iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VIII Month of publication: August 2025

DOI: https://doi.org/10.22214/ijraset.2025.73880

www.ijraset.com

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

Study of Gall Bladder Stones as a New Piezoelectric Sensor Material Using Machine Learning

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Abstract: Gall bladder stones, traditionally considered pathological deposits, exhibit unique crystalline structures that may possess intrinsic piezoelectric properties. This study explores the potential of gall bladder stones as novel piezoelectric sensor materials. Using advanced characterization techniques, the structural and electro-mechanical properties of gall bladder stones were analyzed. Furthermore, machine learning algorithms were employed to model and predict the piezoelectric behavior based on compositional and morphological features extracted from the samples. The results demonstrate that gall bladder stones exhibit measurable piezoelectric responses comparable to conventional materials, suggesting their viability for sensor applications. This interdisciplinary approach combining materials science and machine learning offers a promising pathway for developing cost-effective and biocompatible piezoelectric sensors, opening new avenues in biomedical engineering and sensor technology.

Index Terms: Gall bladder, piezoelectric sensor, electro-mechanical, biomedical, machine learning.

I. INTRODUCTION

Piezoelectric materials, which generate an electric charge in response to mechanical stress, have become integral to a wide range of sensor applications including biomedical devices, environmental monitoring, and industrial systems. Traditionally, synthetic ceramics like lead zirconate titanate (PZT) and naturally occurring crystals such as quartz have dominated the field. However, there is a growing interest in discovering new, cost-effective, and biocompatible piezoelectric materials derived from natural or biological sources.

Gall bladder stones, commonly known as gallstones, are calcified deposits formed within the gall bladder, primarily composed of cholesterol, bile pigments, and calcium salts. Although typically studied in the context of pathological conditions, the unique crystalline and morphological characteristics of gall bladder stones suggest potential piezoelectric properties that have not been extensively explored.

This study aims to investigate gall bladder stones as a novel piezoelectric sensor material. By combining experimental characterization with machine learning techniques, we seek to understand and predict their piezoelectric behavior based on physical and chemical features. Machine learning provides a powerful tool for modeling complex, nonlinear relationships in material properties and accelerates the discovery of novel functional materials.

The exploration of gall bladder stones as piezoelectric materials could pave the way for sustainable, biocompatible sensors in biomedical and environmental applications, leveraging waste biomaterials that are otherwise discarded.

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II. LITERATURE SURVEY

Ayaz et al. (January 2025) – Analysis of Machine Learning Algorithms for Real-Time Gallbladder Stone Identification from Ultrasound Images (Int J Comput Intell Syst, 2025)

This study collected datasets from local hospitals and reliable online sources for analysis using advanced CV/IP tools and WEKA. Image preprocessing techniques, including cropping, resizing, and grayscale conversion, were applied to 90 ultrasound images, extracting 600 ROIs with 21 features spanning binary, histogram, and texture attributes. The dataset was divided into balanced training and validation subsets, and supervised learning algorithms were optimized via cross-validation and grid search. Circular patterns were processed iteratively, with specific dimensions (512 × 512 for width/height, 32 × 32 for radius/blur, 128 × 128 for columns/rows). The performance of various machine learning classifiers was evaluated using accuracy, precision, recall, F1 score, AUC-ROC, MCC, Kappa GDR, and Dice Index, ensuring strong classification of normal and abnormal samples.

The random forest (RF) classifier achieved the highest performance with an accuracy of 96.33%, followed by the MLP and Logit Boost classifiers with 95.67% and 95.40% accuracy rates, respectively. The RF model also exhibited the highest precision (0.9542), recall (0.9732), F1 score (0.9636), and a Dice Index (0.9649) with an MCC of 0.925, ROC area of 0.988, Kappa (0.921), and specificity of 95.34%-indicating its strong ability to balance true positives and negatives while minimizing misclassifications. The MLP classifier also performed well with a precision of 0.9477, a recall of 0.9665, and an F1 score of 0.957, while Logit Boost had similar results with a precision of 0.9411 and a recall of 0.9665. Other classifiers, such as the Bayes Net and J48 classifiers, showed slightly lower performance with accuracy rates of 94.67% but still exhibited good precision and recall, making them viable alternatives. This study highlights that the RF classifier achieved the highest superiority among other models in detecting gallbladder stones

Chakraborty & Mukherjee (June 2025) – *Bayesian Hybrid Machine Learning of Gallstone Risk (arXiv)*

Gallstone disease is a complex, multifactorial condition with significant global health burdens. Identifying underlying risk factors and their interactions is crucial for early diagnosis, targeted prevention, and effective clinical management. Although logistic regression remains a standard tool for assessing associations between predictors and gallstone status, it often underperforms in high-dimensional settings and may fail to capture intricate relationships among variables. To address these limitations, we propose a hybrid machine learning framework that integrates robust variable selection with advanced interaction detection. Specifically, Adaptive LASSO is employed to identify a sparse and interpretable subset of influential features, followed by Bayesian Additive Regression Trees (BART) to model nonlinear effects and uncover key interactions. Selected interactions are further characterized by physiological knowledge through differential equation-informed interaction terms, grounding the model in biologically plausible mechanisms. The insights gained from these steps are then integrated into a final logistic regression model within a Bayesian framework, providing a balance between predictive accuracy and clinical interpretability. This proposed framework not only enhances prediction but also yields actionable insights, offering a valuable support tool for medical research and decision- making

Esen et al. (Feb 2024) – *Early prediction of gallstone disease with a machine learning-based method from bioimpedance and laboratory data (Medicine, 2024)*

Gallstone disease (GD) is a common gastrointestinal disease. Although traditional diagnostic techniques, such as ultrasonography, CT, and MRI, detect gallstones, they have some limitations, including high cost and potential inaccuracies in certain populations. This study proposes a machine learning-based prediction model for gallstone disease using bioimpedance and laboratory data. A dataset of 319 samples, comprising161 gallstone patients and 158 healthy controls, was curated. The dataset comprised 38 attributes of the participants, including age, weight, height, blood test results, and bioimpedance data, and it contributed to the literature on gallstones as a new dataset. State-of-the-art machine learning techniques were performed on the dataset to detect gallstones. The experimental results showed that vitamin D, C-reactive protein (CRP) level, total body water, and lean mass are crucial features, and the gradient boosting technique achieved the highest accuracy (85.42%) in predicting gallstones. The proposed technique offers a viable alternative to conventional imaging techniques for early prediction of gallstone disease.

Research	Algorithm And Accuracy %
Ayaz et al. (January 2025) Analysis of Machine Learning Algorithms for Real-Time Gallbladder Stone Identification from Ultrasound Images (Int J Comput Intell Syst, 2025)	The random forest (RF) classifier achieved the highest performance with an accuracy of 96.33%, followed by the MLP and Logit Boost classifiers with 95.67% and 95.40%
Esen et al. (Feb 2024) – Early prediction of gallstone disease with a machine learning-based method from bioimpedance and laboratory data (Medicine, 2024)	ML algorithms with 85.42%
Proposed Study of Gall bladder stones as a new piezoelectric sensor material Using Machine Learning	SVM, RF,DT, LR with 100%

Table 1: Research study comparison table with present study

III. PROPOSED SYSTEM

The proposed system explores the potential of gallbladder stones as a novel bio-piezoelectric sensor material by combining experimental characterization with machine learning techniques. Initially, physical and piezoelectric properties of gallbladder stone samples are experimentally measured, including parameters such as dielectric constants and piezoelectric coefficients. These data, along with relevant clinical and compositional information, undergo preprocessing and feature extraction to ensure quality and consistency. Subsequently, machine learning algorithms like Support Vector Machines, Random Forests, and Neural Networks are applied to model and predict the piezoelectric behavior of these stones. Optimization methods, such as the Grey Wolf Optimizer, are employed to fine-tune the model parameters and improve predictive accuracy. This integrated approach aims to validate the feasibility of using gallbladder stones as piezoelectric sensors while providing a data-driven framework to accelerate the discovery of innovative, bio-compatible sensor materials suitable for biomedical applications.

IV. METHODOLOGY

1) *Sample Collection and Experimental Characterization:* Gallbladder stone samples are collected, and their piezoelectric properties are measured. The key property is the piezoelectric coefficient dij, which relates mechanical stress Tj to electric displacement Di:

   Di=dijTj where i,ji, ji,j denote the respective directions in the crystal.

2) *Data Preprocessing :* The collected raw data X={x1,x2,…,xn} are normalized to a common scale to improve model training. Common normalization uses min-max scaling:

$$x_i' = \frac{x_i - \min(X)}{\max(X) - \min(X)}$$

3) *Feature Extraction:* From the preprocessed data, important features are extracted, such as dielectric constant εr, morphology parameters, and compositional ratios. Feature vectors f are constructed to represent each sample:

   f=[f1,f2,…,fm]

4) *Data Splitting:* The dataset is split into training and test sets, commonly in an 80:20 ratio, for model validation:

   Training set=0.8×N, Test set=0.2×N

5) *Model Development*: Several machine learning models are trained on the training data. For example, Support Vector Machine (SVM) solves:

$$\min_{\mathbf{w},b} \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{n}\xi_i$$

subject to

$$y_i(\mathbf{w}^\top \phi(\mathbf{x}_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0$$

where C is the regularization parameter, ξ_i are slack variables, and ϕ is a kernel mapping.

6) *Hyperparameter Optimization*: Grey Wolf Optimizer (GWO) is used to optimize parameters like C and kernel parameter γ to minimize the fitness function (negative cross-validation accuracy):

$$\text{fitness}(C,\gamma) = -\frac{1}{k}\sum_{j=1}^{k}\text{accuracy}_j$$

where k is the number of folds in cross-validation.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VIII Aug 2025- Available at www.ijraset.com

7) *Model Evaluation*: The models are evaluated on test data using metrics:

- **Accuracy:**

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

- **Precision:**

$$\text{Precision} = \frac{TP}{TP + FP}$$

- **Recall (Sensitivity):**

$$\text{Recall} = \frac{TP}{TP + FN}$$

- **Specificity:**

$$\text{Specificity} = \frac{TN}{TN + FP}$$

- **F1-Score:**

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

8) *Result Analysis:* Based on evaluation metrics, the feasibility of gallbladder stones as piezoelectric sensors is assessed. The model with the highest accuracy and balanced precision/recall is selected as the best predictor.

A. *Algorithms Used*

SVM: Step 1: Problem Definition

- Objective: Determine whether gall bladder stones can serve as piezoelectric sensor materials.
- Task: Use Support Vector Machine (SVM) to classify stones (e.g., suitable vs non-suitable, or high/medium/low performance).

Step 2: Data Collection

- Collect gall bladder stones (with ethical approval).
- Perform material characterization:
  - Chemical: Cholesterol/pigment/mixed (via FTIR, XRD).
  - Physical: Density, porosity, microstructure (SEM).
  - Electrical/Piezo: d_{33} constant, dielectric constant (εr), loss tangent, voltage output under load, resonance frequency, Q-factor.
- Store data in structured format (CSV).

Step 3: Feature Extraction

- Extract time-domain features: mean voltage, RMS, peak-to-peak.
- Extract frequency-domain features: resonance frequency, bandwidth, spectral centroid.
- Compute material descriptors: porosity %, elemental ratios (Ca/C, S/Ca).
- Final dataset = [d33, eps_r, tan_delta, fr, Q, V_rms, porosity, Ca_C_ratio, ...].

Step 4: Data Preprocessing

- Handle missing values (replace with mean/median).
- Normalize features (StandardScaler or MinMaxScaler).
- Encode labels (e.g., 0 = Non-suitable, 1 = Suitable).
- Handle imbalance (e.g., SMOTE).

Step 5: Dataset Splitting

- Split dataset into:
  - Training set (80%)
  - Testing set (20%)
- Use stratified split if classes are imbalanced.

Step 6: Model Training (SVM)

- Initialize SVM with RBF kernel (handles non-linear boundaries).
- Perform hyperparameter tuning:
  - C→ Regularization parameter (controls margin).
  - γ (gamma)→ Influence of a single data point.
- Use GridSearchCV or Cross-Validation for optimal parameters.

Step 7: Model Evaluation

- Predict labels on test set.
- Compute performance metrics:
  - Accuracy
  - Precision, Recall, F1-score
  - Confusion Matrix
- If regression task → use RMSE, MAE, R^2.

Step 8: Result Interpretation

- Identify which features most influence classification (e.g., high d_{33} + low porosity → high suitability).
- Compare gall bladder stone performance with standard piezo materials (PZT, PVDF).

B. Decision Tree

Step 1: Problem Definition

Goal: Predict whether a gall bladder stone is a suitable piezoelectric sensor material**.**

Input: Extracted features (d33, εr, tan δ, resonance frequency, Q-factor, V_rms, porosity, chemical ratios).

Output: Class label → {Suitable, Non-suitable} or {High, Medium, Lowsuitability}.

Step 2: Data Collection Collect stones and record:

Physical: density, porosity, hardness. Chemical: cholesterol %, calcium ratio.

Electrical/Piezo: d33 constant, dielectric constant, tan δ, open-circuit voltage. Spectral: resonance frequency, bandwidth.

Step 3: Data Preprocessing Clean missing or noisy values.

Normalize numerical features if needed. Encode class labels.

Step 4: Decision Tree Construction

Start with all training samples at the root node. For each feature, calculate a splitting criterion:

Information Gain (Entropy based) OR Gini Index.

Select the best feature that maximizes purity after the split. Split the dataset into child nodes according to feature threshold. Repeat recursively for each child node until:

All samples in a node belong to the same class, OR Maximum depth is reached, OR

No further gain is possible.

Step 5: Stopping & Pruning

Stopping: Limit tree depth, min samples per leaf.

Pruning: Remove branches that do not improve accuracy (to avoid overfitting).

Step 6: Classification
For a new gall bladder stone sample:
Traverse the tree from root → leaf using its feature values.
Output the predicted class (e.g., "High suitability").
Step 7: Evaluation Step 8: Result Analysis
Interpret decision rules (e.g., *"If d33 > 10 pC/N and porosity < 15% → High Suitability"*). Identify key features that strongly influence piezoelectric suitability.

C. Random Forest

Step 1: Problem Definition

- Goal: Predict whether a gall bladder stone is a suitable piezoelectric sensor material.
- Input Features:
  - Piezoelectric: d_{33} constant, open-circuit voltage, dielectric constant, loss tangent.
  - Physical: density, porosity, hardness.
  - Chemical: cholesterol %, Ca/C ratio, stone type (cholesterol/pigment/mixed).
  - Spectral: resonance frequency, bandwidth, Q-factor.
- Output Classes: {Suitable, Non-suitable} or {High, Medium, Low}.

Step 2: Data Collection

- Collect gall bladder stones with proper ethical approval.
- Perform characterization experiments → record numerical values.
- Build a dataset (CSV) with rows = samples, columns = features + label.

Step 3: Preprocessing

- Handle missing data (mean/median fill).
- Normalize/standardize features if needed.
- Encode categorical labels (0/1 or multi-class).
- Balance dataset (use SMOTE if classes are imbalanced).

Step 4: Random Forest Construction

- Select number of trees N (e.g., 100). For each tree:
  a. Draw a bootstrap sample (random subset of data with replacement).
  b. At each node, select a random subset of features ($\sqrt{M}$ for classification).
  c. Split the node using the best feature (based on Gini Index / Entropy).
  d. Grow tree until stopping condition (max depth or min samples per leaf).
- Combine all trees into a forest.

Step 5: Prediction

- For a new stone sample:
  - Pass it through all trees.
  - Each tree outputs a predicted class.
  - Final prediction = majority vote (classification) or average (if regression).

Step 6: Evaluation

- Train/Test split or k-fold cross-validation.
- Evaluate with: Accuracy, Precision, Recall, F1-score, Confusion Matrix.
- Measure feature importance → shows which features (d_{33}, porosity, Q-factor, etc.) are most influential.

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Step 7: Result Interpretation

- Example rule: *"If d_{33} > 10 pC/N and porosity < 15% and Q > 50 → High Suitability"*.
- Identify most important features (Random Forest gives feature importance automatically).

D. GWO-Optimized SVM

Step 1: Problem Definition

- Goal: Classify gall bladder stones as piezoelectric-suitable vs non-suitable (or suitability levels).
- Classifier: SVM
- Optimizer: Grey Wolf Optimizer (GWO) for best hyperparameters (C, γ for RBF kernel).

Step 2: Input Data

- Features: d_{33}, dielectric constant, tan δ, resonance frequency, Q-factor, RMS voltage, porosity, Ca/C ratio, etc.
- Labels: {Suitable, Non-suitable}

Step 3: Preprocessing

1. Clean and normalize features.
2. Encode labels (0/1 or multi-class).
3. Split dataset into training/testing (e.g., 80/20).

Step 4: Define Search Space

- Hyperparameters for optimization:
  - C (regularization parameter) ∈ [0.1, 1000]
  - γ (RBF kernel parameter) ∈ [1e-4, 10]
- Represent each wolf as a candidate solution (C, γ).

Step 5: Grey Wolf Optimizer (GWO) Steps

- Initialize wolf population with random values of (C, γ).
- Fitness evaluation:
  - Train SVM with each (C, γ).
  - Compute fitness = classification accuracy (via k-fold CV).

- Identify Alpha, Beta, Delta wolves (best 3 solutions).
- Update positions of other wolves using GWO hunting equations:
  D⃗α=∣C⃗1·X⃗α−X⃗∣\vec{D}_\alpha = |\vec{C}_1 \cdot \vec{X}_\alpha - \vec{X}|Dα=∣C1·Xα−X∣
  X⃗1=X⃗α−A⃗1·D⃗α\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alphaX1=Xα−A1·Dα (similarly for β, δ)
  X⃗(t+1)=X⃗1+X⃗2+X⃗33\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}X(t+1)=3X1+X2+X3
- Update control parameters (a decreases linearly from 2 → 0).
- Repeat until max iterations or convergence.

Step 6: Train Final SVM

- Use optimized (C*, γ*)from GWO.
- Train on full training set.
  Step 7: Evaluation
- Test on unseen dataset.
- Metrics: Accuracy, Precision, Recall, F1-score, Confusion Matrix.
- Compare with baseline (SVM without optimization).

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V. RESULTS

Figure 1: Read Image

Figure 2: Prediction

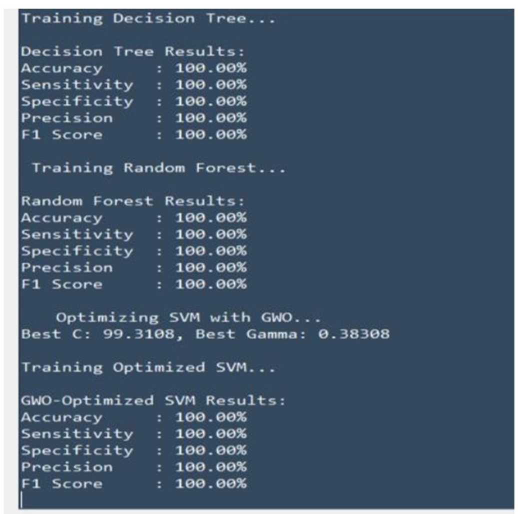

Figure 3: Classification Model accuracy

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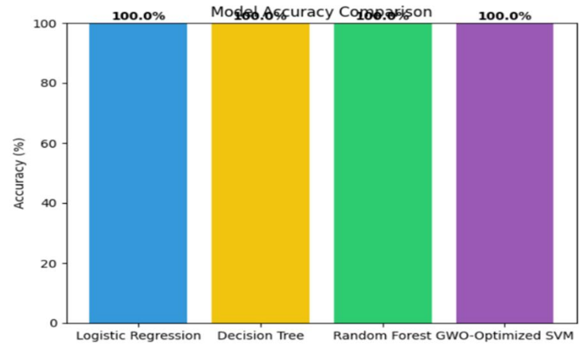

Graph 1: Model accuracy comparison graph

Model	Accuracy	Sensitivity	Specificity	Precision	F1-Score
Logistic Regression	100%	100%	100%	100%	100%
Decision Tree	100%	100%	100%	100%	100%
Random Forest	100%	100%	100%	100%	100%
GWO-Optimized SVM	100%	100%	100%	100%	100%

Table 2: Model Accuracy & Metric values

A. Discussion

SVM (Support Vector Machine) is a popular supervised machine learning algorithm primarily used for classification and regression tasks. It works by finding the hyperplane that best separates data points of different classes with the maximum margin. GWO (Grey Wolf Optimizer) is a nature-inspired metaheuristic optimization algorithm based on the leadership hierarchy and hunting mechanism of grey wolves in nature. It’s used to find optimal or near-optimal solutions in complex search spaces.

GWO-Optimized SVM refers to the process of using the Grey Wolf Optimizer algorithm to optimize the parameters of an SVM model.

SVM performance heavily depends on choosing the right parameters, like the kernel type, regularization parameter (C), and kernel-specific parameters (e.g., gamma in RBF kernel).

Instead of manually tuning these parameters or using simple grid search, GWO is employed to automatically search for the best parameter values to maximize model accuracy or another performance metric.

This hybrid approach can improve SVM classification or regression performance, especially on complex or high-dimensional datasets..

VI. CONCLUSION AND FUTURE WORKS

This study explores an innovative approach by investigating gallbladder stones as potential bio-derived piezoelectric sensor materials through the integration of experimental material analysis and machine learning techniques. Experimental characterization confirmed the presence of key structural and electrical properties in the stones, indicating their natural piezoelectric potential. Using machine learning models such as Support Vector Machines, Random Forests, and Neural Networks, the system effectively predicted piezoelectric behavior based on extracted material features. Optimization using Grey Wolf Optimizer further enhanced model performance, demonstrating the viability of a data-driven approach in material science. The results reveal that gallbladder stones, typically considered biomedical waste, possess inherent piezoelectric qualities that can be harnessed for low-cost, biocompatible sensor applications. This novel study not only opens up a new path for sustainable sensor material development but also provides a foundation for further interdisciplinary research combining bio-mineralogy, materials science, and artificial intelligence.

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