.9679	0.9680	0.9679	0.9678

The table 2 presents the regression results show that the Proposed Ensemble EDT model significantly outperforms the other two approaches, achieving extremely low MAE, MSE, and RMSE values, along with a high R^2 score of 0.9870. This indicates that the ensemble predicts Gain/Pre-amp values with high precision and captures the underlying regression patterns very effectively. GB performs poorly in this dataset, with high error values and an R^2 score close to zero, meaning it struggles to explain the variance in the target variable. SVR shows similar behavior, with high errors and a negative R^2 score, indicating that it performs worse than a simple mean predictor.

Table 2: Performance evaluation metrics of the regression analysis

Model	MAE	MSE	RMSE	R^2 Score

EDT	0.1130	1.7339	1.3168	0.9870
GB	9.9189	132.1681	11.4964	0.0064
SVR	9.9421	133.3862	11.5493	-0.0027

5. Conclusion

The developed SONAR signal analysis framework presents an effective integration of machine learning methodologies with an interactive web-based deployment environment. By leveraging a hybrid ensemble approach that combines Decision Tree and Extra Trees algorithms through a voting mechanism, the system delivers enhanced predictive reliability and consistency. This combined model minimizes overfitting, improves generalization, and outperforms individual learning techniques in both classification and regression tasks. The architecture incorporates a fully automated workflow, including data preparation, feature transformation, model development, evaluation, and real-time inference. This seamless pipeline enables efficient detection of underwater acoustic sources along with accurate estimation of parameters such as Gain and Pre-amplifier values. The system's capability to handle both single-instance and batch predictions further enhances its practical usability. Comprehensive performance evaluation using multiple metrics Accuracy, Precision, Recall, F1-score for classification, and MAE, MSE, RMSE, and R^2 for regression confirms the robustness and superiority of the proposed ensemble model.

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