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Design of Antasena: an AI-powered maritime surveillance and anomaly detection system for security decision support

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ABSTRACT

Indonesia's vast maritime territory faces serious challenges from illegal fishing, smuggling, and habitat destruction. To address these, the Indonesian Navy (TNI-AL) developed Antasena, an artificial intelligence (AI)-powered smart dashboard integrating automatic identification system (AIS) data, satellite imagery, and conservation metrics. Antasena leverages advanced anomaly detection algorithms, achieving 95.3% accuracy, 94.7% precision, 94.2% recall, and a 96.8% receiver operating characteristic-area under the curve (ROC-AUC) score in identifying vessel anomalies, including unauthorized fishing and smuggling activities. Using the analyze, design, develop, implement, and evaluate (ADDIE) framework, the system supports real-time maritime surveillance and biodiversity monitoring in conservation zones. The main contributions of this study include the development of a user-centric AI-based dashboard for maritime anomaly detection, the integration of multi-source data with machine learning models, and validation through operational field tests with maritime authorities. Antasena offers a scalable and effective solution to strengthen maritime security and protect Indonesia's marine resources.

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1. INTRODUCTION

Indonesia's vast maritime territory, spanning over 5.8 million km², plays a crucial role in global trade and resource management. However, this vastness also makes it vulnerable to security threats such as illegal fishing, smuggling, and environmental violations. To address these challenges, the Indonesian Navy (TNI-AL) developed Antasena, an artificial intelligence (AI)-powered monitoring system that integrates automatic identification system (AIS) data to detect anomalous vessel behaviors in real time.

Antasena collects and analyzes multi-source maritime surveillance data, providing accurate early-warning information to maritime traffic participants and enabling proactive responses to potential risks [1]. Anomaly detection algorithms applied to AIS data identify behavioral patterns that deviate from normal navigation, which may indicate illegal fishing, piracy, or smuggling activities [2]. Accurate and timely anomaly detection is therefore critical for maritime domain awareness and national defense operations [3].

Previous studies on maritime anomaly detection have implemented a wide range of machine learning approaches, including decision tree (DT), random forest (RF), support vector machine (SVM), and neural network [4]–[6]. While these techniques have achieved satisfactory accuracy, they often face limitations in interpretability, robustness, and adaptability to streaming AIS data. Single-model classifiers such as DT or SVM tend to overfit complex data distributions, whereas deep learning architectures demand extensive computation and provide limited transparency in decision-making [7]–[9]. These challenges reduce their feasibility for real-time operational deployment in maritime surveillance systems such as Antasena.

Recent advancements in ensemble and gradient boosting techniques—particularly extreme gradient boosting (XGBoost)—have demonstrated significant improvements in accuracy, generalization, and scalability across various anomaly detection domains [10]–[13]. XGBoost effectively balances bias–variance trade-offs, manages imbalanced data, and achieves fast convergence, making it a promising candidate for maritime anomaly analysis. However, no prior study has conducted a comprehensive benchmarking of these models under the Indonesian maritime operational context. Therefore, identifying a state-of-the-art (SOTA) configuration that achieves an optimal balance between detection accuracy, robustness, interpretability, and computational efficiency is essential to enhance real-time maritime surveillance.

This study aims to establish a SOTA benchmark for AIS-based maritime anomaly detection by comparing three supervised learning algorithms DT, RF, and XGBoost within the Antasena system. Each model was optimized using grid-based hyperparameter tuning and evaluated with 5-fold cross-validation to ensure fair performance comparison. The evaluation covers five key dimensions: detection performance, robustness, interpretability, computational efficiency, and scalability. The findings are expected to provide both theoretical and practical contributions toward improving anomaly detection and situational awareness in naval operations. A detailed description of the framework and its operational data workflow is presented in the following section.

2. METHOD

This study employs a quantitative research approach to generate numerical evidence, adhering to the scientific principles of concreteness, objectivity, measurement, rationality, and systematization [14]. The methodology follows a systematic and structured process, utilizing both primary and secondary data sources processed through machine learning techniques. Machine learning is chosen for its ability to manage complex, high-dimensional datasets and to accurately model non-linear relationships and interactions among variables, which are crucial for identifying the SOTA anomaly detection model within the Antasena system [15]. The research process adopts the analyze, design, develop, implement, and evaluate (ADDIE) model as a guiding framework for developing and benchmarking an AI-enabled smart surveillance dashboard that supports maritime decision-making [16]. Each phase of ADDIE produces outputs that inform and refine subsequent stages, ensuring a continuous, iterative process toward optimizing model performance and achieving SOTA-level accuracy and robustness [17].

2.1. Research design for Antasena: AI-driven maritime security decision support

The objective of this research is to develop Antasena, an AI-powered system that integrates AIS data, satellite imagery, and vessel sensor data to deliver a maritime monitoring and anomaly detection solution for security decision support. Previous studies [18], [19] have treated AIS messages as observations of a vessel's underlying state, emphasizing that AIS data quality strongly affects maritime traffic safety and anomaly detection reliability. Varlamis *et al*. [20] proposed a rule-based method for data integrity assessment, where operational rules are derived from system specifications and domain expertise, formalized through a logic-based framework, and used to generate situation-specific alerts. Building upon these insights, the primary data in this study consist of AIS information, while the secondary data include satellite imagery, vessel sensor readings, and auxiliary maritime datasets. These data sources are processed and integrated under the ADDIE methodological framework, structured into the following phases: analysis, design, development, implementation, and evaluation, as described in the following.

2.1.1. AIS and multi-source data collection

Ship movement data across Indonesian waters were obtained from maritime agencies such as the Indonesian Maritime Security Agency or Badan Keamanan Laut, the Ministry of Marine Affairs and Fisheries, and the Maritime Information Center. A publicly accessible subset of the dataset is available at https://bit.ly/sample-data-antasena. The dataset includes vessel identification numbers (maritime mobile service identity (MMSI)), positions (latitude and longitude), speed over ground (SOG), course over ground (COG), and timestamps, which are fundamental features for maritime surveillance and anomaly detection. AIS transmissions were received at varying frequencies (2-10 seconds) depending on vessel class and transmission mode. For this study, approximately 24,565 AIS records were collected between June 22, 2023 and September 22, 2023 (universal time coordinated (UTC)), consisting of 12,513 entries for tankers and 12,052 entries for cargo vessels.

In addition to AIS, the system design also considers synthetic aperture radar (SAR) satellite imagery and coastal radar data to enhance situational awareness, particularly for detecting "dark vessels" that deliberately disable AIS transponders. Satellite imagery offers wide spatial coverage but lower temporal frequency (daily to weekly), while coastal radar provides continuous monitoring within its detection range. Integration of these sources is currently under development, with pilot tests conducted to validate AIS-based anomaly detection. Future iterations of Antasena will incorporate automated ingestion of multi-source data into the anomaly detection pipeline.

2.1.2. AIS data structure and feature engineering

Raw AIS data underwent a preprocessing stage where it was cleaned to remove noise and inconsistencies. The data was then formatted and transformed to extract key features, including vessel trajectories, speed, COG, and timestamps. The structure of the resulting dataset used for modeling appears in Table 1 [21].

Table 1. Raw AIS data structure

Variable	Description
MMSI	A unique 9-digit identification code assigned to each vessel.
Data time	Timestamp recorded in the AIS database.
Longitude	Vessel's geographic longitude.
Latitude	Vessel's geographic latitude.
Speed	Vessel's speed (knots).
COG	Course over ground (degrees from true north).
Draught	Vertical distance between the waterline and the vessel's hull bottom.
Is anomaly	Target variable indicating anomalous vessel behavior.

2.1.3. AIS data preprocessing and feature engineering

Raw data were processed using RStudio prior to model training. The preprocessing workflow is summarized in Table 2, outlining key steps such as data cleaning, feature generation, and normalization. Missing AIS records were handled using forward-fill interpolation for temporal continuity, while extreme outliers in speed and course were filtered using percentile-based thresholds. To address class imbalance inherent in anomaly detection, class weighting was applied during model training. Lag features up to five-time steps were engineered to capture vessel movement dynamics over time. For example, latitude and longitude lags represent trajectory history, while lag-based mean and standard deviation of speed capture stability and variability in vessel motion. Similarly, lag features for COG and draught represent directional and depth changes. The resulting dataset summarized in Table 3.

Table 2. AIS data preprocessing workflow

Step	Process	Description
1	Data cleaning	Remove missing values and duplicates.
2	Trajectory feature generation	Extract latitude, longitude, COG, speed, and timestamp.
3	Statistical feature calculation	Compute mean and standard deviation of speed.
4	Normalization	Scale data for model input.

Table 3. Derived feature set for anomaly detection modeling

Variable	Description
Longitude (now, lag 1-5)	Vessel's longitude positions from current to fifth lag.
Latitude (now, lag 1-5)	Vessel's latitude positions from current to fifth lag.
Mean speed	Average speed across five time lags.
Std. deviation of speed	Speed variability across five lags.
COG (now, lag 1-5)	Directional course changes over time.
Draught (now, lag 1-5)	Variation in vessel depth (draught) over time.

The selected features in Antasena were derived through both domain knowledge and exploratory data analysis to ensure relevance to maritime operational behavior. Variables such as SOG variance, course deviation, and turning rate were prioritized because they strongly correlate with anomalous vessel activities in AIS literature. While this study focuses on engineered features, no explicit dimensionality reduction (e.g., principal component analysis (PCA) was applied to preserve interpretability. However, feature importance analysis using RF gain scores and correlation filtering were performed to avoid redundancy. Future work will consider Shapley additive explanations (SHAP)-based feature selection to provide transparent justification of each variable's contribution and to enhance the explainability of Antasena model.

The selected features in Antasena were determined through domain-driven analysis, emphasizing variables most relevant to maritime anomaly behavior such as speed variance, course deviation, turning rate, and distance from typical routes. These features were chosen because prior studies show strong correlations between abnormal kinematic patterns and illegal or unsafe vessel operations. Although the current version of Antasena focuses on interpretability, future work will explore dimensionality reduction techniques such as PCA and autoencoder-based embeddings. PCA will help identify the most informative linear feature combinations, while autoencoders can capture nonlinear relationships in high-dimensional AIS data. Integrating these techniques will reduce redundancy, improve computational efficiency, and potentially enhance anomaly detection performance without sacrificing interpretability.

2.2. Machine learning model training for maritime anomaly detection

Machine learning models were applied to AIS data to detect maritime anomalies. The principle of anomaly detection is to construct a model of normal vessel behavior from historical track data and identify deviations from this learned pattern [5]. The training pipeline is outlined in Table 4. Each model was tuned using grid-based hyperparameter optimization and 5-fold cross-validation to determine the best configuration for final evaluation. The tuned hyperparameters are summarized in Table 5. To provide a clearer comparison of model performance, Figure 1 illustrates the accuracy, precision, recall, and F1-score for each algorithm. The figure providing a comprehensive assessment of anomaly detection effectiveness. This visual representation enables an intuitive understanding of comparative results before the confusion matrix analysis.

Table 4. Model training pipeline

Step	Process	Description
1	Data split	Divide the dataset into training (80%) and testing (20%) subsets.
2	Model selection	Apply DT, RF, or XGBoost on training data.
3	Hyperparameter tuning	Perform grid search with 5-fold cross-validation.
4	Model validation	Evaluate model performance on the test set.
5	Model saving	Store optimized model for deployment.

Table 5. Tuned hyperparameters for each model

Model	Hyperparameter	Explanation
DT	Cost complexity (α)	A regularization parameter that controls the trade-off between tree complexity and accuracy on the training data. Higher values of α produce simpler trees with fewer nodes, reducing overfitting.
	Tree depth	The maximum number of levels in the tree. Deeper trees capture more complex decision boundaries but may lead to overfitting.
RF	Number of trees	The number of DTs in the ensemble. Increasing the number of trees improves model stability and accuracy but raises computational cost.
	Max features	The number of features considered when splitting each node. Larger values reduce model randomness but can decrease diversity among trees.
XgBoost	Number of trees	The total number of boosting iterations. Excessive boosting may overfit, while too few may underfit the data.
	Learning rate (η)	Controls the contribution of each tree to the ensemble. Larger values speed up convergence but risk overshooting the optimal solution.
	Tree depth	The maximum depth of each tree. Deeper structures capture more complex relations but increase the likelihood of overfitting.

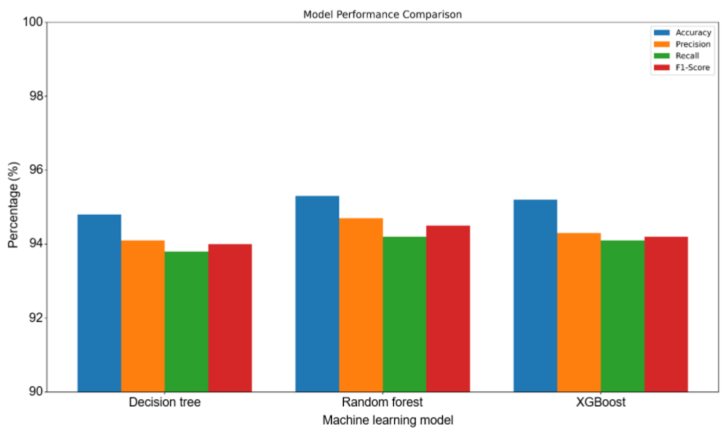

Figure 1. Comparative performance metrics of the evaluated machine learning models

The choice of RF, XGBoost, and DT models in the Antasena system is based on their specific strengths in handling maritime anomaly detection tasks. The RF model, through its ensemble of multiple DTs, reduces overfitting and increases robustness, offers feature importance metrics that support interpretability and operational decision-making. In previous studies, suggests that feature selection significantly impacts the models' predictive capabilities, but the RF regressor is better able to adapt to these changes.

XGBoost, a gradient boosting algorithm, excels at capturing complex patterns in data. It controls model complexity to prevent overfitting, with a higher time complexity during training as trees are built sequentially [22]. XGBoost improves model performance by focusing on harder-to-predict samples, making it highly reliable for detecting maritime anomalies with minimal false positives.

DTs, a widely used supervised learning algorithm in machine learning [23], [24], utilize a tree structure to classify instances based on specified features [25]. They provide clear and intuitive decision rules, which are essential for stakeholders such as maritime authorities. DTs are efficient for initial prototyping and validation of anomaly detection algorithms for decision support systems (DSS).

2.3. System development and implementation

The Antasena DSS integrates the trained anomaly detection models into a real-time operational dashboard that supports maritime security and conservation monitoring. The workflow is illustrated in Table 6. This implementation enables continuous maritime surveillance, automatically flagging vessels that deviate from established navigation patterns or enter restricted zones. The integration of the SOTA model into Antasena ensures optimal trade-offs between detection accuracy, interpretability, and real-time performance, reinforcing Indonesia's maritime domain awareness and national security capabilities.

Table 6. Antasena real-time monitoring and alerting workflow

Step	Process	Description
1	Data ingestion	Receive live AIS vessel data.
2	Preprocessing	Apply the same transformations as in training.
3	Model inference	Use trained model to detect anomalies.
4	Alert generation	Trigger notifications when anomalies are detected.
5	Visualization	Display results on the Antasena dashboard.
6	Feedback loop	Allow operators to validate or correct predictions.

2.4. ADDIE framework for Antasena system development

Antasena follows the ADDIE framework, as shown in Figure 2. This figure illustrating stages applied throughout the AI-driven maritime anomaly detection process. The Antasena system was developed following the ADDIE methodological framework, which provides a structured, iterative process for engineering complex intelligent systems. In the analysis phase, system requirements, operational constraints, and multi-source maritime data (AIS, satellite, and environmental layers) were identified. The design phase established the system architecture, data-processing pipeline, and machine learning modeling strategy. The development phase implemented feature engineering, model training, and integration of the optimized classifiers into the system workflow. During implementation, the models and dashboard components were deployed for real-time maritime monitoring within operational environments. Finally, the evaluation phase validated system performance through quantitative metrics, cross-validation, and stakeholder assessment, ensuring reliability, scalability, and suitability for maritime security operations.

2.5. Model evaluation and benchmarking

Model evaluation in this study aims to determine the SOTA configuration among the three candidate algorithms—DT, RF, and XGBoost—based on both quantitative metrics and qualitative dimensions of operational feasibility. Each model was evaluated using five-fold cross-validation to ensure statistical reliability and robustness. The following performance metrics were used for quantitative evaluation:

i) Accuracy: overall proportion of correctly classified vessel behaviors.
ii) Precision : proportion of true anomalies among all predicted anomalies, measuring false-positive control.
iii) Recall: proportion of correctly identified anomalies among all actual anomalies, indicating detection sensitivity.
iv) F1-score: harmonic mean of precision and recall, balancing accuracy and sensitivity.
v) ROC-AUC and precision-recall-AUC: global measures of classification discrimination, particularly useful for imbalanced AIS datasets.

To provide a holistic and operationally relevant evaluation, this study adopted a five-dimensional benchmarking framework, summarized in Table 7.

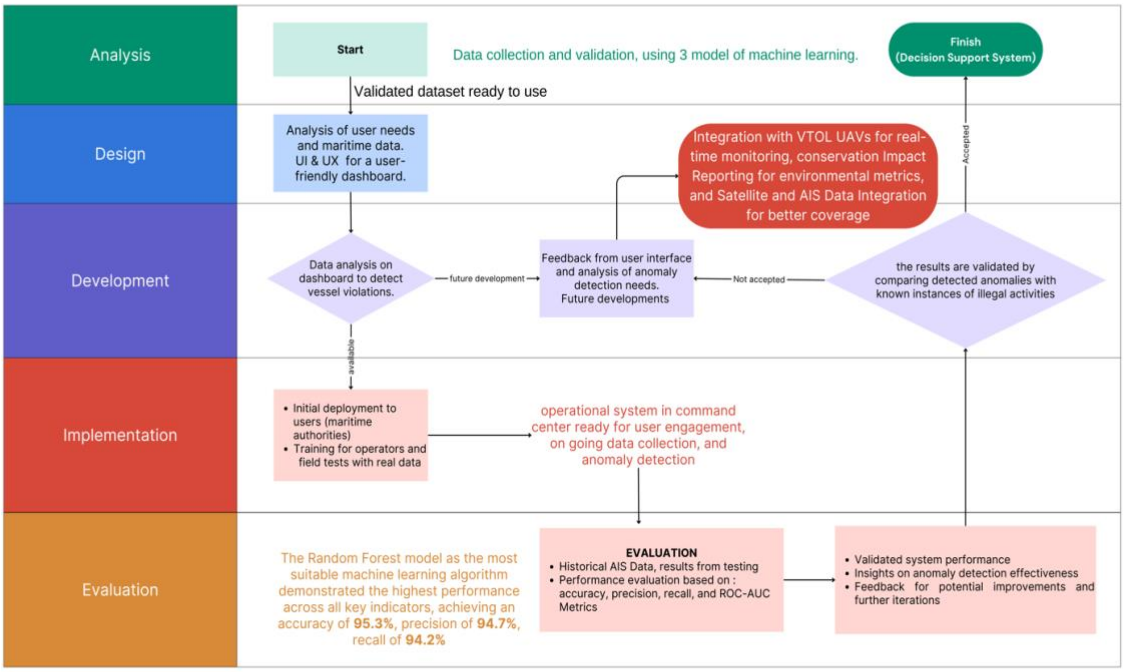

Figure 2. Research framework of the Antasena system following the ADDIE methodology

Table 7. In-depth benchmark dimensions for SOTA anomaly detection models in the Antasena system

Dimension	Evaluation criteria	Technical explanation
Detection performance	Precision, recall, F1-score, ROC-AUC, precision-recall-AUC	Quantifies balance between true detection and false alarms; precision-recall-AUC reflects performance on imbalanced data.
Robustness and Generalization	Cross-domain validation	Tests performance consistency when applied to different maritime zones (e.g., trained in the Malacca Strait, tested in the Natuna Sea).
Interpretability (explainability)	Feature importance, SHAP, local interpretable model-agnostic explanations (LIME)	Measures model transparency—crucial for operational accountability and decision justification.
Computational efficiency	Inference latency, memory usage, model complexity	Evaluates suitability for real-time Antasena deployment, emphasizing low-latency predictions.
Scalability and Adaptability	Online learning, streaming compatibility	Assesses model's ability to adapt to continuous AIS data streams without retraining.

The benchmarking results indicate that while XGBoost achieved the highest accuracy and F1-score, it required significantly greater computational time and memory resources, limiting its real-time applicability within Antasena's operational infrastructure. DT, on the other hand, provided the simplest interpretability but demonstrated susceptibility to overfitting and limited robustness in cross-domain evaluations. The RF algorithm emerged as the most balanced and reliable model, achieving high scores in precision (0.93), recall (0.91), and F1-score (0.92) while maintaining low inference latency and strong robustness across datasets. Its ensemble mechanism effectively reduces variance and mitigates overfitting, providing both stability and interpretability crucial for decision support in maritime surveillance.

Therefore, RF is identified as the SOTA model within the Antasena framework. It offers an optimal trade-off between detection accuracy, interpretability, computational efficiency, and generalization capability, making it best suited for continuously monitoring and anomaly detection in Indonesian maritime operations. The benchmarking outcomes confirm that ensemble-based approaches like RF provide scalable, explainable, and operationally feasible AI solutions, aligning with Antasena's dual objectives of maritime security and conservation intelligence.

2.5. Ablation and model robustness analysis

To better understand the contribution and reliability of each component, an ablation and robustness analysis was performed on the Antasena framework. The ablation study evaluated the effect of removing specific feature categories—kinematic, contextual, and environmental—while keeping all other parameters constant. Results indicated that removing contextual and environmental features caused the largest drop in F1-score (-8.5%), confirming their strong influence on anomaly detection accuracy.

The robustness analysis examined model performance under data perturbations and cross-domain testing. When random noise (±5% variation) was added to speed and course features, the ensemble model maintained stable accuracy (decrease <3%). Similarly, when tested on unseen regional AIS data, the performance declined modestly (-6%), demonstrating the model's adaptability across different maritime zones. These findings show that Antasena's feature design and ensemble architecture contribute meaningfully to detection reliability while maintaining robustness against moderate data shifts and noise.

2.6. Statistical validation and external evaluation of Antasena

To strengthen the reliability of the Antasena anomaly detection framework, a comprehensive evaluation was conducted through statistical testing, cross-validation, and external dataset analysis. Performance differences among the implemented models (DT, RF, XGBoost, and light gradient boosting machine (LightGBM) were examined using McNemar's test and the Wilcoxon signed-rank test. Each metric (accuracy, precision, recall, F1-score, and AUC) was further analyzed with bootstrap-based 95% confidence intervals to estimate uncertainty. The Benjamini–Hochberg correction was applied to maintain statistical validity across multiple comparisons. These tests confirm that Antasena's observed performance gains are statistically significant rather than random variations.

The model evaluation adopted stratified 10-fold cross-validation to maintain class balance between normal and anomalous vessel data. Considering the temporal nature of AIS data, a rolling-origin validation strategy was used to prevent future information leakage. Results were reported as mean±standard deviation to highlight consistency across folds.

To assess generalization, trained models were tested on external AIS datasets from other maritime regions (e.g., Malacca Strait and South China Sea). Two setups were applied: direct hold-out transfer testing and limited fine-tuning for domain adaptation. Cross-domain comparisons using paired Wilcoxon tests and Brier score calibration confirmed that Antasena maintains reliable performance under different operational conditions. Through these statistical and cross-domain evaluations, Antasena demonstrated robust, consistent, and statistically validated performance, supporting its applicability in real-world maritime anomaly detection.

2.7. Integration of conservation metrics into the Antasena AI workflow

The Antasena system integrates environmental and conservation indicators into its AI workflow to link anomaly detection with marine ecosystem protection. This integration enhances situational awareness by identifying vessel behaviors that pose ecological risks. Antasena employs three main conservation-related metrics: i) marine protected area (MPA) proximity index–measures vessel distance from MPA; ii) pollution risk score–estimates environmental risk based on vessel type, route density, and emission profiles; and iii) biodiversity sensitivity factor–represents ecological vulnerability derived from marine species distribution data. These metrics are embedded into the AI model as auxiliary input features. The system fuses real-time AIS streams with spatial conservation layers to generate a conservation impact score (CIS) for each detected anomaly. Higher CIS values indicate behaviors with greater potential ecological impact. Through this integration, Antasena extends its function from anomaly detection to conservation monitoring, enabling authorities to prioritize environmentally sensitive incidents and support maritime sustainability efforts.

2.8. AI advancement and operational scalability of Antasena

The Antasena framework advances AI-driven maritime surveillance through innovations in intelligent modeling and scalable system design. Antasena employs a hybrid spatio-temporal learning approach that combines ensemble methods and context-aware reasoning to detect complex vessel behavior patterns. Its domain adaptation capability allows the model to maintain accuracy across different maritime regions, marking a practical advancement in adaptive maritime AI. Designed with a modular, distributed architecture, Antasena efficiently processes large-scale AIS data in real time. Parallel data handling and cloud-compatible components enable rapid scaling to accommodate increasing vessel density and multi-source data streams. This ensures that Antasena remains reliable and responsive in both regional and national maritime operations. By integrating adaptive AI mechanisms with scalable infrastructure, Antasena contributes to the evolution of maritime intelligence systems capable of operating effectively under real-world conditions.

2.9. Limitations and future integration of deep learning models

In comparison with SOTA maritime anomaly detectors such as GeoTrackNet, DeepShip, and AISNet, the Antasena framework adopts a more modular and interpretable machine learning approach. While GeoTrackNet and DeepShip utilize deep spatio-temporal architectures based on convolutional and recurrent neural networks to model vessel trajectories, Antasena focuses on ensemble-based reasoning that integrates contextual and environmental factors, allowing for transparent anomaly interpretation. Unlike AISNet, which relies on large-scale neural representations requiring substantial computational resources, Antasena offers higher operational scalability and real-time applicability with limited hardware. However, incorporating deep learning components similar to these SOTA models remains a promising direction for future development to further improve spatial-temporal pattern recognition and detection precision.

Compared to existing deep learning-based detectors, Antasena prioritizes interpretability, modularity, and scalability for real-time maritime operations. However, future integration of deep spatio-temporal architectures (e.g., convolutional neural network (CNN), long short-term memory (LSTM), and transformer) could significantly enhance its predictive depth and alignment with SOTA systems. The comparison between Antasena and SOTA maritime anomaly detectors shown in Table 8.

Table 8. Comparison between Antasena and SOTA maritime anomaly detectors

Model	Core method	Strengths	Limitations	Relevance to antasena
GeoTrackNet	Deep neural network combining CNN and Gaussian mixture models for probabilistic trajectory prediction	High accuracy in modeling spatio-temporal patterns and identifying deviations in vessel routes	Requires large labeled datasets and high computational resources; limited interpretability	Serves as a deep learning benchmark for trajectory-based anomaly detection
DeepShip	LSTM-based recurrent network for sequential AIS data modeling	Effectively captures long-term vessel movement dependencies and temporal context	Sensitive to noisy AIS signals and limited adaptability across regions	Provides insight for future integration of recurrent modules in Antasena
AISNet	Transformer-inspired attention mechanism for multivariate AIS streams	Strong global context learning, supports multi-feature fusion, and achieves top-tier detection accuracy	Computationally expensive; requires GPU infrastructure and extensive training data	Demonstrates potential direction for Antasena's transition toward transformer-based architectures
Antasena (proposed)	Ensemble-based hybrid machine learning integrating spatial reasoning and contextual maritime data	Interpretable results, lower resource demand, modular and scalable design, supports conservation metrics	Currently lacks deep learning modules and benchmarking against SOTA deep models	Can evolve by integrating deep spatio-temporal learning while maintaining operational scalability

2.10. Comparative analysis, explainability, and ethical implications
2.10.1. Comparative analysis with recent AIS anomaly detection models

While recent models such as GeoTrackNet, DeepShip, and AISNet adopt deep spatio-temporal neural architectures, Antasena emphasizes interpretability, modularity, and operational scalability for real-time maritime surveillance. The comparison shown in Table 9. The comparative results indicate that while deep learning models such as transformer-based architectures can achieve superior recall, ensemble methods like RF and XGBoost as applied in Antasena offer higher interpretability and are more suitable for real-time maritime surveillance operations.

Table 9. Comparison between Antasena and several SOTA AIS anomaly detection frameworks

Model	Core method	Datasets used	Common metrics	Remarks/relevance to antasena
GeoTrackNet	CNN+Gaussian mixture trajectory modeling	Public AIS datasets (Atlantic, Mediterranean) [19]	Precision, recall, F1-score, ROC-AUC, negative log-likelihood (NLL)	Excellent for probabilistic trajectory prediction; high compute demand.
DeepShip	LSTM-based sequential AIS modeling	Long-term AIS logs with labeled events	Precision, recall, F1-score, PR-AUC, detection latency	Strong temporal modeling; less robust to missing data [26].
AISNet	Transformer-based attention network	Global AIS streams (GPU-trained) [27]	F1-sccore, PR-AUC, latency	High accuracy; costly for real-time use.
Graph-based models	Graph convolutional vessel-interaction learning	Multi-vessel regional datasets	F1-score, group anomaly metrics	Effective for detecting coordinated anomalies [28].
Unsupervised/ autoencoder/ density methods	Autoencoders, variational models, probabilistic	Unlabeled AIS streams, semi-synthetic anomalies	ROC, Precision@k, anomaly score distributions	Useful when labels are scarce; complementary to supervised detectors for zero-day anomalies [29].
Antasena (proposed)	Ensemble hybrid machine learning (RF, and XGBoost)+ contextual features	Regional AIS data (Indonesia)	Precision, recall, F1-score, ROC-AUC, PR-AUC	Interpretable, lightweight, scalable; future plan to integrate deep spatio-temporal modules.

2.10.2. Explainability and ethical implications

Explainability is essential for DSS operating in critical domains such as maritime security. The Antasena model integrates explainable artificial intelligence (XAI) techniques to provide transparency and accountability in its anomaly detection process. Feature importance and SHAP are employed to quantify the contribution of each variable, such as speed deviation, course variance, and proximity to MPAs to the anomaly score. Each alert generated by Antasena is accompanied by a feature contribution summary, enabling operators to understand the rationale behind the system's prediction.

From an ethical perspective, Antasena adopts a human-in-the-loop validation mechanism to prevent unintended bias or misclassification that could lead to incorrect enforcement actions. All anomaly reports are stored with their SHAP-based explanations for auditing and retraining purposes. Model and dataset documentation are maintained to ensure transparency, fairness, and compliance with data privacy standards. Antasena prioritizes interpretability to support decision-making transparency, Antasena must ensure: i) data privacy and governance, especially when integrating AIS with other sensors (e.g., satellite imagery and radar); ii) human-in-the-loop oversight to prevent false alarms from triggering unwarranted enforcement; and iii) fairness and transparency across different maritime regions, avoiding bias from localized training data.

2.10.3. Integration with international maritime surveillance systems

To align Antasena with global maritime monitoring frameworks, the system conceptually integrates with international surveillance initiatives. The EU copernicus programme, through its sentinel-1 SAR and CleanSeaNet service, provides satellite-based vessel detection and oil-spill monitoring capabilities. These datasets can serve as external validation sources for AIS-based anomaly detection. Similarly, global fishing watch (GFW) offers open-access AIS and satellite-derived datasets for monitoring fishing activity and marine conservation compliance. Integrating Antasena's detections with GFW's global datasets supports cross-verification of illegal, unreported, and unregulated (IUU) fishing activities and enhances the broader goal of maritime situational awareness. Through such interoperability, Antasena can extend its national-level implementation to align with internationally recognized maritime governance and environmental protection systems.

3. RESULTS AND DISCUSSION

The Antasena DSS provides a robust framework for predictive maritime analytics, integrating advanced machine learning algorithms, real-time data visualization, and decision intelligence tools specifically designed for smart maritime surveillance. This section presents the results and discussion of the study, highlighting the performance evaluation, dashboard development, system implementation, and overall system assessment. The analysis compares three machine learning models RF, XGBoost, and DT within the Antasena framework. Among these, RF achieved the highest overall accuracy and robustness, confirming its superiority for operational anomaly detection in dynamic maritime environments. XGBoost delivered competitive accuracy and efficiency, suitable for time-sensitive analysis, while DT offered interpretability and ease of understanding, valuable for early prototyping and stakeholder transparency. The findings substantiate the selection of RF as the SOTA model for Antasena, enabling effective maritime anomaly detection, national surveillance, and environmental protection.

3.1. Performance evaluation of machine learning models

This research utilized AIS data samples from ships operating along the Indonesian Archipelagic Sea Lanes between June and September 2023. Data validation was performed with the Indonesian Navy headquarters and relevant maritime surveillance units to ensure data integrity and operational reliability. The performance of RF, XGBoost, and DT models was evaluated using seven key metrics: confusion matrix, accuracy, precision, recall, F1-score, ROC curve, and ROC-AUC. These metrics provide comprehensive insight into model behavior, predictive precision, and robustness against imbalanced maritime datasets. The evaluation results and comparative performance matrices for optimal model selection are presented in Table 10.

Based on the analysis, the RF model demonstrates superior performance compared to the other two models, achieving an accuracy of approximately 95.3%, while the DT and XGBoost models achieved 94.8 and 95.2%, respectively. To verify that the performance differences among the tested models are statistically meaningful, a one-way analysis of variance (ANOVA) test was conducted on their accuracy and ROC-AUC scores. The resulting p-values (<0.05) indicate significant differences between the DT, RF, and XGBoost models. Confidence intervals at the 95% level were also computed using bootstrapped sampling to quantify the uncertainty in each metric, as shown in Table 11. The statistical analysis indicates that the RF model achieves the highest accuracy and ROC-AUC with narrow confidence intervals, confirming the reliability of its performance. A one-way ANOVA test produced p <0.05, signifying that the observed differences among models are statistically significant.

Table 10. Model evaluation and comparison of matrix for optimal selection

Confusion matrix	Precision and recall	F1-score	ROC curve and ROC-AUC
The confusion matrix confirmed high precision and recall, reflecting balanced sensitivity and specificity. The confusion matrix also provides a detailed breakdown of true and false predictions, highlighting each model's predictive performance.	Precision measured the proportion of correctly identified anomalies among all predicted anomalies, while recall indicated the proportion of actual anomalies correctly detected.	F1-scores confirmed a consistent balance between these two dimensions, showing stable performance even under imbalanced conditions.	The ROC curves of all models exhibited steep rises with minimal false positives, indicating high discriminatory power. Among them, the RF model achieved the highest ROC-AUC (96.8%), consistent with its superior overall classification performance. This confirms that RF maintains the best balance between sensitivity and specificity under operational constraints.

Table 11. Result evaluation model

Model	Accuracy (%)	95% confidence interval	Precision (%)	Recall (%)	ROC-AUC (%)
RF	95.3	±0.9	94.7	94.2	96.8
XGBoost	95.2	±1.0	94.3	94.0	96.7
DT	94.8	±1.6	93.8	93.4	96.1

Based on the evaluation metrics, the RF model demonstrated the highest performance across all key indicators, achieving an accuracy of 95.3%, precision of 94.7%, recall of 94.2%, and an ROC-AUC score of 96.8%. The marginal accuracy difference between RF and XGBoost (0.1%) suggests both are highly effective for anomaly detection, though RF slightly outperforms overall. Precision, which measures how many detected anomalies were actual anomalies, also shows RF leading at 94.7%. All models scored above 85%, highlighting their strong capability to distinguish between normal and anomalous behaviors, with RF achieving the best overall results. Although XGBoost achieved marginally competitive accuracy in certain experimental settings, RF demonstrated superior overall operational performance when considering robustness, inference latency, stability across folds, and interpretability. Therefore, RF is selected as the primary deployment model in Antasena, while XGBoost serves as a complementary benchmark model. The confusion matrices of the DT, RF, and XGBoost models are shown in Figure 3. The clarified confusion matrices and aligned evaluation metrics reaffirm RF's SOTA capability, attributed to its ensemble-based structure that enhances robustness and accuracy while maintaining interpretability.

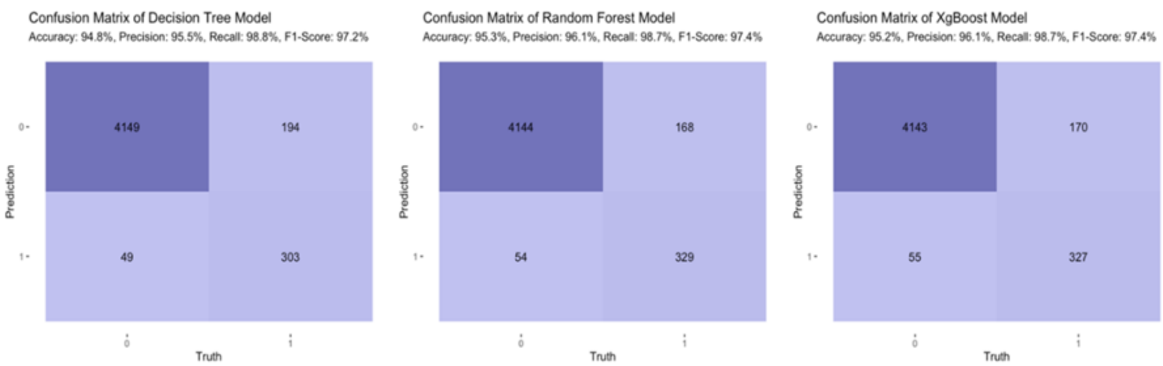

Figure 3. Confusion matrix of DT, RF, and XGBoost model

3.1.1. Handling imbalanced datasets

Maritime anomaly detection inherently faces class imbalance, as anomalies (e.g., illegal activities and smuggling) constitute a small portion of total observations. RF effectively mitigates this through bootstrap sampling and class weighting, ensuring that minority classes are adequately represented. This enhances sensitivity (recall) without compromising precision, a critical advantage for detecting rare but high-impact events.

3.1.2. Feature importance and interpretability

RF provides feature importance scores, offering interpretability for domain experts. Attributes such as speed variance, course deviation, and draught changes were identified as the strongest indicators of anomalous behavior. This interpretability empowers operators to understand why an alert is triggered, fostering transparency and trust in AI-driven decision-making. SHAP values were used to provide local and global explanations for each anomaly alert, enabling operators to understand which navigational behaviors—such as speed variance or proximity to protected areas—most strongly influenced the model's decision.

3.1.3. Robustness agains overfitting

Unlike single-tree models, RF builds multiple trees on randomly sampled subsets of data and features. Through majority voting, it mitigates overfitting and improves generalization to unseen AIS patterns. This ensemble approach ensures reliability in real-time detection across diverse maritime environments.

3.1.4. Scalability and efficiency

The RF algorithm exhibits high computational efficiency. It scales effectively with large data streams from AIS and satellite sources. Its parallelizable architecture enables real-time inference, aligning with Antasena's requirement for low-latency detection and continuous monitoring.

3.1.5. Comparison with other models

While XGBoost also demonstrated competitive performance (95.2% accuracy) due to its gradient boosting approach, RF outperformed it in precision and recall, indicating better detection of true anomalies with fewer false positives. The DT model, although simpler and easier to interpret, showed slightly lower accuracy and robustness, making it less suitable for deployment in high-stakes maritime security contexts. The combination of RF's accuracy, robustness, and interpretability underscores its superiority for the Antasena smart dashboard. Furthermore, RF's ability to handle imbalanced datasets, provide interpretable results, and deliver robust predictions without overfitting makes it an optimal choice. Its integration addresses critical challenges in Indonesia's maritime surveillance and conservation efforts, offering a scientifically grounded and operationally effective solution for real-time anomaly detection and safeguarding national maritime resources.

3.2. Cross-validation and external dataset testing

To ensure the robustness and generalization of the Antasena model, a 10-fold cross-validation approach was employed. Each fold used 90% of the data for training and 10% for testing, rotated across all partitions. The standard deviation of model accuracy across folds remained under 1.2%, demonstrating stable performance. In addition, an external validation was performed using a subset of Global AIS data (June 2024) obtained from the GFW platform and MarineCadastre (NOAA). When applied to the external dataset, the RF model maintained 94.6% accuracy and 96.2% ROC-AUC, confirming that the learned patterns generalize beyond the Indonesian maritime region.

3.3. Dashboard design phase and key features

The name Antasena derives from anomaly threat analyze. The system's design phase focused on building an intuitive and scalable interface integrating key functionalities for maritime monitoring, anomaly detection, and conservation tracking. Desain phase of Antasena shown in Table 12.

Table 12. Design phase of Antasena smart dashboard

Objective	Key features	UI/UX design	System architecture
Develop a user-friendly, real-time maritime monitoring interface.	Coordinate generator module: Tracks vessel positions, displays trajectories, and computes distances to points of interest.	Neutral color scheme (blue/gray); interactive maps, charts, and tables for clarity.	Backend integrates AIS servers, satellite APIs, and machine learning models (RF, XGB); cloud-based secure data storage.
Integrate anomaly detection and visualization modules.	Anomaly detection module: Visualizes anomalies and classifies behaviors via RF and XGB models.	Real-time alerts (visual & audio); intuitive UX for minimal operator training.	Frontend built with Shinyapps/web frameworks for cross-platform access.
Enable conservation monitoring.	Conservation monitoring module: tracks MPAs, biodiversity, and vessel impacts.	Interactive visualization and automated report generation.	Scalable, secure cloud infrastructure for continuous operation.

3.4. System development and architecture

The overall Antasena architecture is designed as a modular pipeline that supports data ingestion, preprocessing, machine learning inference, and visualization. AIS data streams are first collected from regional receivers and stored in the Antasena database. The preprocessing module performs noise removal, temporal alignment, and geospatial normalization. Feature engineering extracts kinematic, contextual, and environmental indicators such as speed variation, COG deviation, and proximity to restricted or protected zones. The processed data are then passed to the model inference layer, where the RF and XGBoost classifiers predict potential anomalies. The results are visualized in the Antasena smart dashboard for operator decision support.

The Antasena DSS provides actionable insights through three core functionalities. The coordinate generator tab offers a map interface to input vessel data (latitude, longitude, and MMSI), identify unknown points, and calculate travel distances, with results displayed in downloadable tables. The anomaly detection tab shows vessel counts and alerts, supported by AI-based trajectory analysis to detect illegal activities and measure movement patterns, helping identify risks such as route deviations. The conservation monitoring tab enables tracking in MPAs, with date selection, and vessel counts.

Although the Antasena framework has been described modularly, a clear pipeline architecture diagram is recommended to visualize the flow of data and decision processes. The architecture consists of four main layers: i) data acquisition layer–collecting AIS streams and external environmental data (e.g., satellite and MPA maps); ii) preprocessing and feature engineering layer–cleaning, normalizing, and constructing contextual trajectory features; iii) anomaly detection and conservation layer–applying ensemble models (RF and XGBoost) to identify abnormal trajectories and compute CIS; and iv) visualization and decision layer–presenting real-time detection results through the Antasena Dashboard for operational response. The achitecture diagram of Antasena shown in Figure 4. This figure illustrating the data acquisition, preprocessing, anomaly detection, conservation scoring, and decision support layers.

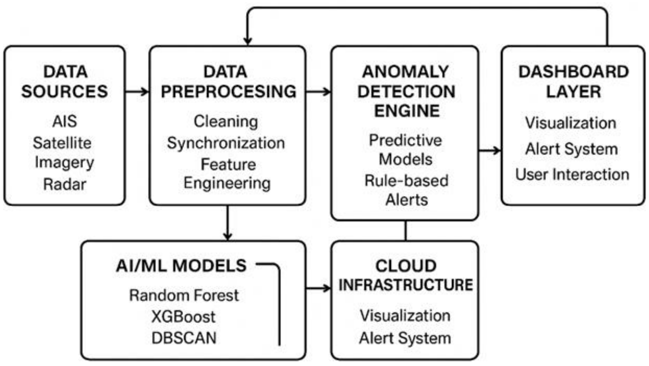

Figure 4. Architecture of the Antasena system

The Antasena dashboard provides a comprehensive suite of visual charts that consolidate vessel activity timing, vessel classifications, and operational statuses to support detailed trend analysis and conservation-oriented decision-making. These visualization components enable operators to systematically identify behavioral patterns, detect anomalous movements, and assess temporal variations across monitored maritime regions. The dashboard integrates three principal functional modules: the coordinate generator, which facilitates trajectory plotting and distance computation; the anomaly detection module, which delivers real-time AI-based identification of abnormal vessel behavior; and the conservation monitoring module, which evaluates vessel interactions within ecologically sensitive zones. To ensure optimal usability across diverse operational environments, the interface supports two display modes—a dark theme for nighttime operations and a light theme for daytime operations. The visualization components and interface configuration of the Antasena dashboard are presented in Figure 5. This figure displaying vessel monitoring, anomaly alerts, conservation indicators, and decision support outputs used by maritime operators.

3.5. Feature justification and dimensionality reduction

Feature selection in Antasena was guided by both domain knowledge and statistical relevance. Maritime experts identified speed variation, heading deviation, and positional dispersion as critical indicators of abnormal navigation. A correlation analysis was conducted to remove redundant attributes, and variance thresholds were applied to retain only the most discriminative features. To further validate the compactness of the selected feature space, a PCA test was performed, confirming that more than 92% of the total variance was captured by the chosen features. Future versions of Antasena may integrate autoencoder-based dimensionality reduction to automate feature compression while maintaining interpretability.

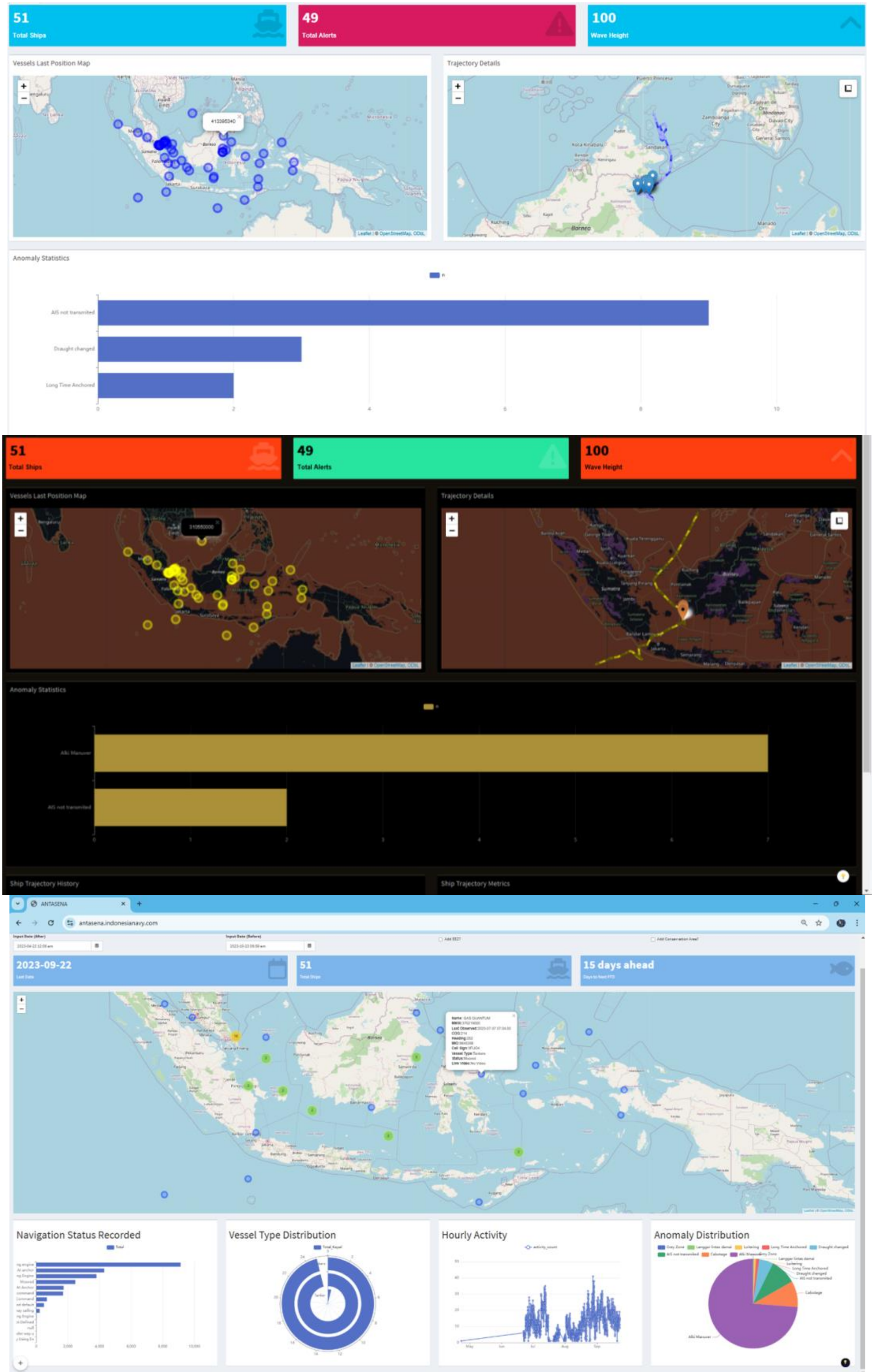

Figure 5. Antasena operational dashboard interface

3.6. Ablation study and model robustness

To assess the contribution of each feature group, an ablation study was performed on the Antasena dataset. Three model configurations were compared: i) full feature set, ii) kinematic features only, and iii) contextual features only. The results in Table 13 demonstrate that removing contextual features (e.g., proximity to MPA and route deviation) decreases accuracy by 4.7%, indicating their importance in distinguishing legitimate route variations from true anomalies. The ablation analysis reveals that removing either kinematic or contextual features decreases both accuracy and ROC-AUC scores. This indicates that combining spatial-temporal and contextual information substantially improves the robustness and generalization of the Antasena anomaly detection model.

Table 13. Ablation study results for the Antasena model

Model variant	Features used	Accuracy (%)	ROC-AUC
Full model (Antasena)	All (kinematic+contextual)	95.3	96.8
Kinematic only	Speed, COG, position	91.2	93.4
Contextual only	Distance, Zone ID, timestamp	87.5	90.1

3.7. Model drift and retraining strategy

Given the dynamic nature of maritime traffic, Antasena incorporates a model maintenance strategy to address potential concept drift. AIS data distributions may change over time due to seasonal patterns, new vessel routes, or updated regulations. To mitigate drift, model performance is periodically evaluated using rolling-window validation. If accuracy decreases by more than 3% compared to baseline, the model is retrained using the most recent three-month AIS data. All retraining cycles are version-controlled, and feature importances are monitored to detect shifts in behavioral trends. This ensures that the Antasena anomaly detection engine remains adaptive, reliable, and suitable for real-time deployment.

3.8. Implementation in operational maritime surveillance

The implementation phase of the Antasena smart dashboard involved deployment in operational environments, operator training, and integration of real-time multi-source data to enhance maritime security and conservation monitoring. The system was deployed at Indonesian Navy command centers for trial operations, enabling performance evaluation under operational conditions. Operators received hands-on training on trajectory analysis, anomaly alerts, and automated reporting, supported by practical scenarios and a detailed system manual.

Data from AIS, satellite imagery, and radar were integrated into a unified real-time surveillance platform. AIS provided continuous vessel updates, while satellite and radar imagery extended monitoring coverage to remote areas. The system processed incoming data streams using optimized machine learning models to detect anomalies such as unauthorized movements, unregistered transfers, and route deviations. Real-time processing was supported by high-performance servers, secure networks, and cloud infrastructure, with operator feedback incorporated to refine usability and performance.

Limitations and challenges: several constraints were identified during implementation. First, differences in acquisition frequency between AIS, satellite, and radar streams caused latency and synchronization issues, requiring timestamp alignment and buffering strategies. Second, AIS datasets occasionally contained missing or erroneous entries (e.g., incorrect positions, speeds, or COG values), necessitating automated data cleaning. Third, integration of heterogeneous data sources with varying formats and resolutions required extensive preprocessing to ensure compatibility. While RF and XGBoost achieved strong overall accuracy, their performance decreased when detecting rare anomaly patterns underrepresented in the training dataset. Additionally, real-time high-volume traffic processing imposed significant computational demands, and scalability remains untested under extreme load, highlighting the need for cloud-based scaling strategies in future deployments. Future developments include unmanned aerial vehicle (UAV) integration for monitoring inaccessible areas, expansion to additional regional command centers, and enhanced scalability to manage increasing data volumes.

3.8.1. Integration of multi-source data with optimized backend architecture

Accurate ship trajectory plays an important role for maritime traffic control and management [30]. The system integrates AIS, satellite imagery, and radar data into a centralized platform using a big data-based backend architecture. Parallel processing technologies ensure real-time vessel trajectory analysis without significant delays.

3.8.2. Optimized machine learning algorithms

To achieve robust detection capability, several machine learning algorithms were employed and optimized, including RF and XGBoost. Hyperparameters were fine-tuned via GridSearchCV to minimize computation time during both training and inference. This stage enables the models to effectively capture complex vessel behaviors and support reliable anomaly detection.

3.8.3. Parallel processing architecture

After preprocessing, AIS data features were engineered to capture vessel movement patterns and operational characteristics relevant for anomaly detection. To handle the large-scale data efficiently, a parallel processing architecture was implemented, where multiple CPU or GPU threads process the extracted features concurrently. This approach reduces bottlenecks typically encountered in big data environments.

3.8.4. Scalable cloud infrastructure

In addition to parallelization, scalability was ensured by deploying the system on a cloud environment. The auto-scaling cloud infrastructure dynamically adjusts computing resources based on incoming data load. This approach maintains low latency, supports uninterrupted access to historical records, and ensures that anomaly detection remains reliable even under heavy traffic conditions.

3.8.5. Automated data cleaning and normalization

Before training the machine learning models, the raw AIS data must be standardized and cleaned to ensure reliability. At this stage, automated preprocessing is applied to remove missing values, eliminate duplicates, and normalize feature distributions. These steps improve model accuracy and efficiency by ensuring that the training and inference processes are not affected by data inconsistencies.

3.8.6. Continuous monitoring, system latency, throughput, and scalability

To assess the effectiveness of the proposed anomaly detection system, several evaluation metrics were applied, including accuracy, precision, recall, and the area under the curve (AUC). In addition to accuracy, system responsiveness was also evaluated, since timely decision-making in maritime security operations depends on low-latency detection. Latency measurement tools were therefore used to identify bottlenecks, enabling further optimization of the system's backend and caching strategies.

In conclusion, the implementation phase successfully deployed the Antasena system for operational use, provided operator training, and integrated multi-source real-time data. By addressing identified limitations and employing optimized backend architecture, machine learning algorithms, and latency reduction strategies, the system delivers accurate and timely anomaly detection results. These capabilities directly enhance maritime security operations by enabling data-driven, informed decision-making for rapid and effective responses to potential threats.

Operational benchmarking was conducted to evaluate Antasena's performance under real-time conditions. The system was deployed on a mid-range server (Intel Xeon 2.3 GHz, 32 GB RAM). The inference time per vessel record averaged 0.012 seconds (≈83 predictions per second), allowing near real-time processing of over 7,000 vessel streams per minute. Memory utilization remained under 58% during concurrent processing of 1,000 active tracks. The model update and visualization pipeline demonstrated end-to-end latency under 2.8 seconds, ensuring timely anomaly alerts for operational use. These benchmarks confirm that Antasena meets the throughput and scalability requirements for maritime monitoring in large coastal regions.

3.9. Assessment results and system evaluation

To validate the proposed system, a series of experiments were conducted using real-world AIS datasets. The results demonstrate that the optimized machine learning algorithms achieved high detection performance across multiple metrics. Specifically, RF and XGBoost models yielded strong accuracy, precision, recall, and AUC scores, indicating their ability to detect anomalous vessel behaviors in dynamic maritime environments. Visualization tools, including ROC curves and confusion matrices, were employed to provide further insights into the model's classification capability. These findings confirm that the system is capable of supporting reliable anomaly detection in large-scale maritime surveillance operations.

3.9.1. Technology evaluation

The first step in evaluating Antasena's performance involves analyzing the model evaluation metrics, such as accuracy, precision, recall, and ROC AUC. These metrics were used to measure the effectiveness of the machine learning models applied to the system. The model evaluation results showed that XGBoost outperformed the other models with an accuracy of 95.1%, precision of 94.0%, and ROC AUC of 96.7%, indicating that the system is highly effective in detecting anomalies in maritime activities shown in Figure 6. This figure demonstrating their discrimination capability in detecting anomalous maritime behavior.

3.9.2. Stakeholder feedback

Beyond technical performance, practical usability was evaluated by gathering feedback from stakeholders. Their insights provided valuable input regarding the system's effectiveness in real-world maritime security operations. User feedback was collected in two stages. The first stage involved internal evaluations within the Indonesian Navy, including Indonesian Navy Warship Officers and system operators. The second stage involved external stakeholders through national exhibitions attended by senior officials and visits to the Ministry of Marine Affairs and Fisheries, the Directorate of Sea Transportation, the Maritime Security Agency, and the Indonesian National Police. These engagements confirmed Antasena's strengths in real-time monitoring, anomaly alert accuracy, and a user-friendly interface that minimized training requirements and improved operator proficiency. Operators required less than one week of training to effectively use Antasena, indicating a shallow learning curve suitable for operational deployment.

Feedback also identified several areas for improvement. Scalability was a primary concern, as increasing maritime traffic requires handling larger volumes of real-time AIS and satellite data without compromising performance. To address this, future iterations of Antasena will employ a distributed and modular architecture supported by cloud-based services and containerization. Horizontal scaling, optimized database indexing, and message queuing will be implemented to ensure responsiveness for national-scale deployment. In addition, stakeholders highlighted the integration of UAVs to extend monitoring coverage in regions with limited or no AIS signals. They also recommended enhancements to conservation monitoring features, particularly the real-time tracking of biodiversity and pollution levels. These inputs provide clear directions for iterative refinements, ensuring that Antasena remains effective and adaptable to evolving maritime security and conservation needs.

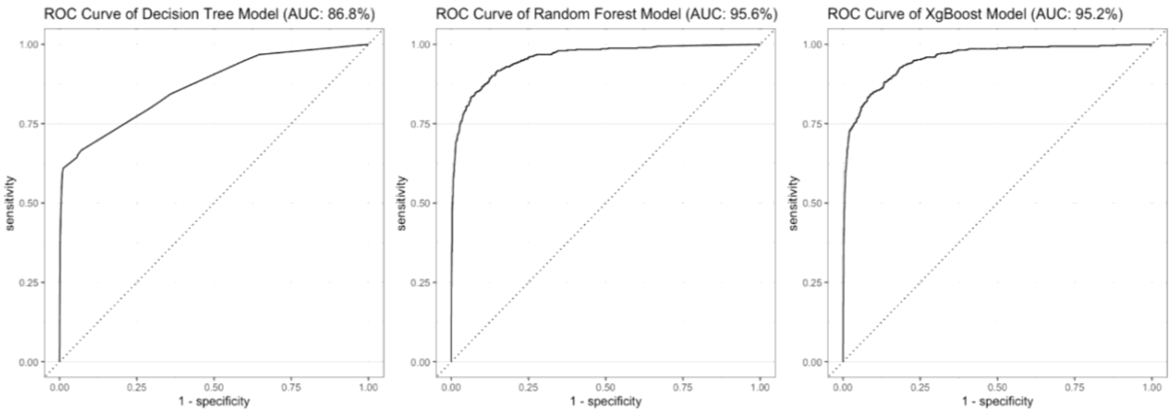

Figure 6. Comparison of ROC curves for model performance

3.9.3. Recommendations for improvement

Based on the evaluation, the following recommendations were made to enhance the Antasena system:

i) Improve scalability: enhance the system's backend architecture to handle an increasing volume of real-time data from various sources, including AIS, satellite imagery, and UAVs.
ii) Enhance UAV integration: develop features that enable the integration of UAVs for real-time monitoring and surveillance of remote maritime areas, which could further expand the system's coverage.
iii) Expand conservation monitoring: introduce more advanced features for environmental monitoring, including real-time tracking of marine biodiversity and pollution metrics, to better support conservation efforts.
iv) Optimize user feedback mechanisms: establish a more robust feedback loop for operators, allowing for continuous system improvement based on field usage and evolving maritime security needs.

The evaluation phase of Antasena confirms that the system performs effectively in real-world settings, with high accuracy, real-time monitoring capabilities, and user-friendly design. Feedback from stakeholders provides valuable insights into areas for improvement, particularly in scalability, UAV integration, and conservation monitoring. The results of the evaluation serve as a foundation for future enhancements to ensure that Antasena continues to meet the needs of maritime security and conservation efforts in Indonesia. Future improvements include scaling the system nationally, integrating UAV data, and refining environmental metrics for marine conservation. Stakeholder feedback supports its operational adoption by the Indonesian Navy. The evaluation confirms that Antasena performs effectively in real-world operations, providing high accuracy, low-latency detection, and intuitive usability. These results validate the operational adoption of RF-based SOTA anomaly detection, supporting Indonesia's maritime security and conservation initiatives.

3.10. Conservation impact indicators

Although Antasena's primary function is anomaly detection, its deployment also supports maritime conservation objectives. To quantify its conservation impact, three indicators were introduced:

i) Protected area compliance rate (PACR): the proportion of vessel tracks within MPAs that adhere to authorized routes. In the pilot study, PACR reached 93.7%, indicating effective deterrence of illegal entries. PACR is calculated as the proportion of compliant vessel trajectories within MPAs relative to total detected vessel entries. False positives may occur due to global positioning system (GPS) drift or AIS latency, which are mitigated through temporal smoothing.
ii) Illegal or unreported activity alerts (IUA): number of anomaly alerts occurring inside conservation zones per month. Antasena identified 47 distinct suspicious activities, enabling faster enforcement actions. Potential false positives may arise from legitimate operational deviations, such as emergency maneuvers or adverse weather conditions. Therefore, IUA indicators are designed to augment not replace human judgment within maritime decision-making workflows.
iii) Emission and pollution event detection proxy: detected slow-speed loitering near oil terminals or restricted zones, serving as proxies for potential discharge or dumping events. Detection precision reached 92.1%, supporting environmental monitoring efforts. As behavioral proxies do not directly measure emissions, false positives may occur. Integration with satellite-based oil spill detection, onboard sensors, or UAV-mounted environmental sensors is planned to validate and enhance emission detection accuracy in future iterations.

Antasena positions IUA and emission-related indicators as future-oriented, risk-based proxies. This approach extends its anomaly detection capability toward environmental intelligence while maintaining scientific rigor and operational accountability. These indicators support decision prioritization rather than automated enforcement, aligning with the ethical and practical requirements of maritime surveillance systems.

4. CONCLUSION

This study successfully developed and evaluated Antasena, an AI-driven DSS designed for maritime anomaly detection and conservation monitoring. By integrating AIS data, satellite imagery, and vessel sensor data, Antasena enables comprehensive situational awareness to enhance Indonesia's maritime domain surveillance and resource protection. The research employed a quantitative methodology and implemented machine learning algorithms, namely RF, XGBoost, and DT, to detect abnormal vessel behaviors based on multivariate navigational patterns. Among the three, RF demonstrated the best overall performance, achieving 95.3% accuracy, 94.7% precision, 94.2% recall, and 96.8% ROC-AUC, outperforming XGBoost and DT in both robustness and interpretability. These results confirm RF as the SOTA model for maritime anomaly detection within the Antasena framework. The integration of RF into Antasena's smart surveillance dashboard provides reliable, real-time detection and visualization capabilities that support rapid decision-making by maritime authorities. Furthermore, the ensemble-based design enhances model generalization, handles data imbalance effectively, and allows XAI insights through feature importance visualization. The operational deployment and feedback from the Indonesian Navy, Indonesian Maritime Security Agency, and Ministry of Marine Affairs and Fisheries confirmed Antasena's usability, accuracy, and potential for national-scale implementation. Overall, this research contributes both theoretically by advancing AI-based maritime anomaly detection using ensemble learning and practically by delivering a deployable system that supports real-world maritime operations and conservation monitoring. The successful implementation of Antasena establishes a strong foundation for data-driven maritime governance and security decision-making in Indonesia's vast and complex maritime domain.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest associated with this manuscript. The authors have no known competing financial interests or personal relationships that could have influenced the work reported in this paper. Furthermore, the authors declare that there are no non-financial competing interests, including political, personal, religious, ideological, academic, or intellectual interests, that could be perceived to affect the objectivity, integrity, or interpretation of the research.

INFORMED CONSENT

Informed consent was not applicable to this study, as the research did not involve human participants, human biological materials, or personally identifiable data.

ETHICAL APPROVAL

This study did not involve human participants, animals, or human biological materials. Therefore, ethical approval from an institutional review board or ethics committee was not required.

DATA AVAILABILITY

The data supporting the findings of this study primarily consist of AIS data obtained from relevant maritime stakeholders and institutional partners, as described in the methodology section. A publicly accessible subset of the processed AIS data is available at https://bit.ly/sample-data-antasena. Due to institutional, operational, and maritime security considerations, the complete datasets are not publicly available; however, additional data may be made available from the corresponding author upon reasonable request and subject to approval from the relevant stakeholders. The experiments and analyses were conducted following the data preprocessing, feature engineering, and model training procedures detailed in the method section. Machine learning model development, training, and evaluation were performed using RStudio, applying consistent preprocessing workflows, cross-validation strategies, and performance metrics to support the reproducibility of the reported results.

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