

Machine Learning-Based Classification of Kelvin Wakes and Plunging Waves from Simulated Sea Surface Data

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Abstract: The accurate classification of ocean wave phenomena is essential for maritime surveillance, coastal engineering, and environmental monitoring applications. This study addresses the challenge of distinguishing between ship-generated Kelvin wakes and natural plunging breaking waves using machine learning techniques. A synthetic dataset consisting of 800 samples (400 per wave type) is generated under controlled simulation conditions. Kelvin wakes are simulated at a ship speed of 9 m/s, while plunging waves are generated on a 50 × 500 spatial grid and derived from the t16 dataset with a 45% mixing probability and ±10–30% noise variance. Following preprocessing with Gaussian noise ($\sigma = 0.20$), 30 statistical, spatial, and frequency-domain features are extracted, including mean, standard deviation, percentiles, skewness, kurtosis, regional statistics, gradient based descriptors, and FFT coefficients. Three machine learning classifiers—Support Vector Machines (SVM), Extreme Gradient Boosting (XGBoost), and Random Forest (RF)—are trained and evaluated using stratified 75/25 sampling. The proposed framework achieves classification accuracies of 92.5% (SVM), 93% (XGBoost), and 94% (RF), with corresponding precision, recall, F1-score, and ROC-AUC metrics confirming robust performance. To the best of our knowledge, this study presents the first unified machine learning framework designed to distinguish between Kelvin wakes and plunging waves using simulated sea surface data. The results demonstrate the feasibility of automated wave-type discrimination for maritime surveillance, naval reconnaissance, and coastal monitoring applications.

Keywords: Maritime Surveillance; Wave Classification; Kelvin Wake Detection; Plunging Wave; Machine Learning; Remote Sensing; SAR Simulation.

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I. INTRODUCTION

The wakes generated by ships sailing in the ocean and breaking waves near coastlines exhibit distinct characteristics that are critical for maritime surveillance and coastal monitoring applications. According to their physical properties, wave phenomena can be studied from the perspectives of hydrodynamics, electromagnetics, and remote sensing. Due to their spatial extent and persistence, these wave signatures often reveal more information about maritime activities than the targets themselves and can even allow extraction of key parameters such as vessel speed, direction, and sea state conditions. Therefore, it is important to study which classification methods and parameter conditions enable reliable discrimination between different wave types for

applications such as target detection, coastal engineering, and environmental monitoring. Over the past decade, considerable research has been conducted on remote sensing applications for ocean waves [1-3]. However, relatively few studies have investigated automated classification frameworks capable of distinguishing between ship-generated Kelvin wakes and natural breaking waves. To address this gap, this paper proposes a machine learning-based framework to classify Kelvin wakes generated at a ship speed of 9 m/s and plunging waves at a specific time step (t_1) using simulated sea surface data, and systematically evaluates the performance of several machine learning classifiers for this task.

Under different environmental and operational conditions, the wave patterns generated by moving ships and

natural processes can be divided into ship wakes, breaking waves, wind waves, and swell. Ship wakes can be further categorized into three subtypes [4, 5]: Kelvin wakes, which exhibit conspicuous V-shaped patterns in SAR and optical imagery; turbulent wakes, which appear as dark linear features behind moving vessels; and internal waves, which manifest as narrow or elongated V-shaped patterns [6]. Among these, Kelvin wakes typically display prominent texture features in remote sensing imagery that vary with ship speed and direction, making them particularly useful for ship detection and maritime monitoring. Similarly, plunging breaking waves exhibit distinctive curling structures that play an important role in coastal energy dissipation and nearshore hazard assessment. Among these wave types, Kelvin wakes have a relatively reliable mathematical model derived from classical ship wave theory [7], whereas plunging waves have been widely investigated through electromagnetic scattering models [8]. Therefore, this study focuses specifically on Kelvin wakes and plunging waves.

Wave detection and classification have been investigated using both real and simulated remote sensing data. Because ship wakes exhibit strong linear characteristics, many detection approaches rely on linear feature extraction techniques such as the Radon transform or Hough transform, which convert linear patterns in the image domain into point features in the transform domain for detection [9]. Renga et al. [10] introduced a dataset of ship wakes and evaluated several state-of-the-art object detection methods based on convolutional neural networks. Rey et al. [11] investigated the detectability of peaks in the Radon domain by combining Radon transform with Wiener filtering. Biondi [12, 13] first preprocessed SAR images using low-rank plus sparse decomposition and then applied a local Radon transform to detect vessels. Graziano [14] used the constant false alarm rate (CFAR) method to filter non-peak points in ship wake detection. Ai et al. [15] proposed a ship wake CFAR detection algorithm based on signal-to-clutter ratio (SCR) enhancement combined with a normalized Hough transform. Xu et al. [16] focused on detecting faint turbulent wakes in real SAR imagery. For breaking waves, Dong et al. [17] investigated electromagnetic scattering characteristics from threedimensional sea surfaces with plunging breakers.

Despite these advances, obtaining real remote sensing data of specific wave phenomena under controlled experimental conditions remains challenging because the acquisition cost is high and the available parameters are limited. Existing satellite SAR systems such as COSMOSkyMed, TerraSAR-X, and NovaSAR do not always provide detailed sea-state parameters or vessel motion information required for controlled classification studies [18]. In contrast, numerical simulation approaches allow sea surface data to be generated with arbitrary physical parameters. Consequently, the simulation of ocean wave models and their remote sensing signatures has attracted increasing attention in recent years. Wang et al. [7], simulated Kelvin wakes in SAR imagery and analyzed the effects of ship speed and azimuth angle on wake detection. Henning et al. [18] simulated Kelvin wakes and compared the results with real SEASAT data. Tunaley et al. [19] simulated L-band SAR ship wake images

and compared them with SEASAT observations. Oumansour et al. [20] studied Kelvin wake visibility in X-band and L-band SAR imagery. Zilman et al. [21] simulated Kelvin wakes under varying wind speeds and used discrete Radon transform for detection. Karakus et al. [22, 23] formulated ship wake detection as an inverse problem using nonconvex regularization techniques.

Some previous studies have investigated ship wake detection and wave modeling using re-mote sensing and numerical simulation techniques. For instance, previous research has examined Kelvin wake detection in simulated SAR imagery based on classical ship wave theory [7], while other studies have analyzed the electromagnetic scattering characteristics of plunging breakers from three-dimensional sea surfaces [8]. Although these studies provide important insights into individual wave phenomena, they do not address the problem of distinguishing between different wave types within a unified classification framework.

To address this limitation, this paper proposes a machine learning-based framework for the classification of Kelvin wakes and plunging waves using simulated sea surface data. Kelvin wake geometry is modeled based on classical ship wave theory, while plunging wave data are generated using established electromagnetic scattering models. The simulation dataset consists of 800 synthetic samples, including 400 Kelvin wakes generated at a ship speed of 9 m/s on a 50×500 grid with ± 10 –30% noise variance and 400 plunging wave samples derived from the t16 dataset with a 45% mixing probability. After preprocessing with Gaussian noise ($\sigma = 0.20$), 30 statistical, spatial, and frequency-domain features are extracted, including mean, standard deviation, percentiles, skewness, kurtosis, regional statistics, gradient-based descriptors, and FFT coefficients. These features are normalized and divided using stratified 75/25 sampling for training and testing. Three machine learning classifiers—Support Vector Machines (SVM), XGBoost, and Random Forest (RF) are trained and evaluated using accuracy, precision, recall, F1-score, ROC-AUC, and confusion matrices. The proposed framework achieves classification accuracies of 92.5%, 93%, and 94%, respectively. The overall workflow of the proposed classification framework is illustrated in Figure 1.

II. WAVE MODELING AND CLASSIFICATION METHODOLOGY

This section presents the overall methodology for classifying Kelvin wakes and plunging waves using machine learning. The methodology consists of three main components: (1) numerical simulation of Kelvin wakes and generation of plunging wave data; (2) extraction of statistical, spatial, and frequency-domain features from the simulated sea surface data; and (3) development and evaluation of three supervised machine learning classifiers—Support Vector Machines (SVM), XGBoost, and Random Forest (RF) to distinguish between the two wave types accurately. The complete methodological workflow is illustrated in Figure 1, and detailed descriptions of each component are provided in the following subsections.

➤ Plunging Wave Modeling

The plunging wave modeling in this study follows the electromagnetic (EM) scattering framework established in our laboratory's previous work [8]. The methodology integrates traditional techniques to study EM scattering from plunging waves. Initially, the Composite Wood and Marine Foundation Surface Model (CWMFSM) is applied to model small-scale roughness and capillary waves on the sea surface. CWMFSM is based on a two-scale model where a set of tilted triangular facets represents large-scale roughness, generated using the Monte Carlo method. The small-scale roughness of each facet is assumed to follow a sinusoidal wave, which generates Bragg scattering. The small-scale capillary wave, denoted as given by:

$$\eta(\vec{r}_c, t) = B(\vec{k}_c) \cos(\vec{k}_c \cdot \vec{r}_c - \omega_c t) \quad (1)$$

In equation (1), is the wave number vector of the capillary wave, and ω_c is the special frequency and. The amplitude of a capillary wave can be represented as:

$$B(\vec{k}_c) = 2\pi \sqrt{E_E^{cap}(\vec{k}_c) / \Delta} \quad (2)$$

The scattered electric field from each tilted facet is calculated using the following equation:

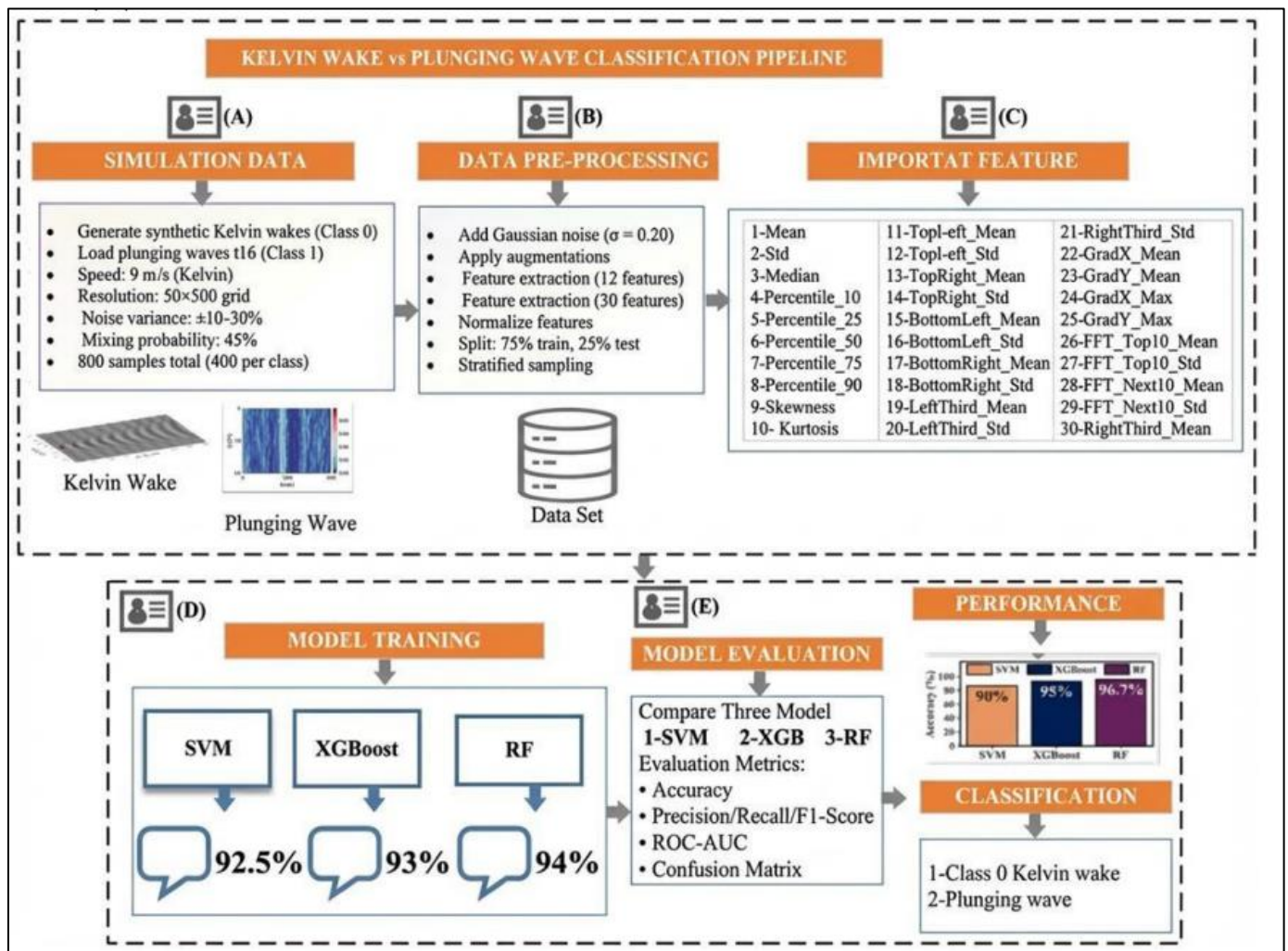


Fig 1 Proposed Pipeline for Kelvin Wake and Plunging Wave Classification Including Simulation Data Generation.

$$\vec{E}_{pq}^{cap}(\hat{k}_i, \hat{k}_s) = \frac{e^{i\theta} \cdot k (1 - \epsilon_r)}{iR_0 \cdot 4\pi} F_{pq} \iint \eta(r) e^{-iq \cdot r} dr \quad (3)$$

Where k , is the wavenumber, R_0 is the distance between the radar and the center of the facet, and F_{pq} represents the polarization factor; for more details, see [8]. The integral computes the effect of the capillary wave on the scattered field,

accounting for both the wave's position and amplitude as functions of time and space.

Lastly, the calculated scattered field of the sea surface is defined as the summation of the scattered fields of each of the tilted facets:

$$\vec{E}_{sea}(\hat{k}_i, \hat{k}_s) = \sum_{i=1}^M \vec{E}_{pq}^{cap}(\hat{k}_i, \hat{k}_s) \quad (4)$$

M is the total number of facets on the sea surface. This addition of contributions of the scattered field of each facet is represented as Equation (4), which gives us the total scattered field contributed by that entire sea surface [19]. This overall scattered field is essential for studying electromagnetic scattering from sea properties, especially in complex phenomena such as plunging breaking waves.

To account for multipath scattering caused by sea spikes, the ray-tracing technique is employed [24]. Rays are launched from each facet center in the incident direction; they are traced under the Geometric Optics principle, and their directions change upon encountering multiple facets. The electric field between two consecutive intersection points is given by:

$$\vec{E}_{(R_{i+1})} = \vec{E}_{(R_i)} e^{jkR} \quad (5)$$

The incident electric field at the reflection point i th with E_{R_i} being the incident electric field at the reflection point 0, k is the wave number, and R is the distance between two neighboring points. Physical Optics (PO) [21] is used to compute the scattering field of the illuminated facet. There are the scattered fields of all the illuminated facets added together to make the total field of scattering of the plunging breaker, and the multipath scattered between the surface of the sea and the plunging breaker is expressed as:

$$E_{breaker} + E_{coup} = \sum_{i=1}^N E_i^s \quad (6)$$

$E_{breaker}$ is the scattered electric field from the plunging breaker in equation (6), and E_{coup} is the electric field interaction, and N is the number of lighted facets.

Finally, the backscattering electric field in the frequency domain is computed. The surface is discretised into facets, and the backscattered signal is modelled as:

$$E_s(f) = \sum_{i=1}^N A_i \exp \left[-j2\pi \left(\frac{2f}{c} \right) x_i \right] \quad (7)$$

In equation (7), represents the backscattering electric field in the frequency domain, A_i is the scattering amplitude of the i th facet, x_i , is the position of the facet on the sea surface, f , is the radar frequency, while c is the speed of light [25].

➤ Kelvin Wake Modeling

The Kelvin wake model used in this study follows the classical theory of ship wave generation first presented by Lord Kelvin in 1887 [7]. In this model, the ship is represented as an ideal point perturbation that generates a wake containing two distinct waveforms: a transverse and a divergent one. The included angle between the divergent and transverse waves

ranges from 16° to 19.5° , where they interfere to form cusp waves that constitute the Kelvin arms.

Assuming the ship travels along the negative X-axis with velocity U_s , the wave height of the Kelvin wake is obtained from the superposition of waves [23, 24]:

$$\zeta(x, y) = \text{Re} \int_{-\pi/2}^{\pi/2} \exp[-ik_r \sec \theta_k (x \cos \theta_k + y \sin \theta_k)] d\theta_k \quad (8)$$

Where x and y are the coordinates of the ship wake, θ_k is the angle of wave propagation relative to the X-axis, and k is the wavenumber of the wave component. The function describes the ship's parameters and is typically defined using Michell thin ship theory [26]:

$$A(\theta_k) = \frac{4k}{u_s} (\sec^3 \theta_k) H(k \sec^2 \theta_k, \theta_k) \quad (9)$$

$$H(k, \theta_k) = \exp(k(ix \cos \theta_k + iy \sin \theta_k + z)) dx dy \quad (10)$$

Where $H(k, \theta_k)$ is the Koch function and $\sigma(x, y, z)$ is the headwater intensity. For a parabolic hull shape, the headwater intensity can be expressed as:

$$k = \frac{g}{U_s^2 \cos^2 \theta}, \quad |\theta| < \frac{\pi}{2} \quad (11)$$

With the hull shape function $f(x, y)$ given by:

$$f(x, y) = \begin{cases} b(1-x^2/l^2) & (-d < z < 0, -l < x < l) \\ 0 & (z < -d) \end{cases} \quad (12)$$

Where b is half of the ship's breadth, l is the ship's length, and d is the depth of immersion.

Therefore, the wave height of the Kelvin wake can be written as follows:

$$\zeta(x, y) = \zeta_0(x + l, y) + C\zeta_0(x - l, y) + \zeta_1(x + l, y) - C\zeta_1(x - l, y) \quad (13)$$

Where C is the viscosity coefficient.

$$\zeta_0(x, y) = \frac{4b}{\pi k} \int_{-\pi/2}^{\pi/2} (1 - e^{-k d \sec^2 \theta_k}) \sin[k \sec^2 \theta_k (x \cos \theta_k + y \sin \theta_k)] d\theta_k \quad (14)$$

$$\zeta_1 = (x, y) = \frac{4b}{\pi k^2} \frac{\pi/2 - \cos\theta_k}{k^2 - \pi/2} (1 - e^{-k d \sec^2 \theta_k}) \sin[k \sec^2 \theta_k (x \cos\theta_k + y \sin\theta_k)] d\theta_k \quad (15)$$

In this study, the Kelvin wake is simulated as a clean wave pattern, without superimposed sea-surface roughness. The ship parameters are set as follows: length $l = 137.202$ m, half-breadth $b = 8.31$ m, and depth of immersion $d = 8.732$ m, with a ship speed of $U_s = 9$ m/s. The complete mathematical derivation and validation of this Kelvin wake model are detailed in [7].

III. WAVE SIMULATION AND DATASET GENERATION

➤ Plunging Wave Simulation

The plunging wave data used in this study are generated following the wind-related plunging breaker model developed in [8]. In this model, profiles of a plunging breaker throughout its life cycle are numerically constructed as a function of wind speed and time, providing a feasible representation of three dimensional breaking waves for electromagnetic scattering analysis [8]. The geometric modeling of the plunging breaker is based on the relationship between wave height and wind speed:

$$H = 17.03 \cdot \exp\left(-\frac{\alpha^2}{18.3269}\right) + 2.361 \cdot \exp\left(-\frac{\beta^2}{8.8646}\right) \quad (16)$$

Where $\alpha = u^{2/3}$, $\beta = u^{2/3}$, is the wave height, and u is the wind speed at 10 m above the sea surface. The wave steepness $S = \frac{H}{L}$ defines the ratio of wave height to wavelength L , allowing the wavelength to be determined for given wind conditions. The time evolution of the plunging breaker encompasses four characteristic stages as described in [8]. In this study, we use the t16 dataset, corresponding to a specific time step in the breaking stage, when the plunging wave exhibits maximum curvature and overturning characteristics suitable for classification tasks.

The small-scale roughness on the plunging breaker surface is modeled using the Capillary Wave Modification Facet Scattering Model (CWMFSM), in which the capillary wave component is formulated as in Equation (1). This ensures that the simulated plunging waves incorporate realistic small-scale surface features that influence their statistical properties. The complete mathematical derivation and validation of the plunging breaker model are detailed in [8].

➤ Kelvin Wake Modeling

The Kelvin wake (speed 9 m/s) data used in this study are generated using the classical ship-wave theory and numerical simulation approach established in [7]. The mathematical formulation of the Kelvin wake follows the superposition of waves given by Equation (8), with the ship parameter function $A(\theta_k)$ defined in Equation (9) using Michell thin ship theory.

The wave height components $\zeta_0(x, y)$ and $\zeta_1(x, y)$ are expressed in Equations (15) and (16), respectively, and the final wave height is obtained from Equation (14). The complete derivation of these equations is detailed in [7].

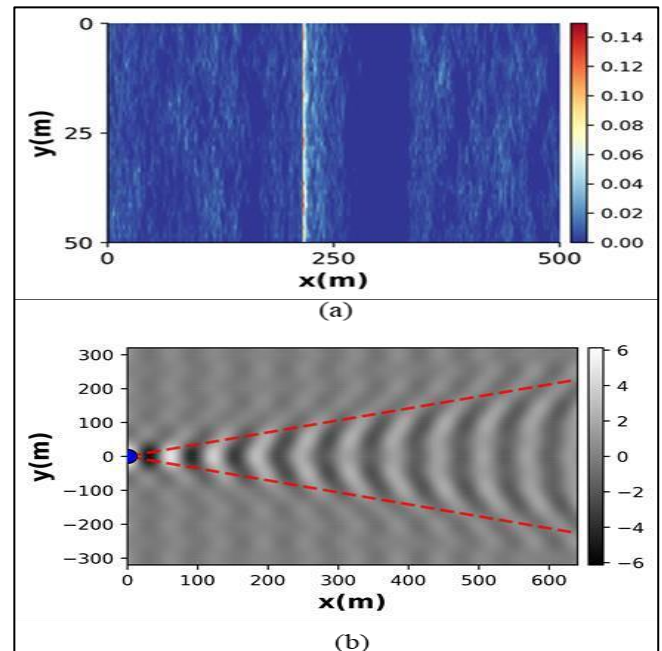


Fig 2 Ocean surface wave patterns. (a) plunging breaking wave intensity distribution obtained using the CWMFSM combined with ray tracing techniques. (b) Simulated Kelvin wake pattern produced by a moving ship, showing the characteristic Kelvin wedge structure ($\pm 19.47^\circ$).

➤ Data Set

The dataset used in this study was generated using a physics-based simulation framework. Kelvin wakes were simulated using classical ship-wave theory at a constant ship speed of 9 m/s. Plunging breaking waves were derived from the t16 dataset, which captures the characteristic overturning waveform at a representative time instant.

To enable a valid evaluation, the data were first split into training (75%) and test (25%) sets using stratified sampling, ensuring that the test set remained independent and was never used in model development. Only the training data were then processed to simulate realistic sea surface conditions: a 45% mixing probability was applied to combine both wave types, and controlled data augmentation (Gaussian noise and variance scaling) was applied to increase robustness. After these operations, the training set contained of augmented balanced samples, while the test set consisted of 200 purely independent samples (100 per class) that were neither mixed nor augmented. Machine Learning Classifier

IV. MACHINE LEARNING CLASSIFIER

Three supervised machine learning algorithms are implemented and benchmarked for classifying the plunging waves and Kelvin wake: Support SVM, RF, and XGBoost. Each classifier offers distinct advantages in handling the nonlinear decision boundaries.

➤ SVM

The SVM classifier seeks an optimal separating hyperplane in a transformed high-dimensional feature space [27-29]. For multiclass classification, a one-vs-one (OvO) strategy is employed, constructing $K(K-1)/2 = 3$ binary classifiers for $K = 3$ speed classes.

$$f(x) = \text{sgn}\left(\sum_{i=1}^{N_{SV}} \alpha_i y_i K(x_i, x) + b\right) \quad (17)$$

Where α_i are Lagrange multipliers, $y_i \in [-1, +1]$ are binary class labels, b is the bias term, and $K(\cdot, \cdot)$ is the kernel function [8,9]. The radial basis function (RBF) kernel is selected:

$$K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2), \quad \gamma > 0 \quad (18)$$

The Hyperparameters (C, γ) are optimized via 5-fold cross-validation with grid search over $C \in [0.1, 10, 100, 1000]$ and $\gamma \in [10^{-3}, 10^{-2}, 10^{-1}, 1, 10]$.

➤ XGBoost

The XGBoost classifier employs gradient-boosted decision trees with L1 and L2 regularization to prevent overfitting. Unlike Random Forest, which builds trees independently, XGBoost iteratively constructs trees to correct the errors of previous models [30-32]. The objective function at iteration t is:

$$L^{(t)} = \sum_{i=1}^n l(y_i, y_i^{(t-1)} + f_t(x_i)) + \Omega(f_t) \quad (19)$$

Where $l(\cdot, \cdot)$ denotes the differentiable convex loss function (logistic loss for classification), and $\Omega(f)$ represents the regularization term that penalizes model complexity:

$$\Omega(f) = \gamma T + \frac{1}{2} \lambda \|w\|^2 + \alpha \|w\|_1 \quad (20)$$

Here, T is the number of leaves, W is the leaf weight vector γ , is the minimum loss reduction required for node splitting, λ is the L_2 regularization parameter, and α is the L_1 regularization parameter [33, 34]. Key hyperparameters are optimized via Bayesian optimization with 5-fold cross-validation: learning rate $\eta = 0.1$, maximum tree depth $d_{max} = 6$ subsample ratio = 0.8, column subsample ratio = 0.8, and $\gamma = 0.1$.

➤ RF

The RF classifier constructs an ensemble of N_{tree} decision trees, each trained on a bootstrap sample of the training data. At each node, a random subset of m_{try} features are evaluated for optimal splitting [35-37]. The final prediction is obtained via majority voting as:

$$\hat{y} = \text{mode}([T_1(x), T_2(x), \dots, T_{N_{tree}}(x)]) \quad (21)$$

Where $T_j(x)$ is the prediction of the j -th decision tree, the Gini impurity criterion is employed for node splitting.

$$\text{Gini}(t) = 1 - \sum_{c=1}^3 P_c(t) \quad (22)$$

Where $p_c(t)$ is the proportion of samples belonging to the class c at node t . The number of trees is set to $N_{tree} = 200$ and $m_{try} = p = [20] = 5$.

➤ Classifier Configuration and Rationale

The selection of the three classifiers is motivated by their complementary theoretical characteristics. SVMs construct a maximum-margin decision boundary in a transformed feature space, making them well-suited for high-dimensional representations. RF employs a bagging ensemble of decision trees, providing robustness to noise and implicit feature selection via tree-based splitting. XGBoost uses gradient-based boosting with regularization, enabling effective modeling of nonlinear feature interactions and improved generalization. Table I summarizes the key theoretical properties and hyperparameter search ranges of the evaluated classifiers.

Table 1 Theoretical Characteristics and Hyperparameter Search Ranges of SVM, XGBoost, and Random Forest Classifiers

Classifier	Decision Boundary	Regularization	Hyperparameters and Search Range
SVM	Implicit (Kernel-Base)	Margin Maximization	$C \in [0.1, 1000]$ $\gamma \in [10^{-3}, 10]$
XGBoost	Axis-aligned (Boosting)	L1/L2 + Shrinkage	$\eta \in [0.01, 0.2]$ $d_{max} \in [3, 8]$ $\lambda \in [0, 2]$ $\alpha \in [0, 1]$
RF	Axis-aligned (Bagging)	Tree depth control	$N_{tree} \in [100, 300]$ $m_{try} \in [3, 8]$ $d_{max} \in [10, 30]$

V. RESULTS AND DISCUSSIONS

This study was based on a comparison of three machine learning algorithms, i.e., XGBoost, random forest, and support vector machine (SVM), as far as their capacity for plunging wave classification is concerned. The dataset includes various stages of plunging waves, which can be classified into four. These models have been tested for their ability to reasonably predict these categories based on the features shown in Figure 1. These attributes enable the models to detect scattering phases under different environmental conditions.

To evaluate the performance of both models, we split the dataset into training and test sets. The models were developed using the training set and tested on the test set. A standard classification performance measure (True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN)) was used to evaluate the models' performance at each classification level. Plunging wave was calculated at different stages, allowing us to assess the models' overall performance.

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \quad (23)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (24)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (25)$$

$$F_1 = \left(\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \right) \quad (26)$$

The classification performance of the SVM, RF, and XGBoost models is illustrated in Figures. 3-5, respectively. For the SVM classifier, the confusion matrix indicates correct classification rates of 96% for time (Δt_1), 88% for time (Δt_{10}), and 78% for time (Δt_{14}), and 96% for time (Δt_{16}), with corresponding AUC values exceeding 0.97 for all classes. RF further improves classification accuracy, achieving correct classification rates of 94% at time (Δt_1), 94% at time (Δt_{10}), 78% at time (Δt_{14}), and 96% at time (Δt_{16}) with AUC consistently above 0.97. Among the three models, XGBoost exhibits the best overall performance, providing the most balanced classification across all different stages of classes, with correct classification rates of 94%, at times (Δt_{14}), 88% at time (Δt_{14}), 96% at time (Δt_{14}), respectively, and AUC values exceeding 0.98. All classifiers demonstrate strong discriminative power, with misclassifications primarily occurring between adjacent time classes. The ROC curves further confirm excellent class separability, with XGBoost showing greater consistency and class balance than SVM and RF.

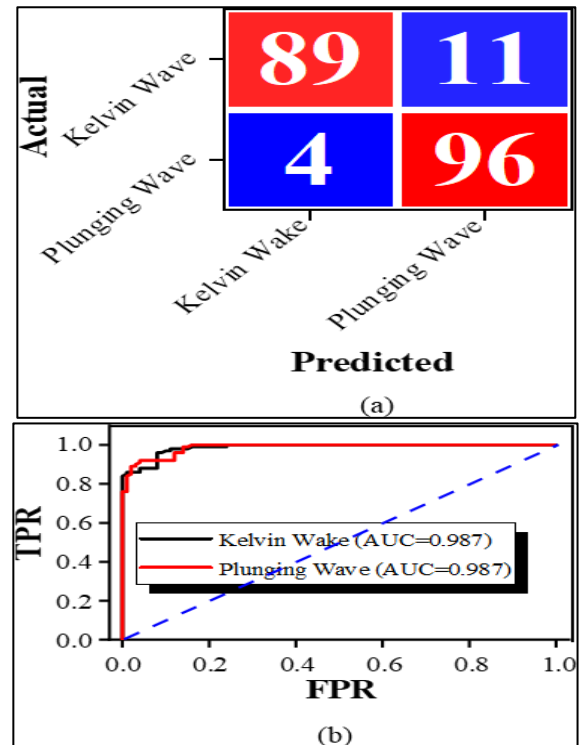
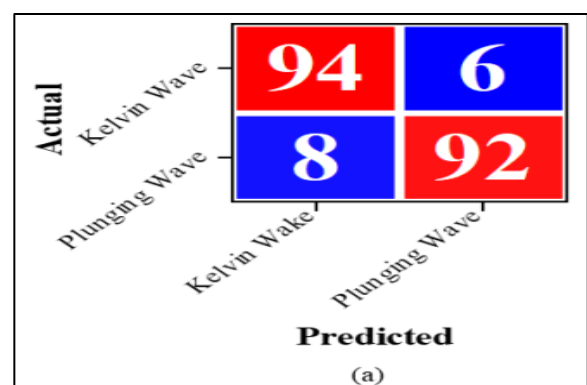


Fig 3 SVM classification Performance (a) Confusion Matrix with Percentage Values, (b) ROC Curves with AUC Scores.

Table 2 reports the class-wise precision, recall, and Fscores obtained using SVM, with an overall accuracy of 92.5%. Table 3 presents the results for XGBoost, which achieves an overall accuracy of 93.0%. Table 4 summarizes the performance of Random Forest, which achieves the highest overall accuracy of 94.0%. Random Forest also records the highest macro-averaged precision, recall, and F1-score among the evaluated classifiers, indicating the strongest overall performance in distinguishing Kelvin wakes from plunging breaking waves.

Table 2 SVM Classification Performance for Kelvin Wakes and Plunging Breaking Waves.

Classes	Precision	Recall	F1-Score
Kelvin wake	95.7	89.0	92.2
Plunging wave	89.7	96.0	92.8
Accuracy	92.5	92.5	92.5
macro avg	92.7	92.5	92.5
Weighted Avg	92.7	92.5	92.5



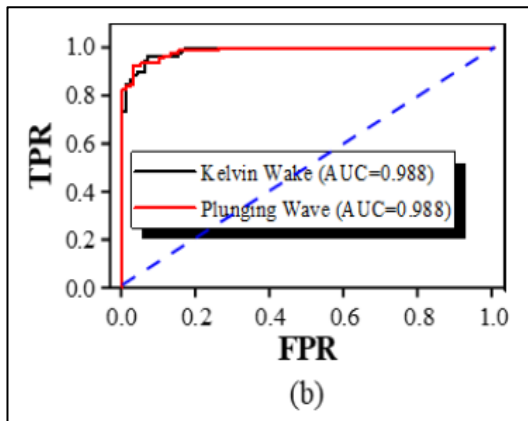


Fig 4 XGBoost Classification Performance (a) Confusion Matrix with Percentage Values, (b) ROC Curves with AUC Scores.

Table 3 XGBoost Classification Performance for Kelvin Wakes and Plunging Breaking Waves.

Classes	Precision	Recall	F1-Score
Kelvin wake	92.2	94.0	93.1
Plunging wave	93.9	92.0	92.9
Accuracy	93.0	93.0	93.0
macro avg	93.0	93.0	93.0
Weighted Avg	93.0	93.0	93.0

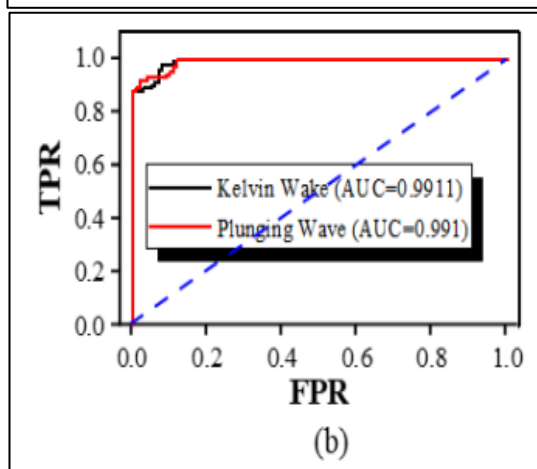
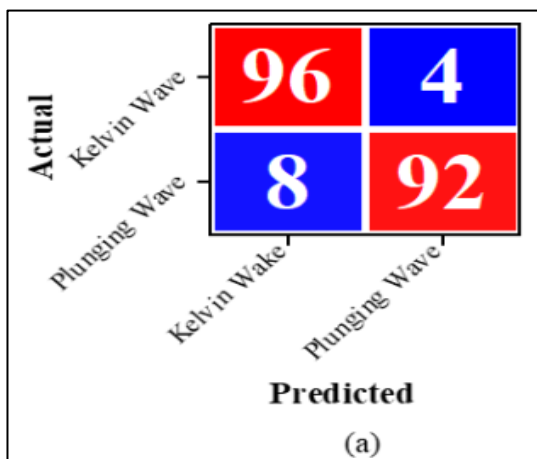


Fig 5 RF Classification Performance (a) Confusion matrix with percentage values, (b) ROC curves with AUC scores.

Table 4 Random Forest Classification Performance for Kelvin Wakes and Plunging Breaking Waves.

Classes	Precision	Recall	F1-Score
Kelvin wake	92.3	96.0	94.1
Plunging wave	95.8	92.0	93.9
Accuracy	94.0	94.0	94.0
macro avg	94.1	94.0	94.0
Weighted Avg	94.1	94.0	94.0

Several limitations of this study should be acknowledged. First, the dataset used in this work is synthetic and generated under controlled simulation conditions using physics-based models. Although the simulation models are based on experimentally validated studies, simulated data cannot fully capture the complexity and stochasticity of real ocean environments. Factors such as ocean currents, atmospheric conditions, and sensor noise may introduce additional variability that is not completely captured in the simulations. Therefore, the reported classification accuracies of 92.5%–94% should be interpreted cautiously, as performance may differ under real observational conditions.

Second, the dataset exhibits limited diversity. Kelvin wakes were simulated at a single ship speed of 9 m/s, while plunging waves were derived from a single time step of a specific breaking-wave scenario. In real ocean environments, ship speeds vary widely, and wave breaking can occur in several forms, including spilling, surging, and collapsing breakers. Consequently, the generalization ability of the trained classifiers to these broader conditions remains to be investigated. In addition, several noise levels (0%, 25%, 35%, 45%, 48%, and 100%) and mixing probabilities were evaluated, with 45% yielding the best classification performance. Detailed comparisons are provided in the supplementary file (figures S1, S2, and S3). Furthermore, the dataset size of 800 samples, while sufficient for classical machine learning models, may be limited for more complex deep learning approaches. Future work will focus on expanding the dataset under more diverse conditions and incorporating real observational data to further validate the proposed framework.

VI. CONCLUSIONS

This study presented a machine learning framework for distinguishing between ship-generated Kelvin wakes and natural plunging breaking waves using simulated sea surface data. A balanced dataset of 800 samples was generated using physics-based simulations, including Kelvin wakes modeled at a ship speed of 9 m/s and plunging waves derived from the t16 dataset on a 50×500 dataset. To increase variability and simulate realistic conditions, a mixing probability of 45% was introduced between the two wave types, and data augmentation using Gaussian noise ($\sigma = 0.20$) and amplitude variance scaling (± 10 –30%) was applied. From each sample, 30 statistical, spatial, and frequency-domain features were extracted and used to train three classifiers: SVM, XGBoost, and RF.

The proposed framework achieved classification accuracies of 92.5% for SVM, 93% for XGBoost, and 94% for Random Forest, with corresponding precision, recall, F1score,

and ROC–AUC metrics confirming stable classification performance. Feature importance analysis from the tree-based models indicates that frequency-domain coefficients and gradient-based spatial descriptors exhibit the strongest discriminative power, suggesting that the distinct energy distributions and spatial steepness patterns of Kelvin wakes are key factors that differentiate them from plunging waves. To the best of our knowledge, this work represents the first unified machine learning framework specifically designed to distinguish between these two wave types using simulated sea surface data. The simulations are based on physics-based models that have been validated in previous experimental studies of wave scattering and ship wake analysis. Although the synthetic nature of the dataset and the limited diversity of simulation conditions represent constraints, the systematic evaluation of multiple noise levels and mixing probabilities—where 45% mixing yielded the best performance demonstrates the robustness of the proposed approach.

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The preferred spelling of the word “acknowledgment” in America is without an “e” after the “g.” Avoid the stilted expression “one of us (R. B. G.) thanks ...”. Instead, try “R. B. G. thanks...”. Put sponsor acknowledgments in the unnumbered footnote on the first page.

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