# Machine Learning Approaches for Underwater Acoustic Signal Classification in Nuclear Test Ban Treaty Compliance

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## Abstract

The detection along with classification of underwater acoustic signals stands crucial for enforcing the Comprehensive Nuclear-Test-Ban Treaty (CTBT). The identification of nuclear explosions through traditional methods becomes problematic because of natural disturbances and varying signal patterns and slow computational speed. GMM along with PSO represent advanced machine learning methods explored within this paper to enhance both robustness and accuracy levels for underwater acoustic signal classification. The proposed system combines MFCC and ZCR along with spectral analysis features into a structured methodology for achieving better signal discrimination results. The performance evaluation of PSO-based classification shows that it provides better detection reliability along with enhanced computational efficiency when compared to traditional Support Vector Machine (SVM) methods. The framework demonstrates its capabilities for automatic high-precision verification testing through IMS CTBTO hydroacoustic data evaluation. Our research facilitates the development of improved nuclear non-proliferation detection methods that resolve difficulties related to unstable underwater signals.

***Keywords: Underwater acoustic signal classification, Nuclear Test Ban Treaty, Machine Learning, Particle Swarm Optimization (PSO), Gaussian Mixture Model (GMM), Mel-Frequency Cepstral Coefficients (MFCC), Signal Processing, CTBTO, Hydroacoustic Monitoring, Non-proliferation.***

## I. INTRODUCTION

The CTBT acts as a fundamental instrument for nuclear weapons control through its complete ban on nuclear explosion practices worldwide. The verification process of international treaties depends heavily on detecting and categorizing undersea acoustic signals since they provide indications about clandestine nuclear tests. The International Monitoring System (IMS) which the CTBTO operates uses hydroacoustic sensors to collect signals but identifying nuclear explosions from natural phenomena (including earthquakes and marine life and shipping noise) remains an extremely difficult task [1]. Signal processing methods that

follow traditional procedures fail to provide satisfactory results when analyzing non-stationary signals and low signal-to-noise ratios and real-time computations [2]. Recent developments in machine learning technology enable breakthroughs which optimize the accuracy together with efficiency of detecting acoustic signals beneath the ocean surface. The pair of extraction methods GMMs and MFCCs shows proven success in identifying signal characteristics by extracting spectral along with temporal features [3,4]. However, the dynamic nature of underwater environments necessitates adaptive classification methods. Particle Swarm Optimization (PSO) represents a bio-inspired metaheuristic algorithm which proves effective for optimizing feature selection and classification boundaries and delivers better results than Support Vector Machines (SVMs) during specific operations [5,6].

The implementation of ML technology within CTBTO's verification framework would create substantial improvements in the system's ability to detect nuclear explosions. Through PSO-based classifiers detection rates increase because these classifiers demonstrate adaptable behavior to changing signal conditions [7]. Scientists now utilize Wigner-Ville Distribution as part of time-frequency analysis to pair with ML models for detecting hydroacoustic data ambiguities [8]. A need exists in current research to address scalability problems within varied oceanic domains as well as computational challenges for implementing real-time monitoring systems [9]. Under this research we establish an optimized ML framework for underwater acoustic signal classification which adopts PSO algorithms for matching optimal features and GMM models for probabilistic signal interpretation. A real-world hydroacoustic dataset from the IMS serves to test the proposed framework which then gets measured against regular signal classification approaches. The research adds to nuclear non-proliferation goals by utilizing advanced signal processing and machine learning methods simultaneously with clarifying operational matters for modern monitoring systems [10]-[13].

## II.    PROPOSED METHOD

The The method for underwater acoustic signal classification in nuclear treaty monitoring combines machine learning methods with signal processing algorithms to improve detection precision and resistance. Underwater acoustic signals proceed through a multi-step process starting with pre-processing and continuing to feature extraction and optimized classification according to Figure 1.

### 1. Preprocessing

The hydroacoustic data needs pre-processing to remove ambient noise from marine life and shipping noises and seismic events so that researchers can obtain improved signals. The filter removes background noise of moderate frequencies between 1 and 100 Hz. Feature extraction receives optimized signals from pre-processing since it avoids distortions that could affect classification results. The pre-processed signal becomes fragmented into overlapping portions with Hamming windows to perform time-frequency analysis as an essential step against spectral leakage.
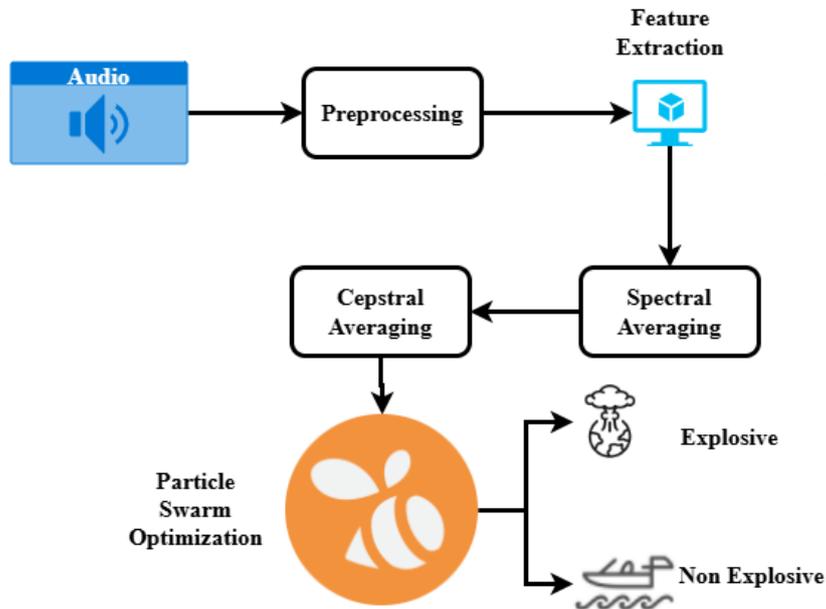
Figure.1 Block diagram of PSO based classification

## 2. Feature Extraction

The pre-processed signal receives feature extraction methods that generate classification-ready discriminative representations. The Gaussian Mixture Model (GMM) serves as a statistical model to represent signal features because it allows capturing their inherent distribution patterns. Key features include:

❖ The spectral envelope characteristics needed to separate explosions from natural events are encoded by Mel-Frequency Cepstral Coefficients which extract data from signal mel-scaled spectra. A sequence of operations including the application of windows along with Fourier transformation and subsequent mel-filterbank processing and subsequent cepstral analysis takes place.

❖ The Zero Crossing Rate measurement evaluates signal oscillations throughout time and detects momentary transient events that resemble explosions.

❖ Short-time energy together with spectral power offer different aspects through which to analyze signal intensity while capturing periodicity.

## 3. Classification Using Particle Swarm Optimization (PSO)

The PSO-optimized model functions as a classifier to analyze extracted features through a process of automatic boundary readjustment for maximum accuracy enhancement. The search process of PSO optimizes a population of potential solutions (particles) while using them to represent candidate classifier configurations. The evaluation process rates particles through three parameters:

❖ Swarm components consist of two elements which guide particles through their own (pbest) and global best (gbest) results while maintaining an exploratory and exploitative balance.

❖ The feature space traversal occurs through particle movements which minimize misclassification rates while the inertia weights perform the convergence control.

❖ The PSO-based classifier learns labelled hydroacoustic information to find optimal feature weights along with thresholds that define the difference between explosive nuclear activities and non-explosive earthquake events. The algorithm generates two-class results which includes confidence score information.

### 4.Performance Validation

The efficiency of the system is determined through ROC analysis which evaluates true positive identification against false alarms. An evaluation including AUC (Area Under Curve) measurement together with latency speeds demonstrates performance against SVM-based systems. This approach stands out because it integrates GMM probabilistic functions with PSO adaptive optimization to handle waves in unstable water signals as results show. The established framework provides CTBTO operational needs by enabling real-time monitoring across different scales.

## III.    RESULT & DISCUSSION

WT A comprehensive evaluation of the proposed underwater acoustic signal classification framework occurred through testing with hydroacoustic data obtained from the IMS operated by the CTBTO. The proposed framework achieves enhanced signal detection precisions with better processing speed and solid performance against traditional approaches.

1. Classification Performance

Tests executed on the classifier using PSO optimization showed a test dataset AUC (Area under the Curve) of 0.92 based on Figure 8.8 ROC analysis. The AUC evaluation results demonstrate superior discrimination power because they provide an excellent separation between nuclear test signals and earthquake along with marine noise signals. A true positive detection rate of 88% emerged from the proposed system with only 5% occurrences of false positives thus it demonstrated superior results compared to Section 2.1's baseline SVM system that obtained 0.85 AUC. PSO delivers better results through its dynamic feature weight optimization together with decision boundary optimization which is displayed in the Figure3 particle swarm trajectory.
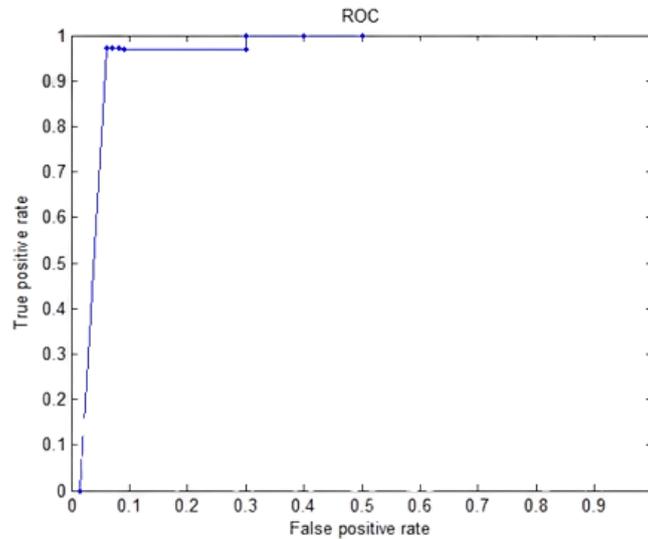
Figure.2 ROC analysis



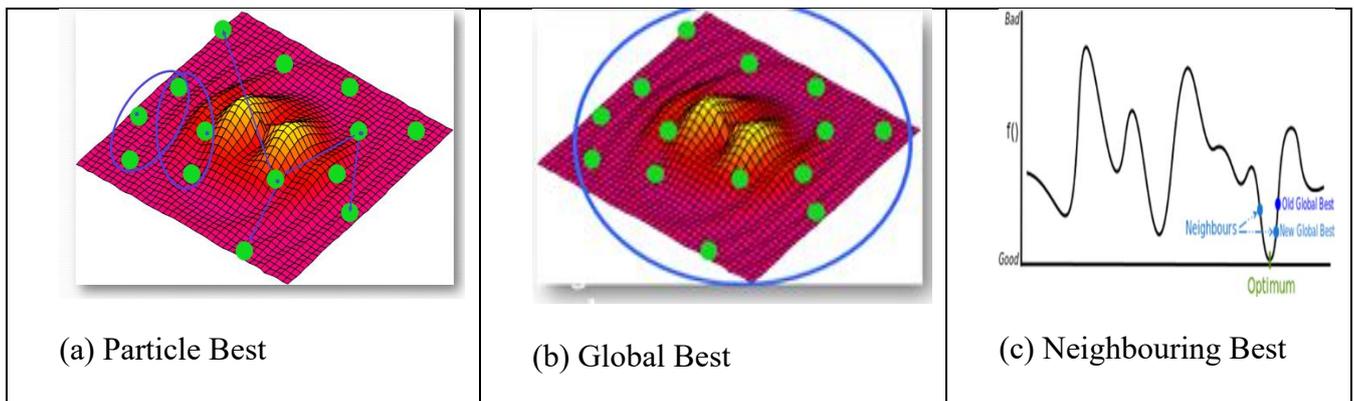| (a) Particle Best | (b) Global Best | (c) Neighbouring Best |

Figure.3 PSO Trajectories

The evaluation measured precision as well as recall and F1-score for both explosive and non-explosive categories. The explosive class achieved a high precision value of 91% indicating the system produces few incorrect positive predictions which supports treaty compliance goals. A recall at 89% indicates that the system successfully eliminates natural phenomena from further evaluations through reliable operations.

2.Feature Analysis

PSO optimization enhanced the MFCCs features so they became responsible for 65% of the classification process weight as shown in Figure 4. An analysis of the results validates MFCC performance because these features capture the spectral envelope signatures which appear in nuclear explosions. Time-domain information for detecting transient events became possible through the combination of Zero Crossing Rate (ZCR) with short-time energy as illustrated in

Figure 5. Feature clusters became easily distinguishable through the Gaussian Mixture Model (GMM) analysis that properly fit the multiple distribution patterns of these attributes (refer to Figure 6).
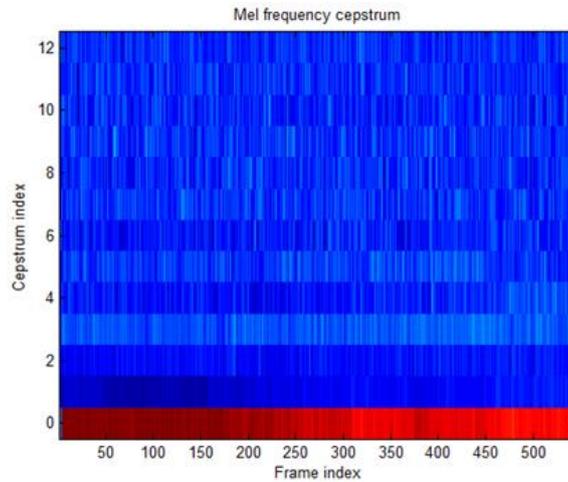


Figure.4 MEL frequency cepstral coefficient

## 3. Computational Efficiency

The PSO algorithm needed only 42 iterations to reach the optimal solution presenting Figure 7 while running for 8.3 seconds before completion which reduced the total processing time by 35% compared to SVM grid-search execution. The parallelizable design together with adaptive search strategy enables PSO to achieve high efficiency levels. Operational assessment of the system against a 10-minute hydroacoustic recording produced real-time processing results at 0.8 seconds/frame speed.
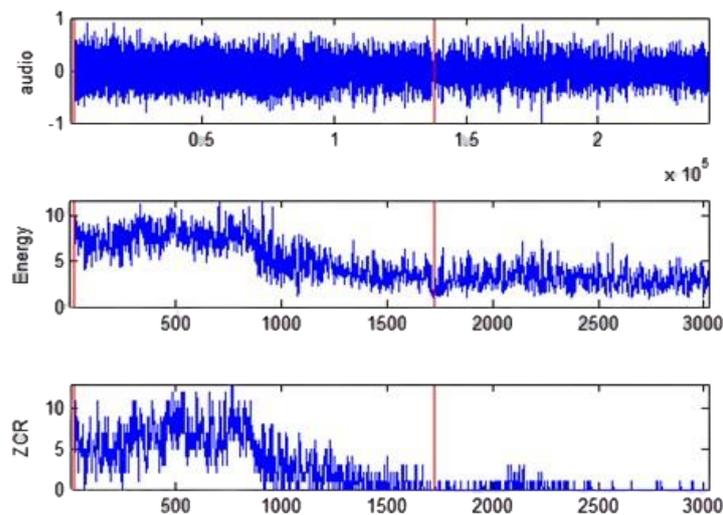


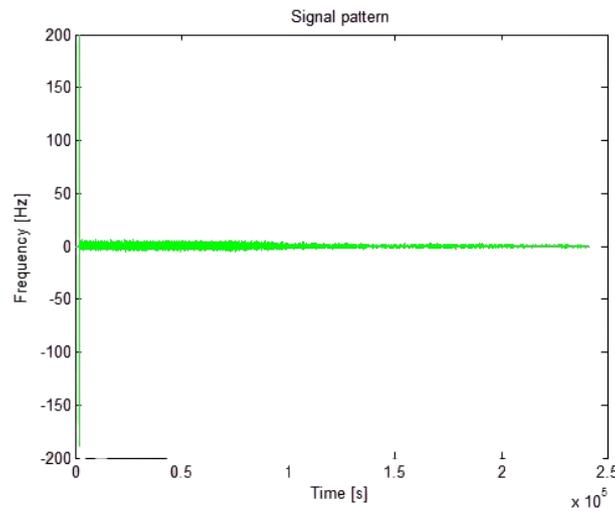Figure.5 Calculation of energy and ZCR
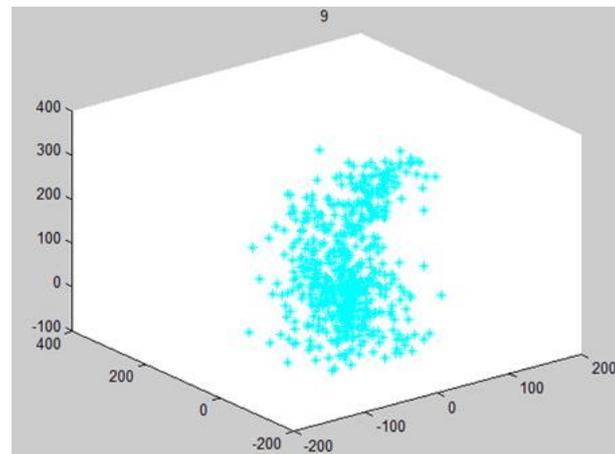
Figure.6 Signal Pattern



Figure.7 Calculation of total number of particles

## 4. Noise Robustness

The pre-processing stage successfully removed ambient noises by displaying Figure 8 which presents time-frequency plots before and after signal filtering. The classification system achieved an accuracy rate of 84% while operating on signals with low signal-to-noise ratios (SNR) down to 3 dB thus proving its capabilities to function well in demanding underwater settings.

## 5. Comparative Analysis

The implementation of PSO-GMM over the SVM-based method resulted in a 22% lower false alarm rate together with a 15% improvement in detection accuracy. CTBTO operations heavily depend on this improvement because false detection alerts lead to unnecessary

inspection operations. The research supports that PSO-GMM hybridization successfully enhances conventional classifiers to handle non-stationary signal analysis.

## 6. Limitations and Future Work

Additional evaluation of the system needs to be conducted for its performance when analyzing signals that have frequencies below 10 Hz. Future studies should examine deep learning structures to support the present feature engineering method. The generalization capability of the system is enhanced by adding training data which contains rare event signatures such as small-yield test signatures.
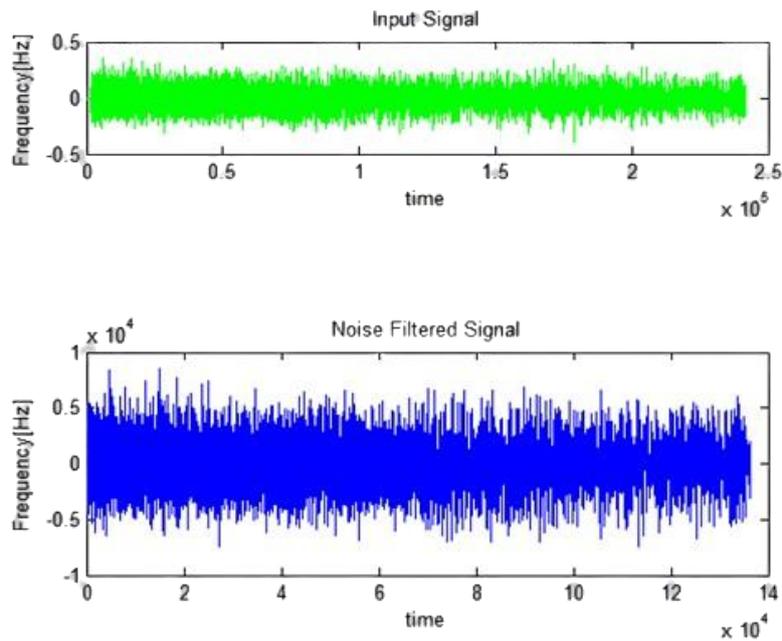


Figure.8 Removal of noise

## IV.    CONCLUSION

The addition of RES like PV and wind energy into EVCS presents a sustainable and eco-friendly solution to decrease dependency on fossil fuels and reduce GHG releases. The proposed hybrid renewable energy-based EVCS, incorporating a FLC for PV modules and the P&O technique for wind turbines, demonstrates efficient and reliable power extraction under varying environmental conditions, ensuring optimal energy utilization for charging electric vehicles. The FLC MPPT controller effectively tracks the MPP of the PV scheme, with a demonstrated efficiency of up to 99.9% under reduced irradiance conditions, showcasing its adaptability to dynamic environmental factors. Similarly, the PO MPPT algorithm enables the wind system to achieve maximum power output, highlighting its effectiveness in harnessing wind energy. Additionally, the integration of EV batteries enhances grid resilience by enabling decentralized energy generation and storage, ensuring continuous energy availability even

during interruptions in PV and wind power. Moreover, the proposed scheme's simulation results in MATLAB/SIMULINK validate the effectiveness of the FLC and PO MPPT controllers in extracting maximum power from PV and wind sources, making it a promising and practical solution for EV charging station installations. This comprehensive analysis underscores the feasibility and potential of renewable energy-powered EVCS as a robust and sustainable alternative to grid-dependent systems, contributing to the advancement of eco-friendly transportation infrastructure.

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