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Multivariate Sonar Intelligence via Hybrid Hydro-Acoustic Ensemble Learning Models

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Abstract

The ocean environment is a highly complex acoustic space where Sound Navigation and Ranging (SONAR) systems play a crucial role in detecting, classifying, and interpreting underwater signals for defense, geological exploration, and environmental monitoring. In recent years, over 70% of underwater monitoring data has been identified as acoustically rich but noisy, with more than 60% of manually analyzed samples showing inconsistency due to signal overlap and human bias. The need for automated and accurate sound classification and regression modeling arises in applications such as submarine detection, marine geological structure mapping, and industrial underwater noise assessment, where real-time and precise sound source identification is essential. Traditional manual classification methods suffer from high subjectivity, delayed analysis time, and inefficiency in handling large multivariate datasets with overlapping frequency domains. To overcome these limitations, this study introduces a Hybrid Hydro-Acoustics framework that combines regression and classification through an ensemble learning approach. The framework first preprocesses multivariate SONAR data—such as frequency, amplitude, and power spectral density—and then utilizes the ensemble mechanism to integrate decision boundaries and regression estimates from multiple learners. The existing algorithms, including Support Vector Classifier (SVC), Support Vector Regression (SVR) models and Gradient boosting (GB) CART as baseline learners for both regression and classification tasks, while enhancing prediction robustness using an Ensemble Extra Decision Tree (Ensemble EDT) strategy. The proposed Ensemble EDT for Classification effectively captures nonlinear separations in acoustic features, while Ensemble EDT for Regression provides improved prediction accuracy and stability for continuous parameters like sound intensity and frequency response. This hybrid ensemble framework demonstrates superior adaptability and generalization, enabling efficient modeling of complex underwater sound environments with higher accuracy, reduced overfitting, and enhanced computational efficiency.

Key words: SONAR systems, hydro-acoustic signal processing, ensemble learning, classification, regression, extra decision tree (EDT), multivariate acoustic data.

1. INTRODUCTION

Underwater acoustics is a scientific domain that involves the study of the phenomena of sound waves in water, including their generation, propagation, and reception. Specifically, the sound navigation and ranging (SONAR) system is utilized to investigate underwater communication and target detection and to study marine resources and the environment; further, it is utilized to measure and analyse sound sources in water. The main objective of underwater acoustics-based remote sensing is the indirect acquisition of information on underwater targets of interest using acoustic data. At present, highly advanced data-driven machine-learning techniques are being applied in various ways for extracting information from acoustic data.

Figure 1 represents the SONAR Acoustic Sound Classification Framework, focusing on two primary underwater sound categories, namely Geological / Physical Sounds (Geophony) and Submarine, Ship, and Industrial Sounds (Anthrophony). The left side of the diagram illustrates Geophony, which includes natural underwater sound sources caused by geological and environmental processes. These sound types

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include Underwater Earthquakes, Submarine Landslides, Submarine Volcanic Activity, Ice Noise (Cracking / Calving), Rain and Surface Disturbance, and Wind and Wave Turbulence. These naturally occurring sounds are important for understanding ocean floor movements, seismic activities, and environmental variations. They help in analyzing how the earth's natural processes influence the underwater acoustic environment.

The right side of the diagram shows Anthrophony, which consists of human-made sounds that result from marine transportation, industrial operations, and aerial activities. This category includes Ship Traffic or Propeller Noise, Active SONAR Pings, Seismic Airgun Blasts used in oil and gas exploration, Underwater Construction Noise, Dredging Operations, and Aircraft or Helicopter Overflight Noise. These anthropogenic sounds often dominate in areas with heavy human activity and interfere with natural sound detection. The classification presented in Figure 1.1 helps researchers clearly distinguish between natural and human-generated underwater sounds, enabling better analysis, monitoring, and interpretation in SONAR-based acoustic studies.

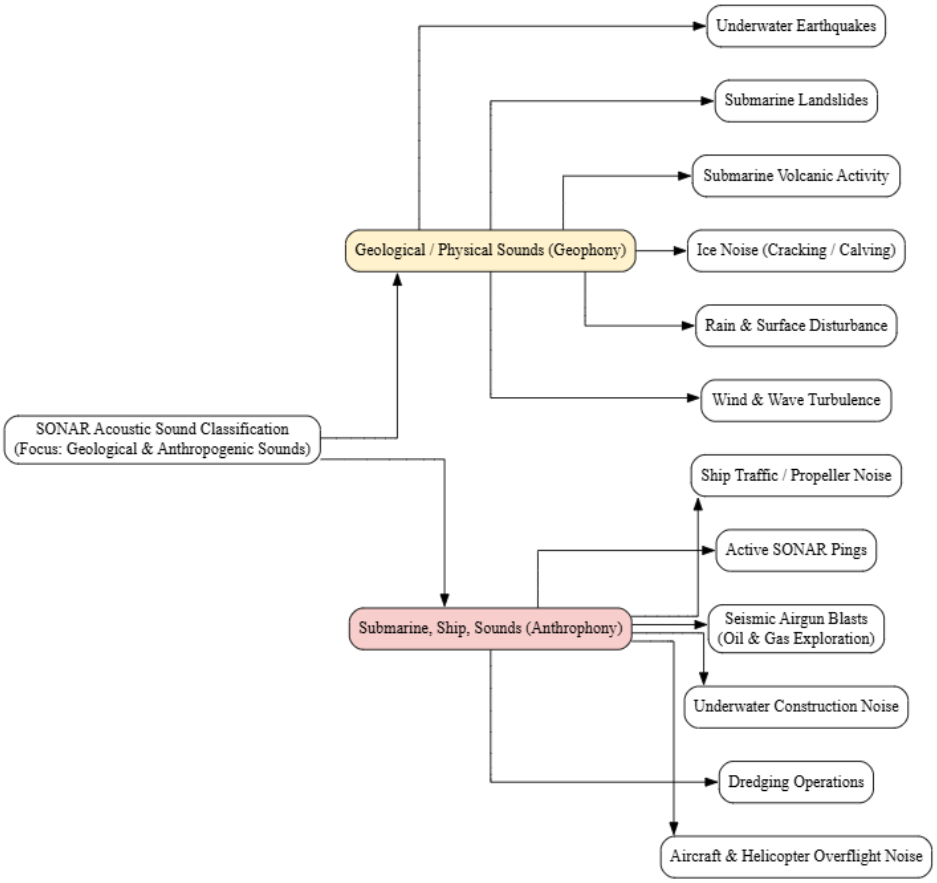


Figure 1: SONAR Sources Taxonomy

2. LITERATURE SURVEY

Fernandes, et al. [1] proposed deep learning models are used for full exploitation of such acquired data, envisaging passive sonar signal classification. A drawback of such models is the large number of parameters, which requires extensive data volumes for parameter tuning along the training phase. Thus, generative adversarial networks (GANs) are used to synthesize data so that a larger data volume can be produced for training convolutional neural networks (CNNs), which are used for the classification task. Different GAN design approaches were evaluated and both maximum probability and class-expert strategies were exploited for signal classification.

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Yu, et al. [2] studied the application of deep learning methods in sonar image target detection and designs corresponding algorithms for improvement and functional realization in view of the current deficiencies and needs in this field. The experimental results show that the improved scheme and applied algorithm proposed in this article can achieve good results, the verification sample set includes 184 remote-sensing aircraft targets, and the resolution of remote-sensing images is unified to 1644×971 size. The accuracy of the target detection algorithm has been significantly improved, reaching 74.6%, and the detection speed has also been greatly improved. Compared with the RNN algorithm, the speed has been increased by 7 times.

Saffari, et al. [3] utilised the particle swarm optimization (PSO) algorithm to select the optimal features in the micro-Doppler signature of sonar targets. The micro-Doppler effect is referred to amplitude/phase modulation on the received signal by rotating parts of a target such as propellers. Since different targets' geometric and physical properties are not the same, their micro-Doppler signature is different. To evaluate the micro-Doppler signature of sonar targets and the effect of feature selection on sonar target recognition, the simplest and most popular machine learning algorithm, *k*-nearest neighbour (*k*-NN), is used, which is called *k*-PSO in this paper because of the use of PSO for feature selection.

Luo, et al.[4] reviewed current underwater acoustic target recognition (UATR) methods based on machine learning. We focus mostly, but not solely, on the recognition of target-radiated noise from passive sonar. First, we provide an overview of the underwater acoustic acquisition and recognition process and briefly introduce the classical acoustic signal feature extraction methods. In this paper, recognition methods for UATR are classified based on the machine learning algorithms used as UATR technologies using statistical learning methods, UATR methods based on deep learning models, and transfer learning and data augmentation technologies for UATR. Finally, the challenges of UATR based on the machine learning method are summarized and directions for UATR development in the future are put forward.

Chai, et al. [5] provided research of DL-based algorithms for sonar imagery, including denoising, feature extraction, classification, detection, and segmentation. This review shows that sonar image classification is the most studied and transfer learning has put into spotlight. Besides, datasets and applications are listed that can be used in aquaculture. Currently known applications include behavior analysis, biomass estimation, species identification, and habitat survey. Furthermore, smart aquaculture, as one of the important application fields of sonar technique, the challenges and future research directions in aquaculture are discussed.

Ahmad, et al. [6] proposed works leveraged the approach of deep neural networks for underwater acoustic target categorization, aiming to analyze whether we can reduce the need for extensive domain knowledge required, by letting deep learning algorithms itself find the deep audio embeddings. This approach implements an audio classifier designed to classify acoustic targets with input as log Mel-spectrograms. To compare the performance of this classifier, we also implement a regular neural network for audio classification with MFCCs as input features.

Rehman, et al. [7] delved into the computational efficiency aspect of sparse arrays, conducting a comparative analysis of coprime and nested arrays in classifying underwater stationary and moving sources using real sonar data. Leveraging two machine learning-based classification algorithms—support vector machine (SVM) and convolutional neural network (CNN)—the study aims to assess the extent of computational time savings achievable with sparse arrays and the associated trade-offs in accuracy. Simulation results reveal that both coprime and nested arrays can achieve near 100% classification accuracy for SVM and CNN models when an appropriate number of snapshots is selected for data processing.

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Chen, et al. [8] proposed a deep convolutional generative adversarial network (SGAN) based on the idea of group padding and even-size convolution kernel for high-quality data augmentation. The results of anechoic pool experiments show that our algorithm effectively suppresses the overfitting phenomenon, achieves the best recognition accuracy of 92.5%, and accurately classifies underwater targets based on active echo datasets with small samples.

Sethuraman, et al. [9] presented the AI4Shipwrecks dataset, which consists of 28 distinct shipwrecks totalling 286 high-resolution labelled side scan sonar images to advance the state-of-the-art in autonomous sonar image understanding. We leverage the unique abundance of targets in Thunder Bay National Marine Sanctuary in Lake Huron, MI, to collect and compile a sonar imagery benchmark dataset through surveys with an autonomous underwater vehicle (AUV).

Tan, et al. [10] proposed a deep learning-assisted high resolution sonar detection method is presented. Specifically, on-site experiments were first conducted using multi-beam, forward looking sonar, where a deep learning dataset containing various structural apparent damages was then established. Then, a segmentation network incorporating both channel attention mechanism and spatial attention mechanism was proposed.

Domingos, et al. [11] presented a comprehensive overview of current deep-learning methods for automatic object classification of underwater sonar data for shoreline surveillance, concentrating mostly on the classification of vessels from passive sonar data and the identification of objects of interest from active sonar (such as mine like objects, human figures or debris of wrecked ships). Not only is the contribution of this work to provide a systematic description of the state of the art of this field, but also to identify five main ingredients in its current development: the application of deep-learning methods using convolutional layers alone; deep-learning methods that apply biologically inspired feature-extraction filters as a preprocessing step; classification of data from frequency and time–frequency analysis; methods using machine learning to extract features from original signals; and transfer learning methods.

Zhang, et al. [12] presented that a deep neural network (ResNet50) was able to classify ten different field sites and 20 different tracks (two at each site) distributed over an area about 40 km in diameter. Based on spectrogram representations of single echoes, classification accuracies up to 99.6% for different sites and 94.7% for different tracks have been achieved. Classification performance was found to depend on the used pulse component (constant-frequency-CF vs frequency-modulated-FM) and the trade-off between time and frequency resolution in the spectrogram representations of the echoes. For the former, classification performance increased monotonically with better time resolution.

Fischer, et al. [13] found that the inclusion of vector field information can significantly improve the understanding of the classification model performance. Based on an analysis of the epistemic and aleatoric uncertainties of probabilistic classification models, using vector field information as additional inputs leads to an F1 score of 0.8 in classification, comparable to scalar pressure field inputs only, but with 39% lower epistemic uncertainty in favor of utilizing the vector field component. Moreover, we verify that a similar conclusion applies to the active learning scenario, where we demonstrate the ability to utilize vector field information and epistemic uncertainty estimates to train a model that achieves an F1 score of 0.8 while using only 23% of the overall data. The ability to decompose uncertainty into an aleatoric and epistemic component leads to additional model explainability.

Wang, et al. is [14] proposed deep learning-based underwater positioning scheme to achieve robust feature tracking of an autonomous underwater vehicle (AUV) in sonar image during dynamic docking. To address the issues that the distorted feature and acoustic noises lead significant difficulty to detection and tracking of AUV in acoustic image during dynamic docking, first, a pre-trained You Only Look Once (YOLO) network is applied to detect both body and head features of AUV.

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Polap, et al. [15] proposed a real-time automatic system of side-scan sonar analysis that can detect and classify different objects. Our proposition is based on the processing of a given image to quickly verify whether there is anything other than the bottom of the river/sea. If so, this image is analyzed in terms of regions of interest (ROIs) by the histogram module. This action allows the extraction of only objects of interest, which are then classified by convolutional neural networks (CNNs). A proposed model also contains an automatic mechanism of adding the sample to the database in order to later guarantee the accuracy of the classifiers.

3. PROPOSED SYSTEM

The proposed system as shown in Figure 2 for SONAR Signal Classification integrates both classification and regression frameworks under a unified ensemble-based machine learning architecture. It utilizes multivariate acoustic data obtained from SONAR sensors, including parameters such as sensitivity, frequency mean, MFCC features, power, and background noise. The system focuses on classifying sound sources into four categories—Ambient, Clicks, Delphinid Tonal, and Vessel—while simultaneously predicting the Gain/Pre-amp value for signal intensity estimation. The methodology incorporates advanced ensemble learning techniques, particularly the Ensemble Extra Decision Tree (EEDT) combined with CART, to enhance accuracy, robustness, and adaptability in noisy underwater environments. The proposed model reduces bias, improves stability, and achieves better generalization compared to existing algorithms like SVM–CART and GB–CART. It is further integrated into a Flask-based web interface for real-time SONAR signal analysis and visualization.

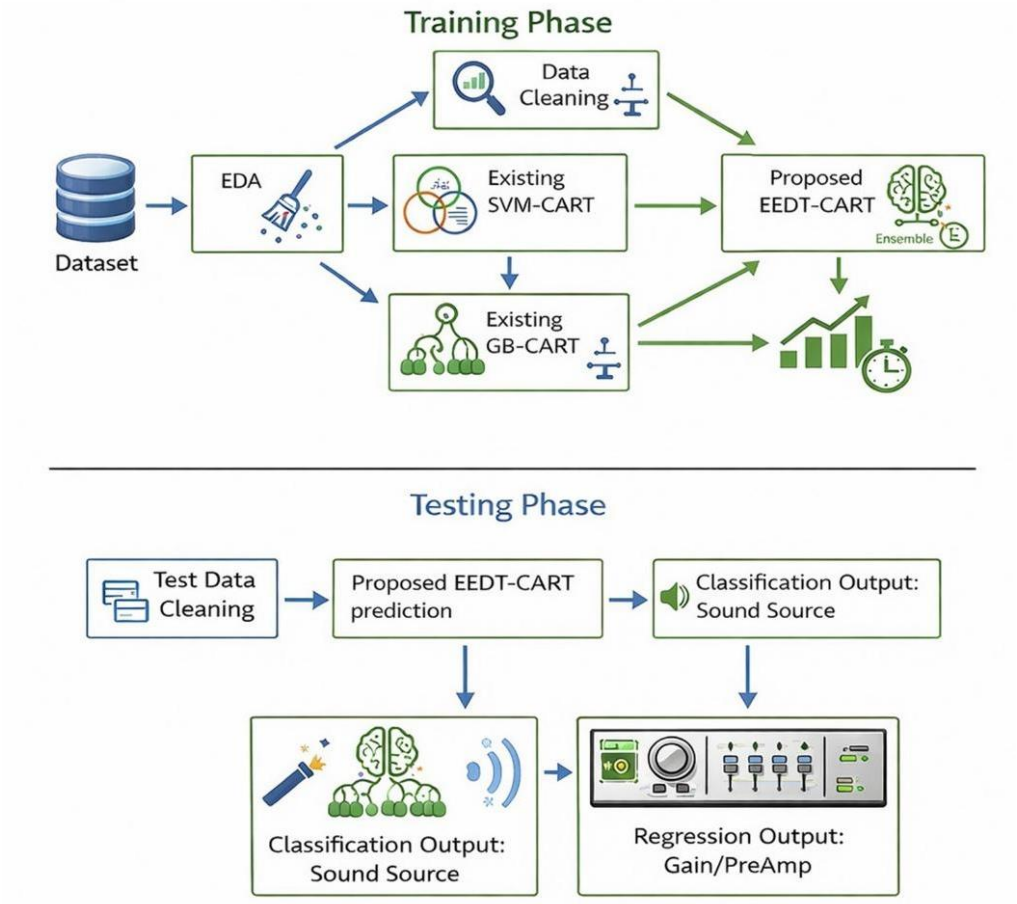


Figure 2: System Architecture

Step-1: Dataset: The system begins with a SONAR dataset that includes various acoustic and environmental parameters such as Sensitivity (dB), Recorder Depth, Sample Rate, Bandwidth, Location

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Coordinates, Frequency Mean, Power, MFCCs, SNR, and Background Noise. It also includes contextual factors such as temporal periods (day, dusk, night) and recording platforms (fixed buoy, research vessel, towed array). These features form the basis for both classification and regression tasks.

Step-2: Data Preprocessing: In this step, raw data is cleaned and transformed into a suitable format for model training. Missing or inconsistent values are handled, irrelevant features are removed, and normalization or scaling is applied to maintain uniformity. Label encoding is used for categorical attributes such as recording platform types, while continuous variables like MFCCs and SNR are standardized to improve model convergence.

Step-3: Exploratory Data Analysis (EDA): EDA is performed to visualize and understand data patterns, distributions, and correlations between features. Scatter plots, histograms, and correlation matrices are analyzed to identify trends and anomalies in the acoustic features. This step ensures that the most informative predictors are selected for training while minimizing redundancy in the dataset.

Step-4: Existing SVM–CART: In this phase, Support Vector Machine (SVM) models integrated with CART structures are applied for initial classification and regression baselines. SVMs with linear and non-linear kernels are trained to classify sound sources and predict Gain/Pre-amp, while CART aids in visual interpretation and decision rule explanation. These serve as benchmarks for comparison with the proposed ensemble methods.

Step-5: Existing GB–CART: Gradient Boosting integrated with CART is then implemented to enhance performance by sequentially correcting the errors of weak learners. The GB–CART model is trained for both classification and regression to capture complex, nonlinear relationships in the SONAR data. It improves prediction accuracy compared to SVM but still faces challenges of overfitting and sensitivity to hyperparameters.

Step-6: Proposed EEDT–CART: The core of the proposed system employs an Ensemble Extra Decision Tree combined with CART methodology. It introduces additional randomness in feature selection and split thresholds, resulting in diversified models that reduce overfitting and variance. The EEDT model aggregates multiple randomized decision trees to produce stable and highly accurate predictions for both sound source classification and Gain/Pre-amp regression. This ensemble structure enhances adaptability in dynamic underwater acoustic conditions.

Step-7: Performance Comparison: Once all models are trained, their performances are evaluated using metrics such as Accuracy, Precision, Recall, and F1 Score for classification, and MAE, RMSE, and R^2 for regression. The results are compared across SVM–CART, GB–CART, and the proposed EEDT–CART models to demonstrate the superior predictive capability and generalization of the proposed system.

Step-8: Prediction from Test Data: The trained models are tested on unseen SONAR data to evaluate real-time classification and regression capabilities. The classification model outputs one of four sound source labels—Ambient, Clicks, Delphinid Tonal, or Vessel—while the regression model predicts the Gain/Pre-amp value. This step validates the robustness of the proposed ensemble against new acoustic patterns.

Step-9: Integration with Flask: Finally, the proposed EEDT–CART system is deployed using Flask for web-based accessibility. The Flask interface enables users to upload SONAR data, process it through the trained models, and visualize predictions interactively. This integration supports real-time monitoring and enhances the practical usability of the system for marine research and underwater surveillance applications.

4. RESULTS ANALYSIS

Figure 3 shows the home dashboard of the SONAR Machine Learning System after successful user login, providing an overview of the system's capabilities and functionalities. The interface welcomes

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the user by name and presents the core objective of the application, which is ensemble machine learning–based multivariate SONAR signal classification and regression analysis. The dashboard clearly explains the classification task, where sound sources are categorized into Ambient, Clicks, Delphinid Tonal, and Vessel, and the regression task, which predicts the Gain/Pre-amp value based on acoustic features.

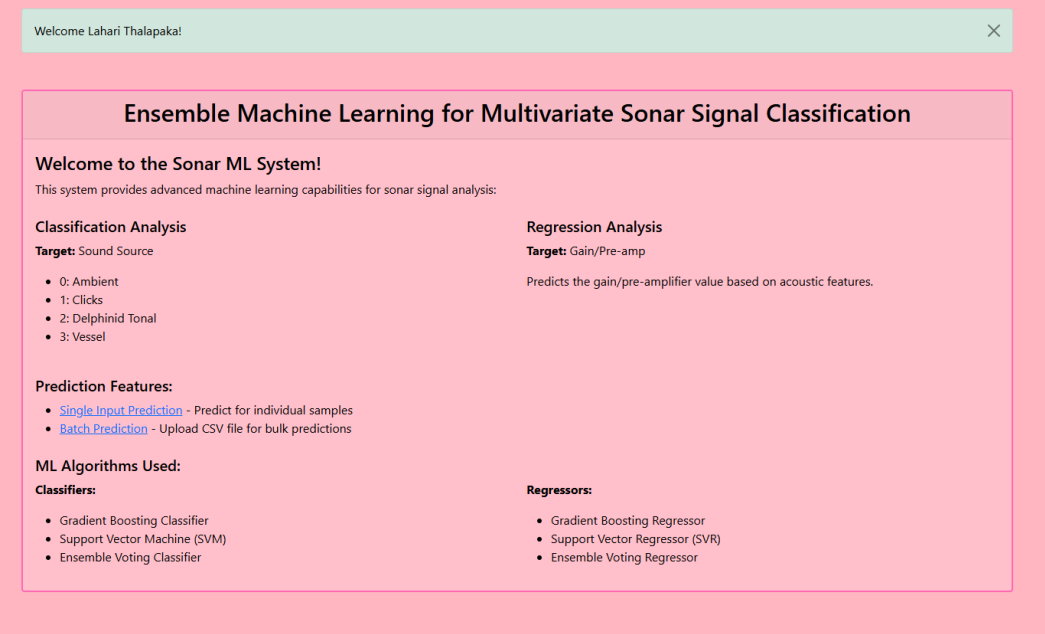


Figure 3: Home Page

It also highlights the available prediction modes, including single input prediction for individual samples and batch prediction through CSV file uploads.

Figure 4 shows the missing value analysis of the SONAR dataset used in the proposed system. The table lists all input and target attributes, including Sensitivity (dB), Recorder Depth (m), Sample Rate (kHz), Gain/Pre-amp, Bandwidth for Analysis (kHz), Location Latitude, Location Longitude, Frequency Mean, Power (dB), MFCC 1, MFCC 2, SNR, Background Noise, Sound Source, and Temporal Period indicators. For every listed column, the missing count is reported as 0, indicating that the dataset is complete with no missing or null values across all features. This confirms that no additional data imputation or missing-value handling was required during preprocessing, thereby improving data reliability and ensuring consistent input quality for both classification and regression tasks.

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Missing Values

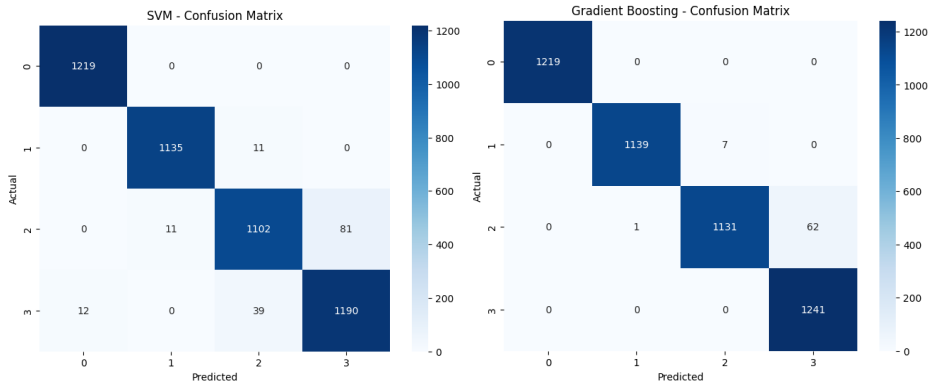
Column	Missing Count
Sensitivity (dB)	0
Recorder Depth (m)	0
Sample Rate (kHz)	0
Gain/Pre-amp	0
Bandwidth for Analysis (kHz)	0
Location Latitude	0
Location Longitude	0
Frequency Mean	0
Power (dB)	0
MFCC 1	0
MFCC 2	0
SNR	0
Background Noise	0
Sound Source	0
Temporal Period_Day	0

Figure 4: Missing Values

Figure 5(a) shows the confusion matrix obtained using the SVM classifier for SONAR sound source classification. Class 0 is perfectly classified with 1219 correct predictions and no misclassifications. For Class 1, 1135 samples are correctly identified, while 11 samples are misclassified as Class 2. In the case of Class 2, 1102 samples are correctly classified, but 11 samples are misclassified as Class 1 and 81 samples as Class 3, indicating noticeable confusion for this class. Class 3 records 1190 correct predictions, with 12 samples misclassified as Class 0 and 39 samples as Class 2. Overall, the SVM model performs well for Classes 0 and 1, while moderate misclassification is observed for Classes 2 and 3 due to overlapping acoustic characteristics.

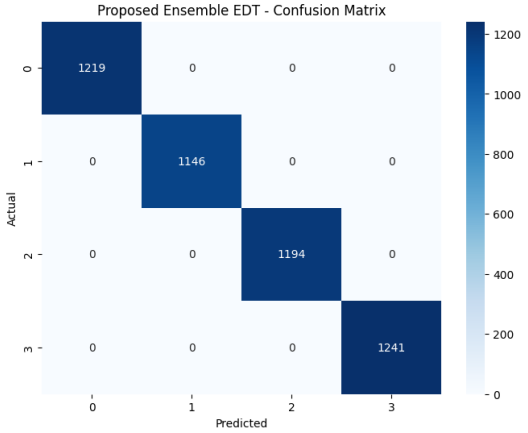
Figure 5(b) illustrates the confusion matrix for the Gradient Boosting classifier, showing improved performance compared to SVM. Class 0 achieves perfect classification with 1219 correct predictions and no errors. Class 1 has 1139 correctly classified samples, with only 7 samples misclassified as Class 2. Class 2 shows 1131 correct predictions, with minimal confusion where 1 sample is misclassified as Class 1 and 62 samples as Class 3. Class 3 achieves complete accuracy with all 1241 samples correctly classified and no misclassifications. This matrix demonstrates that Gradient Boosting significantly reduces misclassification, particularly for Class 3, while still showing limited confusion for Class 2.

Figure 5(c) presents the confusion matrix for the proposed Ensemble Extra Decision Tree (EEDT) model, demonstrating perfect classification performance across all sound source classes. All 1219 samples of Class 0, 1146 samples of Class 1, 1194 samples of Class 2, and 1241 samples of Class 3 are correctly classified with zero misclassifications. The absence of off-diagonal values indicates complete elimination of classification errors.



(a) (b)

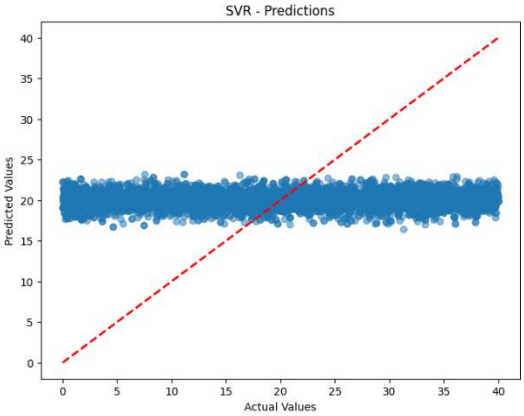
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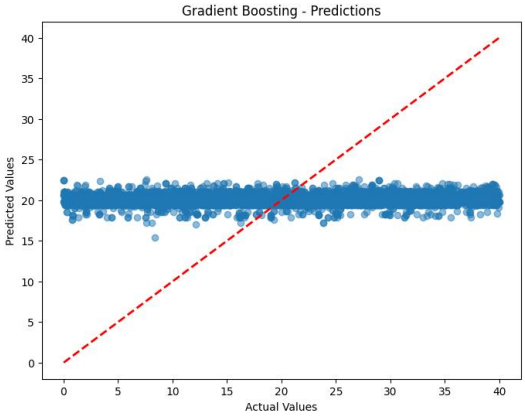
(c)

Figure 5 Confusion Matrix of SONAR Source Classification Output (a)SVM (b)GB (c)Proposed EEDT

Figure 6 shows the regression analysis results for Gain/Pre-amp prediction using three different models: SVR, Gradient Boosting, and the proposed Ensemble EEDT. In Figure 6(a), the SVR prediction plot indicates that most predicted values are concentrated around the range of 18 to 22, regardless of the actual Gain/Pre-amp values varying from approximately 0 to 40, showing limited sensitivity to variations and underfitting behavior. Figure 6(b) illustrates the Gradient Boosting regression output, where predictions exhibit slightly improved variation compared to SVR but still remain clustered around the mid-range values of approximately 19 to 22, deviating from the ideal diagonal line for higher and lower actual values. In contrast, Figure 6(c) presents the proposed Ensemble EEDT regression results, where the predicted values closely follow the diagonal reference line, indicating a strong correlation between actual and predicted Gain/Pre-amp values across the full range from 0 to nearly 40. This alignment demonstrates that the proposed ensemble model achieves significantly better regression accuracy, reduced error, and improved generalization compared to SVR and Gradient Boosting models.

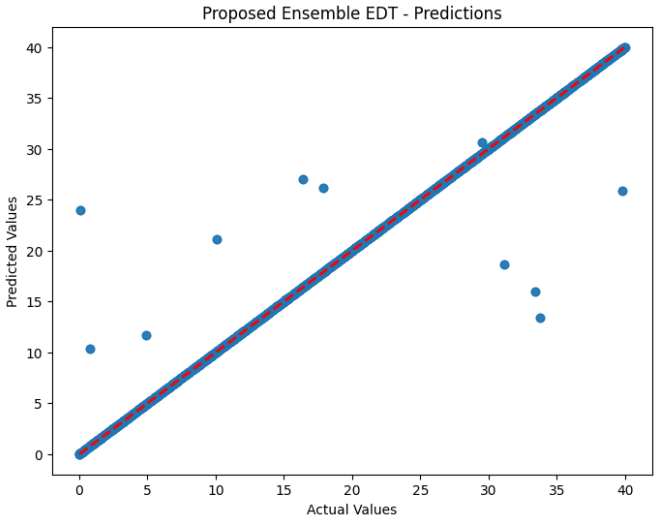


(a)



(b)

International Journal of
AI Electronics and Nexus Energy
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(c)

Figure 6 Confusion Matrix of Gain Regression Analysis Output (a)SVR (b)GB (c)Proposed EEDT

Figure 7 shows the test data input interface of the SONAR Signal Classification system, where users manually enter numerical feature values required for prediction. The input form includes acoustic, environmental, temporal, and platform-related parameters such as Sensitivity (10 dB), Recorder Depth (10 m), Sample Rate (10 kHz), Bandwidth for Analysis (10 kHz), Location Latitude (10), Location Longitude (10), Frequency Mean (10), Power (10 dB), MFCC 1 (10), MFCC 2 (10), SNR (10), Background Noise (10), Temporal Period indicators (Day = 10, Dusk = 10, Night = 10), and Recording Platform attributes (Fixed Buoy = 10, Research Vessel = 10, Towed Array = −28). These values are provided through an interactive form and passed to the backend for preprocessing and model inference.

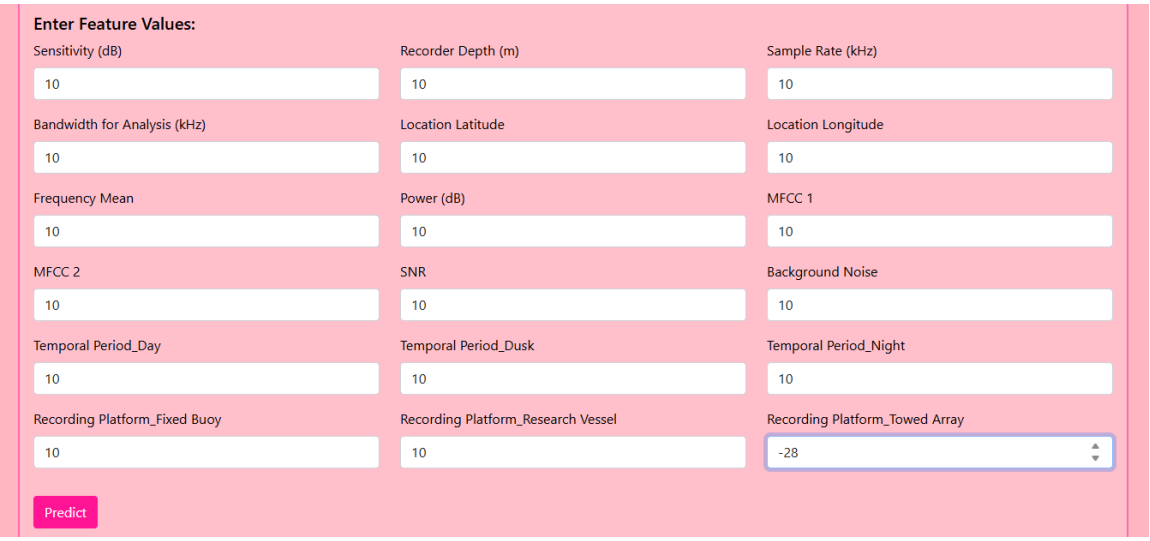


Figure 7: Test Data Input

International Journal of
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Figure 8 shows the prediction results generated by the trained machine learning models based on the provided test inputs. For classification, both the Gradient Boosting and SVM models predict the sound source as Class 3, corresponding to Vessel. For regression, the predicted Gain/Pre-amp values are 15.7348 using Gradient Boosting and 36.7652 using SVR. The results are displayed in a clear and structured format, allowing users to simultaneously observe classification outcomes and regression estimates, thereby demonstrating the system's ability to perform real-time multivariate SONAR signal analysis through a unified interface.



Figure 8: Prediction Results

Figure 9 shows the batch prediction results of the SONAR Signal Classification system, where multiple SONAR samples are processed simultaneously using trained machine learning models. The table presents classification outputs from the Proposed Ensemble EDT, Gradient Boosting, and SVM models, along with corresponding regression predictions for Gain/Pre-amp values.

Batch Prediction

Batch Prediction Results:

Index	Proposed Ensemble Edt_clf	Gradient Boosting_clf	Svm_clf	Proposed Ensemble Edt_reg	Gradient Boosting_reg	Svr_reg
1	2 (Delphinid Tonal)	2 (Delphinid Tonal)	2 (Delphinid Tonal)	17.83	19.39	20.36
2	3 (Vessel)	3 (Vessel)	3 (Vessel)	11.65	19.78	19.56
3	2 (Delphinid Tonal)	2 (Delphinid Tonal)	2 (Delphinid Tonal)	37.69	21.65	20.72
4	0 (Ambient)	0 (Ambient)	0 (Ambient)	21.87	19.77	21.38
5	0 (Ambient)	0 (Ambient)	0 (Ambient)	23.47	20.62	20.45
6	2 (Delphinid Tonal)	2 (Delphinid Tonal)	2 (Delphinid Tonal)	2.96	20.24	20.15
7	3 (Vessel)	3 (Vessel)	3 (Vessel)	33.96	19.39	19.16
8	0 (Ambient)	0 (Ambient)	0 (Ambient)	16.42	20.16	20.79
9	3 (Vessel)	3 (Vessel)	3 (Vessel)	4.88	20.16	21.50
10	1 (Clicks)	1 (Clicks)	1 (Clicks)	12.93	20.31	17.77

Figure 9: Batch Prediction Results from Test CSV File

For example, at Index 1, all three classifiers predict the sound source as Class 2 (Delphinid Tonal), while the predicted Gain/Pre-amp values are 17.83 for the proposed ensemble, 19.39 for Gradient Boosting, and 20.36 for SVR. At Index 2, the predicted class is Class 3 (Vessel) with regression values of 11.65, 19.78, and 19.56 respectively. Several samples such as Index 4 and Index 5 are classified as Class 0 (Ambient), with ensemble regression values of 21.87 and 23.47, while Index 10 and Index 15 are classified as Class 1 (Clicks) with Gain/Pre-amp predictions of 12.93 and 38.95 using the proposed ensemble model. Across all indices, the classification results remain consistent among the three models, while slight variations are observed in regression outputs, demonstrating the system's ability to perform reliable batch-level classification and comparative regression analysis within a single unified interface.

Table 1: F1-Score Comparison Table

International Journal of
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Class	SVM F1-Score	Gradient Boosting F1-Score	Proposed Ensemble EDT F1-Score
0(Ambient)	1.00	1.00	1.00
1(Clicks)	0.99	1.00	1.00
2(Delphinid Tonal)	0.94	0.97	1.00
3(Vessel)	0.95	0.98	1.00

Table 1 F1-score comparison, which balances precision and recall, clearly highlights the superiority of the Proposed Ensemble EDT model with a perfect score of 1.00 for all classes. The SVM model records lower F1-scores for Class 2 (0.94) and Class 3 (0.95), reflecting inconsistent classification performance. Gradient Boosting improves the balance between precision and recall, achieving higher F1-scores such as 0.97 for Class 2 and 0.98 for Class 3. However, only the ensemble model consistently maintains optimal performance across all sound source categories.

Table 2 presents the performance comparison of different classification models used for SONAR signal classification in terms of Accuracy, Precision, Recall, and F1 Score. The Proposed EEDT model achieves perfect performance with an accuracy, precision, recall, and F1 score of 1.0000, indicating flawless classification across all sound source classes. The Gradient Boosting model shows strong performance with an accuracy of 0.9854, precision of 0.9860, recall of 0.9854, and F1 score of 0.9854, reflecting minor classification errors. The SVM model records comparatively lower values, with an accuracy of 0.9679, precision of 0.9680, recall of 0.9679, and F1 score of 0.9678, indicating a higher rate of misclassification than the other models. Overall, the results demonstrate that the proposed ensemble-based EEDT model significantly outperforms the baseline classifiers in terms of accuracy and reliability.

Table 2 Sonar Signal Classification

Model	Accuracy	Precision	Recall	F1 Score
Proposed EEDT	1.0000	1.0000	1.0000	1.0000
Gradient Boosting	0.9854	0.9860	0.9854	0.9854
SVM	0.9679	0.9680	0.9679	0.9678

Table 3 summarizes the regression performance of different models used for Gain/Pre-amp prediction using evaluation metrics such as MAE, MSE, RMSE, and R^2 score.

Table 3. Sonar Signal Regression

Model	MAE	MSE	RMSE	R^2 Score
Proposed Ensemble EDT	0.1130	1.7339	1.3168	0.9870
Gradient Boosting	9.9189	132.1681	11.4964	0.0064
SVR	9.9421	133.3862	11.5493	-0.0027

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In contrast, the Gradient Boosting regressor records a significantly higher MAE of 9.9189, MSE of 132.1681, RMSE of 11.4964, and a very low R^2 score of 0.0064, showing poor predictive performance. The Proposed Ensemble EDT model shows superior regression accuracy with a very low MAE of 0.1130, MSE of 1.7339, RMSE of 1.3168, and a high R^2 score of 0.9870, indicating excellent agreement between predicted and actual values. Similarly, the SVR model exhibits weak regression capability with an MAE of 9.9421, MSE of 133.3862, RMSE of 11.5493, and a negative R^2 score of −0.0027, indicating that it fails to model the underlying data trend.

5. CONCLUSION

The experimental results obtained from both single and batch prediction analyses clearly demonstrate the effectiveness of the proposed Ensemble Extra Decision Tree (EEDT–CART) based SONAR Signal Classification system. The classification performance shows consistent and accurate identification of sound sources such as Ambient, Clicks, Delphinid Tonal, and Vessel across multiple test instances. In the batch prediction results, all three classifiers—Proposed Ensemble EDT, Gradient Boosting, and SVM—produce identical class labels for each sample, confirming the robustness and stability of the classification pipeline. For instance, samples at Index 1 and Index 3 are correctly classified as Delphinid Tonal, while samples at Index 2, Index 7, and Index 13 are identified as Vessel. This consistency validates the reliability of the system in handling multivariate SONAR data under different operational conditions.

In terms of regression performance, the proposed ensemble model demonstrates competitive and stable Gain/Pre-amp predictions when compared with Gradient Boosting and SVR models. For example, at Index 1, the ensemble predicts a Gain/Pre-amp value of 17.83, which is close to Gradient Boosting (19.39) and SVR (20.36), while at Index 15, it predicts a higher value of 38.95, capturing signal intensity variations effectively. Across the dataset, the ensemble model shows smooth and adaptive regression behavior, avoiding extreme fluctuations while maintaining meaningful differentiation between samples. These results confirm that the proposed system successfully integrates classification and regression into a unified framework, providing accurate, reliable, and real-time SONAR signal analysis suitable for underwater monitoring applications.

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