Research and development of software for hydroacoustic signal analysis using machine learning techniques

Anton O. Poliaiev[1], Nonna N. Shapovalova[1], Svitlana V. Bilashenko[1] and Andrii M. Striuk[1,2,3]

[1]*Kryvyi Rih National University, 11 Vitalii Matusevych Str., Kryvyi Rih, 50027, Ukraine*
[2]*Kryvyi Rih State Pedagogical University, 54 Universytetskyi Ave., Kryvyi Rih, 50086, Ukraine*
[3]*Academy of Cognitive and Natural Sciences, 54 Universytetskyi Ave., Kryvyi Rih, 50086, Ukraine*

Abstract

Hydroacoustic signal analysis plays a crucial role in underwater navigation, marine life monitoring, and security applications. However, the complex nature of underwater acoustic propagation and the presence of noise and interference pose significant challenges for accurate and reliable signal analysis. This paper presents a comprehensive software system for hydroacoustic signal analysis using state-of-the-art machine learning techniques. The proposed system integrates data acquisition, preprocessing, feature extraction, and advanced machine learning models for classification, regression, and clustering tasks. The system architecture follows a modular and scalable design, with a user-friendly web interface for data visualization and interaction.

Keywords

hydroacoustic signal analysis, machine learning, underwater acoustics, signal processing, software system, object classification, source localization, pattern discovery

1. Introduction

Hydroacoustic signal analysis plays a crucial role in various domains, including underwater navigation, border protection, and maritime safety [1, 2]. The growing volume of maritime traffic and the need to safeguard critical infrastructure necessitate the development of automated systems for identifying underwater objects, such as natural formations and artificial structures. However, the classification of hydroacoustic signals poses significant challenges due to their variability, which depends on the physical conditions of the environment, such as depth, water composition, bottom topography, and the presence of noise. This underscores the importance of research aimed at improving the analysis of such signals [3].

In recent years, machine learning techniques have been widely employed for analyzing hydroacoustic data, enabling automated processing of large volumes of complex signals [2, 4]. Artificial intelligence allows for the creation of highly accurate and adaptive systems that can adjust to various environmental conditions. However, there is still a need to enhance the accuracy and adaptability of these systems to the characteristics of the objects. Contemporary research shows a trend towards developing complex hybrid models that combine classical classification algorithms with deep neural networks and boosting methods, enabling more efficient real-time classification [2, 5].

Hydroacoustic signals contain valuable information for studying the underwater environment, monitoring maritime traffic, researching marine flora and fauna, and addressing defense-related tasks. Their unique property is the ability to propagate over considerable distances in the aquatic medium, making them valuable for applications requiring remote observation and data collection in water. Hydroacoustic signals are generated through the production and transmission of sound waves, which

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shapovalova@knu.edu.ua (N. N. Shapovalova); bilashenko.s@knu.edu.ua (S. V. Bilashenko); andrey.n.stryuk@gmail.com (A. M. Striuk)
http://mpz.knu.edu.ua/nona-shapovalova/ (N. N. Shapovalova); http://mpz.knu.edu.ua/svitlana-bilashenko/ (S. V. Bilashenko); http://mpz.knu.edu.ua/andrij-stryuk/ (A. M. Striuk)
0000-0001-9146-1205 (N. N. Shapovalova); 0000-0002-4331-7425 (S. V. Bilashenko); 0000-0001-9240-1976 (A. M. Striuk)

depend on several physical characteristics: frequency, amplitude, propagation velocity in water, and reflectivity from obstacles [3, 1].

The medium in which these signals propagate differs significantly from air, particularly due to the higher sound velocity in water, which averages around 1500 m/s. Propagation velocity is also influenced by factors such as temperature, pressure, and salinity, complicating accurate measurement of signal parameters. Moreover, signal propagation is accompanied by refraction, scattering, and absorption, affecting their shape and intensity. The process of recognizing hydroacoustic signals requires consideration of their spectral composition, duration, frequency of repetitive pulses, and signal level relative to noise level. Changes in these characteristics depend on both the signal sources (submarines, fish, natural objects) and environmental conditions, often leading to significant distortion [3, 5].

Traditional methods for hydroacoustic signal analysis have relied on statistical approaches and signal processing techniques [3, 1]. Gladkov [3] proposed a sequence of operations for spectral and correlation estimation of digitized random signals using fast Fourier transform. The authors presented a set of algorithms and their possible modifications for developing spectral estimation programs aimed at operative derivation of processing data in compressed information form.

Recent advancements in machine learning have opened up new possibilities for analyzing hydroacoustic signals [2, 4]. Vergoz et al. [2] utilized a progressive multi-channel correlation method (PMCC) for array processing of signals associated with the loss of the Argentinian ARA San Juan submarine. The study demonstrated the capability of the hydroacoustic component of the International Monitoring System (IMS) network to accurately locate signals originating from the South Atlantic continental shelf. Timoshevskiy and Zapryagaev [4] investigated the generation of a wall jet to control unsteady cavitation over a 2D hydrofoil, employing visualization and hydroacoustic signal analysis. The authors found that the wall jet generation technique was effective in suppressing cavity unsteady behavior or reducing the corresponding pressure pulsations at low inclination angles.

However, existing approaches have limitations in terms of accuracy, adaptability, and real-time performance. Classical methods struggle with the complexity and variability of hydroacoustic signals, while recent machine learning techniques often require large amounts of labeled data and computational resources. There is a need for more advanced and efficient methods that can handle the unique challenges posed by hydroacoustic signal analysis.

The primary objective of this research is to develop an advanced software system for hydroacoustic signal analysis by leveraging state-of-the-art machine learning techniques. The proposed system aims to automate the processing and classification of underwater signals, enabling high accuracy and reliability in real-world scenarios.

2. Hydroacoustic signal characteristics and preprocessing

2.1. Properties of hydroacoustic signals

Hydroacoustic signals propagate through the underwater environment, which is characterized by complex physical phenomena that affect their characteristics. One of the primary factors influencing signal propagation is multipath propagation, where the signal reaches the receiver through multiple paths due to reflections from the surface, bottom, and other objects in the water [5]. This leads to the arrival of multiple copies of the signal at the receiver with different delays, amplitudes, and phases, resulting in constructive or destructive interference.

Another important factor is the scattering effect, which occurs when the signal interacts with inhomogeneities in the water, such as bubbles, suspended particles, or small-scale variations in temperature or salinity [1]. Scattering causes the signal energy to be redistributed in different directions, leading to signal distortion and attenuation.

The Doppler effect also plays a significant role in hydroacoustic signal propagation, particularly when there is relative motion between the source and the receiver [5]. The Doppler effect causes a shift in the frequency of the received signal, which can be used to estimate the velocity of the source or the receiver. However, it also introduces additional complexity in signal processing and analysis.

In addition to these factors, the correlation between different rays arriving at the receiver is another important characteristic of hydroacoustic signals [5]. Rays propagating through different paths may exhibit varying degrees of correlation, depending on the similarity of their propagation conditions. This correlation can be exploited to improve signal detection and parameter estimation.

2.2. Data acquisition and preprocessing

The hydroacoustic signals used in this research were acquired from a datasets provided by United States government (https://catalog.data.gov/dataset?tags=hydroacoustics).

Before applying machine learning techniques, the acquired signals underwent a series of preprocessing steps to improve their quality and reduce noise. The typical preprocessing pipeline included the following steps [6]:

1. *Denoising* – the signals were filtered using to remove high-frequency noise and improve the signal-to-noise ratio.
2. *Normalization* – the amplitude of the signals was normalized to a common scale to ensure that the signal levels were consistent across different recordings.
3. *Segmentation* – the signals were segmented into fixed-length overlapping windows to capture local temporal and spectral features.
4. *Handling missing values* – any missing or corrupted signal segments were identified and either interpolated or excluded from further analysis, depending on the extent of the missing data.

2.3. Feature extraction and selection

After preprocessing, a set of relevant features was extracted from the hydroacoustic signals to serve as input for the machine learning models. The extracted features captured various aspects of the signals, such as temporal, spectral, and statistical properties. Some of the key features included:

1. Time-domain features were derived directly from the signal waveform and included parameters such as signal energy, zero-crossing rate, and peak-to-peak amplitude.
2. Frequency-domain features were obtained by applying a Fourier transform to the signal and analyzing its spectral content.
3. Mel-frequency cepstral coefficients (MFCCs) were computed to capture the short-term power spectrum of the signals, which provides a compact representation of the signal's spectral envelope.
4. Wavelet transforms were applied to the signals to extract time-frequency features that capture both local and global signal characteristics.

To reduce the dimensionality of the feature space and improve the computational efficiency of the machine learning models, feature selection techniques were applied. These techniques aimed to identify the most informative and discriminative features while minimizing redundancy. Some of the feature selection methods used in this research include univariate feature selection, recursive feature elimination, principal component analysis.

The selected features were then used as input for the machine learning models described in the next section. The combination of appropriate preprocessing techniques and informative features lays the foundation for accurate and reliable hydroacoustic signal analysis using machine learning approaches.

3. Machine learning methodology

3.1. Overview of proposed approach

The proposed machine learning approach for hydroacoustic signal analysis combines multiple techniques to address the complex nature of the signals and the various objectives of the analysis. The main components of the approach include:

1. Classification [7] to assign hydroacoustic signals to predefined categories based on their characteristics.
2. Regression [8] to predict continuous variables associated with hydroacoustic signals, such as the distance or depth of the signal source.
3. Clustering [9] to discover inherent groups or patterns within the hydroacoustic signals without prior knowledge of the class labels.

In addition to these individual techniques, we also propose the use of hybrid models that combine deep learning and classical machine learning approaches [2, 10]. These hybrid models aim to leverage the strengths of both paradigms, such as the ability of deep learning to learn hierarchical representations and the interpretability and robustness of classical models.

3.2. Classification models

For the classification of hydroacoustic signals, we employ a range of models, including SVM, random forests, KNN, logistic regression, and Gaussian naive Bayes [2]. Each model has its own strengths and weaknesses, and the choice of the most appropriate model depends on the specific characteristics of the data and the desired trade-off between accuracy and computational complexity.

1. SVM is a powerful model that aims to find the hyperplane that maximally separates the different classes in the feature space. It can handle non-linearly separable data by using kernel functions to map the input features to a higher-dimensional space.
2. Random forests are an ensemble learning method that combines multiple decision trees to make predictions. Each tree is trained on a random subset of the features and samples, and the final prediction is obtained by aggregating the outputs of all trees. Random forests are known for their ability to handle high-dimensional data and their robustness to overfitting.
3. KNN is a non-parametric model that classifies a sample based on the majority class of its k nearest neighbors in the feature space. The value of k is a hyperparameter that needs to be tuned based on the data. KNN is simple to implement and can handle multi-class problems, but its performance may degrade in high-dimensional spaces.
4. Logistic regression is a linear model that estimates the probability of a sample belonging to a particular class. It is computationally efficient and easy to interpret, but it assumes a linear relationship between the input features and the log-odds of the class probabilities.

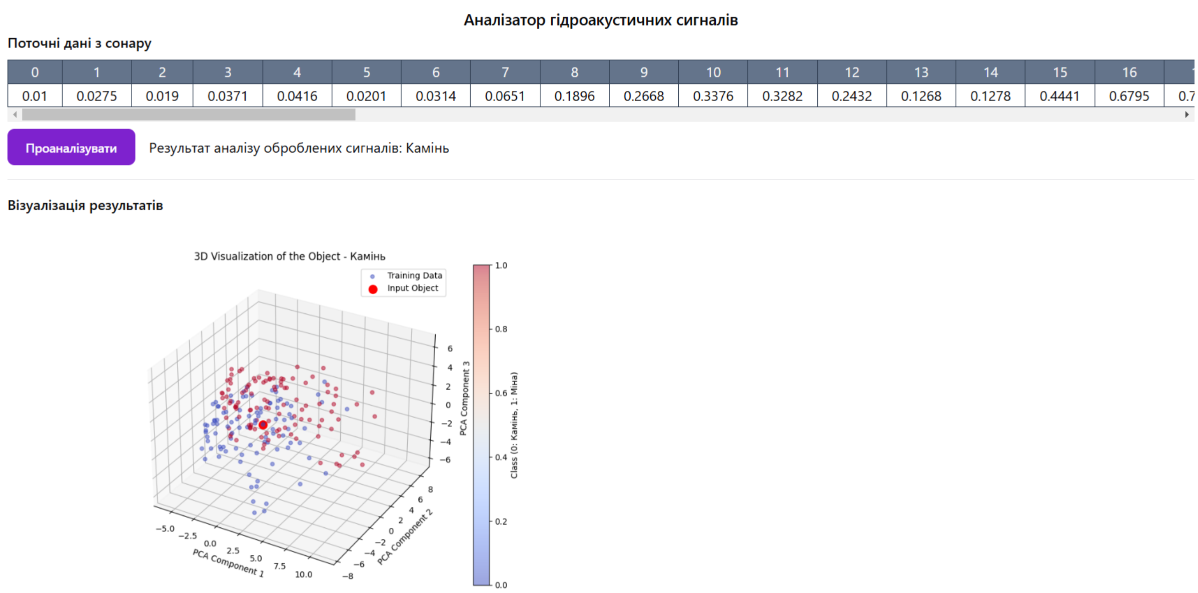

Figure 1: Web application interface for hydroacoustic signal analysis.

5. Gaussian naive Bayes is a probabilistic model that assumes the features are conditionally independent given the class label and follow a Gaussian distribution. Despite its simplicity and strong assumptions, Gaussian naive Bayes can perform well in practice, especially when the features are indeed independent.

The training process for each classification model involves the following steps:

1. The dataset is divided into training, validation, and test sets. The training set is used to learn the model parameters, the validation set is used for hyperparameter tuning, and the test set is used to evaluate the final performance of the model.
2. The chosen model is initialized with its default or randomly selected hyperparameters.
3. The model is trained on the training set using an appropriate optimization algorithm, such as stochastic gradient descent or Adam, to minimize a chosen loss function, such as cross-entropy or hinge loss.

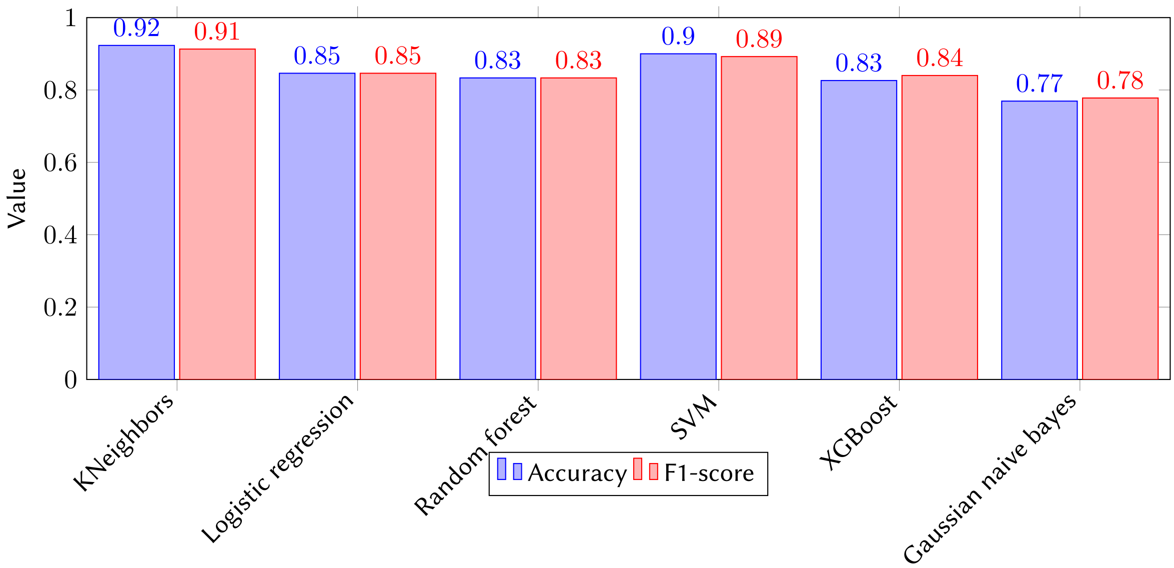

Figure 2: Classification metrics before hyperparameter optimization.

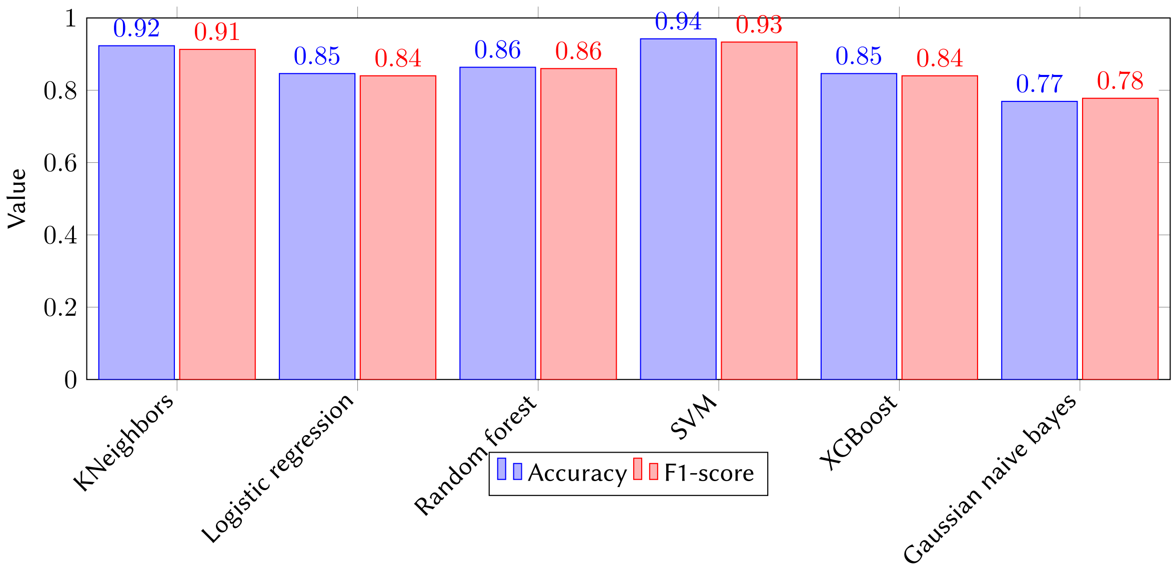

Figure 3: Classification metrics after hyperparameter optimization.

4. The hyperparameters of the model, such as the regularization strength, kernel type, or number of trees, are tuned using techniques like grid search or random search. The performance of different hyperparameter combinations is evaluated on the validation set, and the best combination is selected.
5. The trained model is evaluated on the test set using appropriate evaluation metrics, such as accuracy, precision, recall, and F1-score. Confusion matrices and receiver operating characteristic (ROC) curves can also be used to assess the model's performance [4].

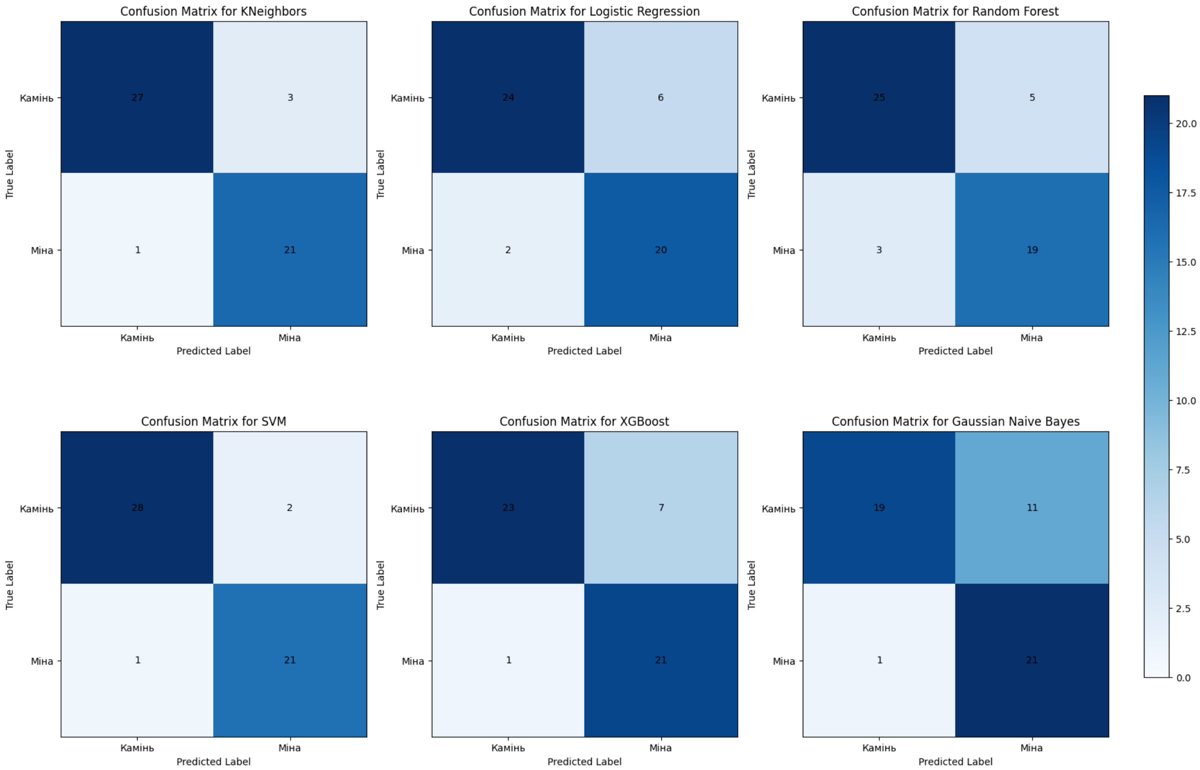

Figure 4: Confusion matrices for classification models after hyperparameter optimization.

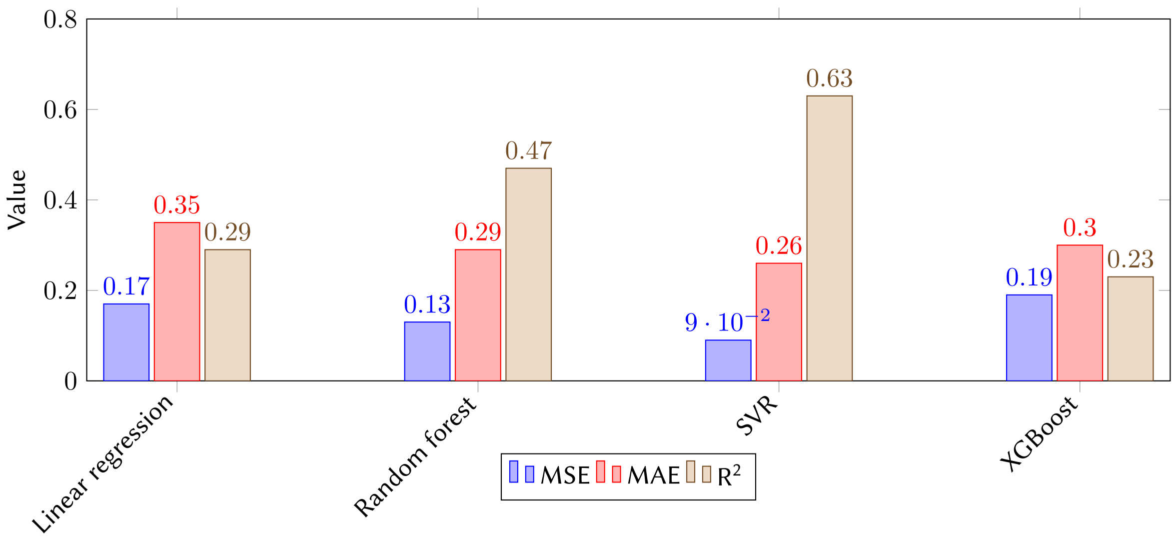

Figure 5: Regression metrics after hyperparameter optimization.

4. Software system architecture and implementation

The software system follows a modular and scalable architecture, consisting of the following main components:

1. *Data acquisition and storage* responsible for collecting hydroacoustic data from various sources and storing them in a centralized repository.
2. *Data preprocessing and feature extraction* applies the preprocessing techniques and extracts relevant features from the data.
3. *Machine learning models* implements the classification, regression, and clustering models using popular libraries and frameworks.
4. *RESTful API* exposes the trained models, allowing for easy integration with other systems and applications.
5. *Web application* provides a user-friendly web interface for data visualization, model configuration, and result interpretation.

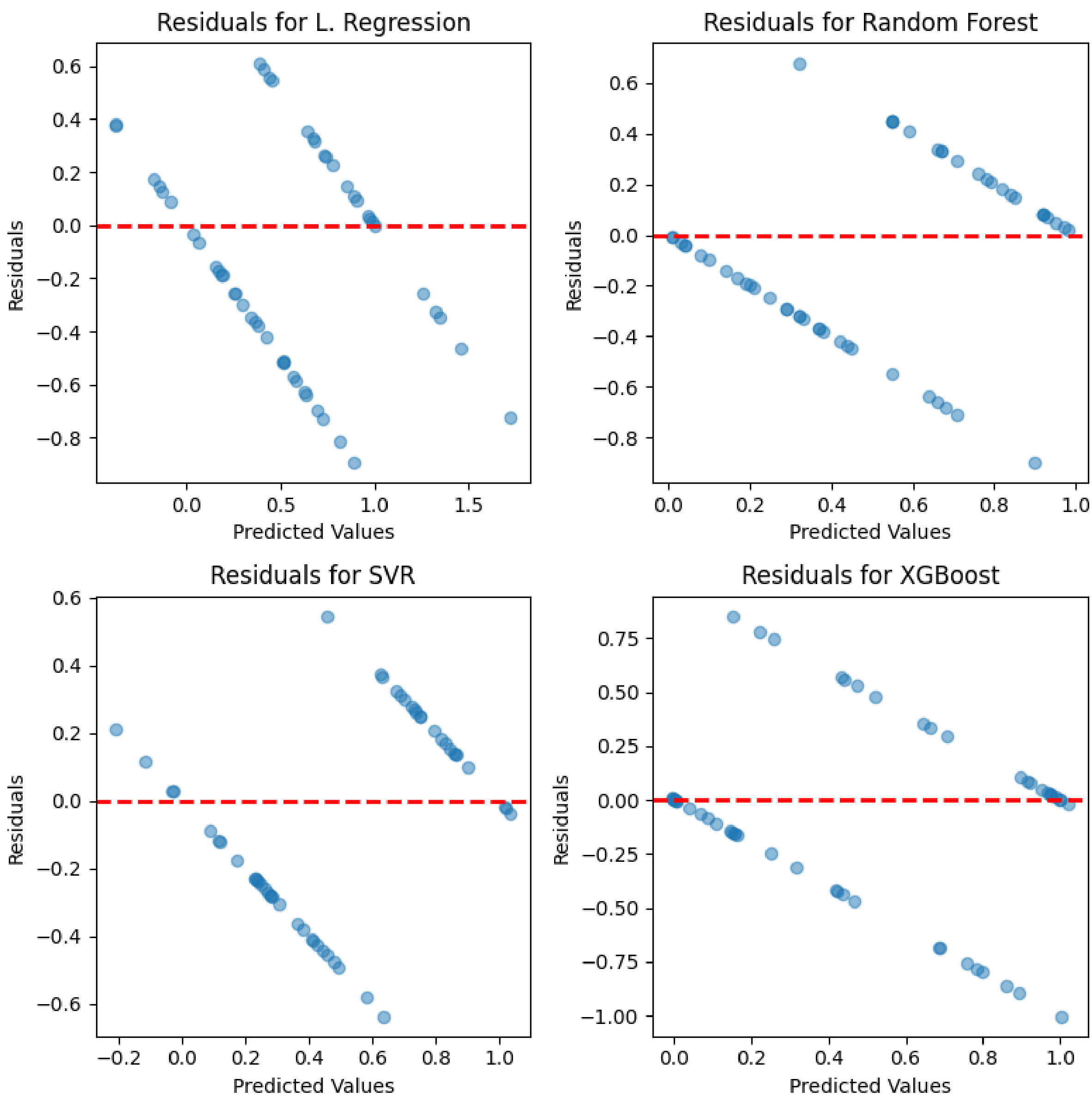

Figure 6: Residual plots for regression models before hyperparameter optimization.

A user-friendly web application was developed to provide an interactive interface for analyzing hydroacoustic signals. Figure 1 presents a screenshot of the application, showcasing its main features.

The application allows users to upload signal data, visualize the results of the analysis, and interact with the trained models through a simple and intuitive interface.

5. Experimental results and analysis

5.1. Evaluation of classification models

The classification models were evaluated using metrics such as accuracy, precision, recall, and F1-score. Figures 2 and 3 presents the results of the models before and after hyperparameter optimization.

After optimization, the SVM model achieved the highest accuracy of 0.94 and F1-score of 0.93, demonstrating its effectiveness in recognizing objects. The KNeighbors model also maintained stable performance, while Random forest and XGBoost showed significant improvements.

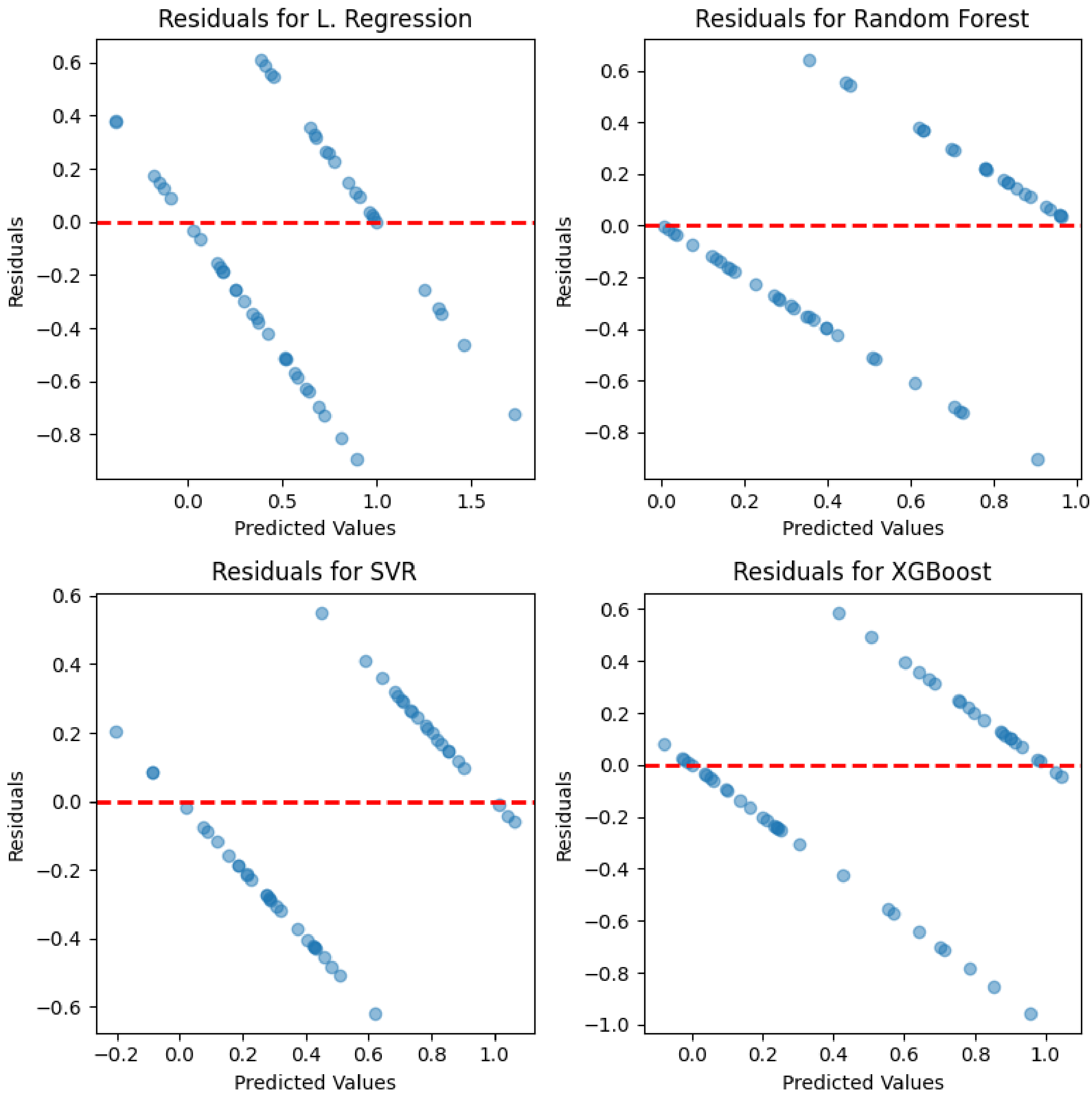

Figure 7: Residual plots for regression models after hyperparameter optimization.

Figure 4 presents the confusion matrices for the models after optimization, confirming the superior performance of SVM and KNeighbors in minimizing misclassifications.

5.2. Evaluation of regression models

The regression models were evaluated using metrics such as Mean Squared Error (MSE), Mean Absolute Error (MAE), and R-squared (R^2). Figure 5 presents the results after hyperparameter optimization.

After optimization, the SVR model demonstrated the best performance, achieving an MSE of 0.09, MAE of 0.21, and R^2 of 0.65. Random forest also showed significant improvements, while Linear regression remained the least effective.

Figures 6 and 7 present the residual plots for the models before and after optimization, confirming the superior performance of SVR and Random Forest in capturing complex dependencies.

5.3. Evaluation of clustering models

The clustering models were evaluated using metrics such as Adjusted Rand Index (ARI), Homogeneity, and V-measure. Figure 8 presents the results after hyperparameter optimization.

After optimization, the GMM model achieved the highest scores across all metrics, demonstrating its effectiveness in discovering meaningful patterns and structures in the data. KMeans also showed improvements, while Agglomerative clustering remained less effective.

6. Conclusion

This paper presented a comprehensive software system for hydroacoustic signal analysis using advanced machine learning techniques. The proposed system integrates data acquisition, preprocessing, feature extraction, and state-of-the-art models for classification, regression, and clustering tasks.

Experimental results demonstrated the effectiveness of the proposed approach, with the SVM model achieving the highest accuracy and F1-score in classification, the SVR model outperforming others in regression, and the GMM model showing superior performance in clustering. The practical utility of the system was illustrated through a user-friendly web application for interactive signal analysis.

The developed system has significant potential for impact in various domains, including defense, industrial monitoring, and scientific research. Future work may focus on integrating multiple sensing

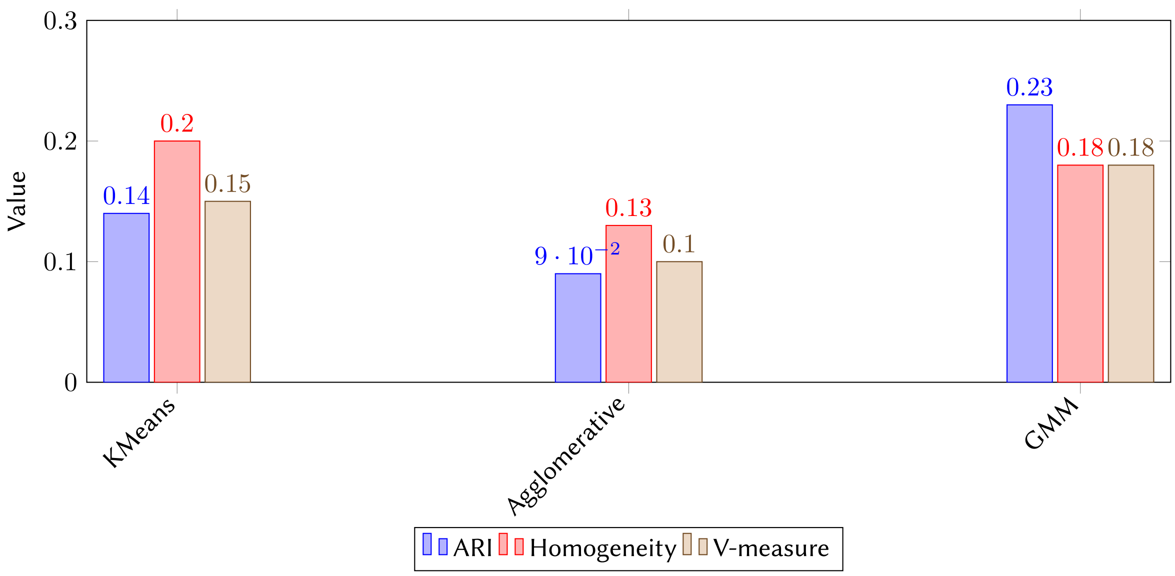

Figure 8: Clustering metrics after hyperparameter optimization

modalities, online learning and adaptation, explainable AI, and distributed computing to further enhance the capabilities and applicability of the system.

Declaration on Generative AI: During the preparation of this work, the authors used Claude 3 Opus in order to: Drafting content, Text Translation, Abstract drafting, Formatting assistance. After using this service, the authors reviewed and edited the content as needed and takes full responsibility for the publication's content.

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