

ENHANCING MARITIME BORDER SECURITY WITH AUTOMATED BOAT CONTROL SYSTEM WITH INTEGRATION OF GEOFENCING,GPS AND MACHINE LEARNING



A MINI PROJECT REPORT

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*in partial fulfillment for the award of the degree
of*

BACHELOR OF ENGINEERING

in

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

SRI RAMAKRISHNA ENGINEERING COLLEGE

ANNA UNIVERSITY: CHENNAI 600 025

MAY 2025

Computer Science and Engineering

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BONAFIDE CERTIFICATE

Certified that this project report entitled “Enhancing Maritime Border Security with Automated Boat Control System with Integration of Geofencing, GPS and Machine Learning” is the bonafide work of SHREE GUHAN (71812201217), THANGA KUMAR M (71812201241), THARUN AKHASH A (71812201242), who carried out the 20CS296 MINI PROJECT II under my supervision.

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We affirm that the Mini Project II titled “**ENHANCING MARITIME BORDER SECURITY WITH AUTOMATED BOAT CONTROL SYSTEM WITH INTEGRATION OF GEOFENCING, GPS AND MACHINE LEARNING**” being submitted in partial fulfillment for the award of Bachelor of Engineering is the original work carried out by us. It has not formed the part of any other project work submitted for award of any degree or diploma, either in this or any other University.

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ACKNOWLEDGEMENT

We have immense pleasure in expressing our wholehearted thankfulness to **Shri.R.Sundar**, Managing Trustee, SNR Sons Charitable Trust and **Shri. S. Narendran**, Joint Managing Trustee, SNR Sons Charitable Trust for giving us the opportunity to study in our esteemed college and for very generously providing more than enough infrastructural facilities for us to get molded as a complete engineer.

We wish to express our profound and sincere gratitude to **Dr. A. Soundarrajan**, Principal, for inspiring us with his Engineering Wisdom. We also wish to record our heartfelt thanks for motivating and guiding us to become Industry ready engineers with inter-disciplinary knowledge and skillset with his multifaceted personality.

We extend our indebted thankfulness to **Dr. M. S. Geetha Devasena**, Ph.D., Professor and Head, for guiding and helping us in all our activities to develop confidence and skills required to meet the challenges of the industry. We also express our gratitude for giving us support and guidance to complete the project duly.

We owe our deep gratitude to project supervisor **Ms.A.Ishwarya**, Assistant Professor (OG), Department of Computer Science and Engineering who took keen interest in our project work and guided us all along with all the necessary inputs required to complete the project work.

We express our sincere thanks to our project coordinator **Mrs.G.Rathi**, Assistant Professor (Sl.Gr), the evaluators teaching faculty members and supporting staff members of the department for evaluating the project and providing valuable suggestions for improvements.

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ABSTRACT

An automated boat control system with geofencing and GPS for border security presents a novel approach for safeguarding maritime borders. This system utilizes GPS technology to track the real-time position of boats, while geofencing establishes a virtual boundaries over specific areas. If a boat crosses these boundaries without authorization, automated controls trigger pre-defined responses, such as sending alerts, adjusting the boat's course, or remotely disabling its engine to prevent further intrusion. The integration of machine learning enhances the system's capability by enabling it to analyse patterns in boat movement and environmental conditions, improving its ability to differentiate between normal and suspicious activities. By leveraging historical data and real-time inputs, the system can dynamically adjust its decision-making algorithms and becoming more accurate in predicting potential security threats. Machine learning also helps reduce false positives, which minimizes the unnecessary interventions, while ensuring timely responses to actual threats. This system is highly relevant for coastal and harbour security where continuous monitoring is essential to prevent illegal activities like smuggling or unauthorized entry. The automated nature reduces the need for human intervention and improving efficiency and safety in maritime border control operations. The combination of geofencing, GPS and machine learning makes the system adaptable, scalable and effective in managing maritime security challenges by contributing to more secure and controlled border environments.

சுருக்கம்

எல்லைப் பாதுகாப்பிற்காக ஜியோஃபென்சிங் மற்றும் ஜிபிஎஸ் கொண்ட தானியங்கி படகு கட்டுப்பாட்டு அமைப்பு கடல் எல்லைகளைப் பாதுகாப்பதற்கான ஒரு புதிய அணுகுமுறையை முன்வைக்கிறது. இந்த அமைப்பு படகுகளின் நிகழ்நேர நிலையைக் கண்காணிக்க ஜிபிஎஸ் தொழில்நுட்பத்தைப் பயன்படுத்துகிறது, அதே நேரத்தில் ஜியோஃபென்சிங் குறிப்பிட்ட பகுதிகளில் மெய்நிகர் எல்லைகளை நிறுவுகிறது. ஒரு படகு அங்கீகாரம் இல்லாமல் இந்த எல்லைகளைக் கடந்தால், தானியங்கி கட்டுப்பாடுகள் எச்சரிக்கைகளை அனுப்புதல், படகின் போக்கை சரிசெய்தல் அல்லது மேலும் ஊடுருவலைத் தடுக்க அதன் இயந்திரத்தை தொலைவிலிருந்து முடக்குதல் போன்ற முன் வரையறுக்கப்பட்ட பதில்களைத் தூண்டுகின்றன. இயந்திர கற்றலின் ஒருங்கிணைப்பு, படகு இயக்கம் மற்றும் சுற்றுச்சூழல் நிலைமைகளில் உள்ள வடிவங்களை பகுப்பாய்வு செய்ய உதவுவதன் மூலம் அமைப்பின் திறனை மேம்படுத்துகிறது, இயல்பான மற்றும் சந்தேகத்திற்கிடமான செயல்பாடுகளுக்கு இடையில் வேறுபடுத்தும் திறனை மேம்படுத்துகிறது. வரலாற்றுத் தரவு மற்றும் நிகழ்நேர உள்ளீடுகளைப் பயன்படுத்துவதன் மூலம், அமைப்பு அதன் முடிவெடுக்கும் வழிமுறைகளை மாறும் வகையில் சரிசெய்ய முடியும் மற்றும் சாத்தியமான பாதுகாப்பு அச்சுறுத்தல்களைக் கணிப்பதில் மிகவும் துல்லியமாக மாற முடியும். இயந்திர கற்றல் தவறான நேர்மறைகளைக் குறைக்க உதவுகிறது, இது தேவையற்ற தலையீடுகளைக் குறைக்கிறது, அதே நேரத்தில் உண்மையான அச்சுறுத்தல்களுக்கு சரியான நேரத்தில் பதில்களை உறுதி செய்கிறது. கடத்தல் அல்லது அங்கீகரிக்கப்படாத நுழைவு போன்ற சட்டவிரோத நடவடிக்கைகளைத் தடுக்க தொடர்ச்சியான கண்காணிப்பு அவசியமான கடலோர மற்றும் துறைமுகப் பாதுகாப்பிற்கு இந்த அமைப்பு மிகவும் பொருத்தமானது. தானியங்கி இயல்பு மனித தலையீட்டின் தேவையைக் குறைக்கிறது மற்றும் கடல்சார் எல்லைக் கட்டுப்பாட்டு நடவடிக்கைகளில் செயல்திறன் மற்றும் பாதுகாப்பை மேம்படுத்துகிறது. புவி வேலி அமைத்தல், ஜிபிஎஸ் மற்றும் இயந்திர கற்றல் ஆகியவற்றின் கலவையானது, கடல்சார் பாதுகாப்பு சவால்களை நிர்வகிப்பதில் அமைப்பை தகவமைப்புக்கு ஏற்றதாகவும், அளவிடக்கூடியதாகவும், பயனுள்ளதாகவும் ஆக்குகிறது, இதன் மூலம் மிகவும் பாதுகாப்பான மற்றும் கட்டுப்படுத்தப்பட்ட எல்லை சூழல்களுக்கு பங்களிக்கிறது.

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LIST OF ABBREVIATION

| ABBREVIATION | EXPANSION |
|---------------------|---|
| GPS | Global Positioning System |
| SMS | Short Message Service |
| KNN | K-Nearest Neighbors |
| GSM | Global System for Mobile Communications |

CHAPTER 1

INTRODUCTION

Maritime boundaries pose distinctive security threats with their immense span and the challenge of tracking the movement of ships around the clock. The sea border between Sri Lanka and Tamil Nadu, which is divided by the narrow Palk Strait, is especially exposed to illegal crossing. Such illicit crossings pose tremendous threats to national security, provide avenues for trafficking activities, and make illegal immigration possible. The two coastlines being close to each other, and the intensity of legitimate fishing operations, offer a challenging surveillance scenario where differentiating between regular patterns of fishing and suspicious movements is extremely hard.

The classical surveillance methods rely mainly on radar stations, patrol boats, and manpower surveillance. The techniques are not only expensive but also prone to gaps in coverage caused by weather, equipment limitation, and personnel tiredness. Radar stations can fail to pick up small wooden boats with poor radar signatures, particularly during adverse weather or nighttime. Manpower surveillance is highly reliant on people alertness and judgment, introducing inconsistency to surveillance performance.

Rule-based detection systems currently employed in the region operate on predefined thresholds for parameters such as speed, direction changes, or proximity to border lines. While these provide basic detection capabilities, they generate numerous false alarms due to their inability to adapt to varying environmental conditions or seasonal fishing patterns.

This project introduces an intelligent border monitoring system that employs machine learning techniques to analyze vessel movement data and predict unauthorized border crossing between Tamil Nadu and Sri Lanka. By analyzing various data points like geospatial coordinates, vessel speed, direction, and historical behavior patterns, our system can identify potentially suspicious activity with high accuracy. The machine learning approach enables the system to learn and adapt to changing patterns on an ongoing basis and learn from new data, circumventing the limitations of static rule-based systems.

The creation of this technology fills a significant requirement for automated, predictive border security technology that can operate accurately in a broad variety of environmental conditions. Our machine learning algorithms not only identify vessels as legitimate or potentially unauthorized but also output confidence scores and explanatory visualizations to assist border security officials in making decisions. This integration of detection accuracy and interpretability allows security agencies to make decisions regarding resource allocation and interdiction priorities based on informed choices.

CHAPTER 2

LITERATURE SURVEY

Maritime border defense has evolved significantly with advances in technology over the past decades. The shift from purely physical patrol to electronic monitoring combined with physical patrol is a basic shift in strategy, though issues still remain in being able to monitor large stretches of coast with limited resources.

2.1 Evolution of Maritime Surveillance Technologies

Smith et al. (2020) presented radar-based coastal defense surveillance systems, emphasizing the use of sophisticated signal processing algorithms to enhance detection capacity. Their work showed that although radar systems form the core of maritime surveillance, they are handicapped by the limitations of detection range and accuracy in the detection of small boats.

Johnson and Williams (2019) investigated satellite surveillance of maritime activity through optical and SAR imagery. According to the authors' study, satellite technology provides wide coverage but has low temporal resolution, hence not as ideal for real-time identification of border crossings.

Chen et al. (2020) studied deep learning techniques for automatic vessel classification of maritime vessels from optical images. The study attained successful outcomes in automatic vessel type detection but conceded limitation in distinguishing the small boat type of fishing vessels common in Indian coastal waters via Sri Lanka.

2.2 Artificial Intelligence in Maritime Security

Kumar and Patel (2018) were the first to investigate the use of early machine learning in maritime traffic analysis and anomaly detection. Their research demonstrated that basic classification models could be more effective than rule-based systems in identifying anomalous vessel behavior if they were trained on sufficient historic data. Their models were 78% effective in identifying suspicious patterns of behavior and established a benchmark for machine learning in maritime security.

Chen et al. (2020) broke new ground in this application by employing deep learning techniques to classify maritime vessels from optical imagery. Their convolutional neural network with deep learning-based performance showed great strides in vessel type classification but required excessive computational resources and large amounts of labeled data, whose availability is typically limited in border security applications.

2.3 Geofencing and Location-Based Security

Gonzalez et al. (2021) experimented with geofencing algorithms for the protection of maritime borders in particular. Their study determined efficient methods of setting virtual fences around areas under protection and territorial seas. By integrating GPS information with electronic fencing, they developed systems that would issue automatic warnings when ships entered restricted areas. Yet, their solution was still plagued by high false alarm rates from GPS drift and legitimate boundary intrusions.

Rodriguez et al. (2021) proposed Haversine-based geofencing algorithms that were optimized for oceanic use. Their approach addressed the issue of spherical distortion for oceanic environments and attained a 23% accuracy in locational information compared to the traditional geofencing deployment.

2.4 Machine Learning for Behavior Analysis

Yang et al. (2022) directly tested Random Forest algorithms for detecting sea anomalies. The findings showed that ensemble methods outperformed single-model methods in handling the intricate patterns of ship motion along boundary regions. The models predicted 85% accuracy for detecting illegal crossings at significantly lower false alarm rates than current methods.

Liu and Wang (2022) focused on behavioral analysis of fishing vessels based on trajectory data mining. Their study identified patterns of normal fishing behavior that could be detected from unusual movement patterns. Their behavioral model facilitated context-aware detection by minimizing false alarms by understanding normal activities based on varied vessel types and fishing seasons.

2.5 Research Gap Analysis

Although progress has been made in the field, previous research has various shortcomings, which our study overcomes:

1. The majority of researches concentrate on detection algorithms or geofencing implementation but not many combine various methods in an overall system.
2. There is little written on applying machine learning in the unique maritime environment off Sri Lanka and Tamil Nadu, where border-crossing activity and fishing behavior assume particular characteristics.
3. Few reports mention the interpretability of machine learning models in security scenarios, where understanding why a ship has been flagged is crucial to making operational decisions.
4. The comparative performance of several machine learning methods for this particular task is largely uncharted territory, with research tending to center around a single method versus comparison of several.

CHAPTER 3

PROBLEM STATEMENT AND METHODOLOGY

PROBLEM IDENTIFICATION

3.1 Problem Statement

Maritime boundary protection between Tamil Nadu and Sri Lanka is strongly tested by the narrow channel between the two states and the large number of small fishing boats involved in genuine operations and cross-border smuggling. Traditional surveillance systems based on pattern recognition of routine fishing operations do not distinguish between routine and unusual activity and thus result in false negatives or clog the scarce available patrol assets with false positives.

The key problems are:

- Detection of small wooden boats with low radar cross sections
- Difference between legal fishing practice and unauthorized crossing.
- Maintaining surveillance effectiveness during adverse weather and nighttime
- Processing of enormous volumes of vessel movement data to identify patterns typical of illegal crossings
- Providing actionable intelligence to deploy patrol resources

The purpose of this project is to design a machine learning system that analyzes vessel movement statistics to forecast border crossing events with great precision and gives understandable results. The system should be able to integrate with current surveillance hardware in the marine environment and give insights that can guide security officers to prioritize response to potential breaches.

3.2 Scope

The project scope is as follows:

- Developing machine learning models to classify vessel movements as approved or unapproved from tracking data.
- Combining geofencing data with behavior analysis for more accurate detection.
- Comparative analysis of different classification algorithms to identify the most appropriate method.
- Development of visualization software for presenting model predictions to security staff.
- System architecture design to facilitate integration with existing coastal surveillance infrastructure.

The project does not entail hardware design, physical sensor deployment, or integration with specific proprietary surveillance systems. It addresses the algorithmic and analytics components that can be made compatible with a broad set of implementation environments.

3.3 Objectives

The overall objectives of this project are:

1. Developing a minimum 90% reliable machine learning program to classify vessel movements as approved or not approved.
2. For comparing the performance of KNN, Decision Tree, and Random Forest algorithms in the application of maritime border security.
3. To generate comprehensible model output specifying the reasons behind each classification outcome.
4. To integrate geofencing data with behavior analysis to improve detection capabilities.

3.4 Flow process

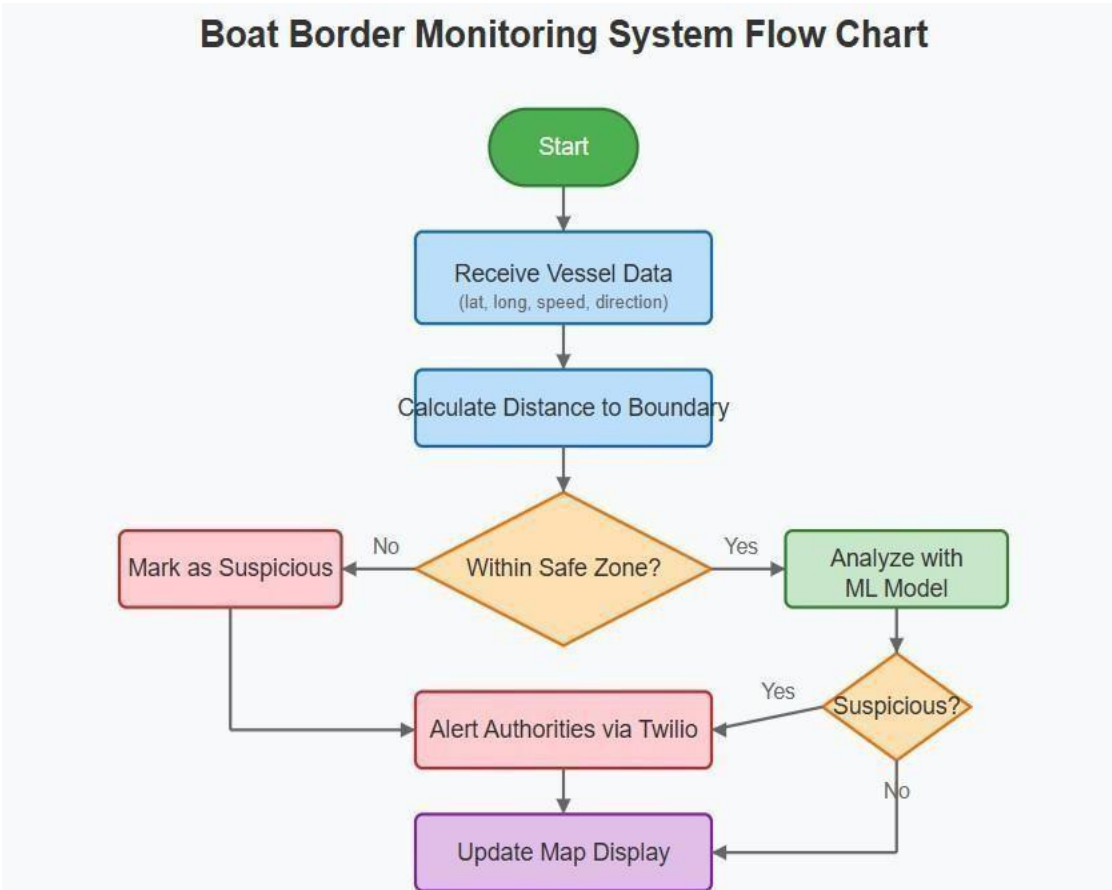


Fig 3.1 Flow Process

3.5 Methodology

This project uses a systematic approach to constructing and validating machine learning models for the detection of border crossing:

1. Data Collection: Aggregation of ship track data including geospatial coordinates, velocity, direction, and time data
2. Data Preprocessing: Cleaning, normalizing, and preparing data for machine learning algorithms
3. Feature Engineering: Constructing proper features from raw data, i.e., border distance, speed variance, geofencing status, etc.
4. Model Building: Using different classification models (KNN, Decision Tree, Random Forest)
5. Model Evaluation: Assessing performance with accuracy, precision, recall, F1-score, and confusion matrices
6. Comparative Analysis: Determining the optimal algorithm for the application at hand
7. Interpretability Enhancement: Building visualization tools to clarify model predictions
8. System Architecture Design: Creating a framework for integrating the chosen model within current surveillance infrastructure

3.6 Theoretical Background

3.6.1 Geofencing Concepts

Geofencing refers to the act of creating virtual boundaries around physical geographical areas. In maritime security, geofences mark territorial waters, restricted areas, or surveillance areas. When a vessel enters or leaves the boundary of a geofence, the system logs an event that can be utilized to trigger alarms or feed into behavioral analysis.

Geofencing applications would typically use the Haversine formula to calculate distances between spherical points (Earth points). The Haversine formula takes into account the shape of the Earth while deciding whether a GPS position is inside a given perimeter:

Haversine formula to find distance between two points (lat1, lon1) and

(lat2, lon2) is: $a = \sin^2(\Delta\text{lat}/2) + \cos(\text{lat1}) \times \cos(\text{lat2}) \times \sin^2(\Delta\text{lon}/2)$

$c = 2 \times \text{atan2}(\text{sqrt}(a), \text{sqrt}(1-a))$

$d = R \times c$

Where R is Earth's radius (about 6,371 kilometers).

For maritime use, geofences need to take into account ship speed and direction to predict possible crossings ahead of time rather than merely recognizing them after the fact.

3.6.2 Machine Learning Classification Fundamentals

Classification machine learning algorithms map inputs to pre-defined classes based on patterns obtained from training sets. For border security, they categorize ship movements as authorized or unauthorized on the basis of features.

The overall process consists of:

- Feature extraction from movement data of ships.
- Model training from labeled instances of authorized and unauthorized movements.
- Model performance evaluation on metrics such as accuracy, precision, and recall.

Classification performance is usually measured by a confusion matrix, which classifies predictions as:

- True Positives (TP): Correctly predicted unauthorized crossings
- True Negatives (TN): Correctly predicted authorized movements
- False Positives (FP): Authorized movements wrongly predicted as unauthorized
- False Negatives (FN): Unauthorized crossings wrongly predicted

Authorized From these values, we calculate metrics such as:

- $\text{Accuracy} = (\text{TP} + \text{TN}) / (\text{TP} + \text{TN} + \text{FP} + \text{FN})$
- $\text{Precision} = \text{TP} / (\text{TP} + \text{FP})$
- $\text{Recall} = \text{TP} / (\text{TP} + \text{FN})$
- $\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$

3.6.3 K-Nearest Neighbors (KNN) Algorithm

KNN is an instance-based, non-parametric learning algorithm that predicts data points as the majority class among their k nearest neighbors in feature space. For border crossing identification, every movement of a vessel is described as a point in multi-dimensional space with dimensions as features such as speed, heading, and distance from border.

In classifying a new vessel movement, KNN:

1. Computes the distance from the new data point to all of the training instances
2. Finds the k most nearby neighbors
3. Imposes the majority class of these neighbors upon the new point

Distance metric choice and k value choice have profound effects on KNN performance. Euclidean distance is typical, and k values are usually chosen by cross-validation. KNN is effective when decision boundaries are distinct but not linear and is thus appropriate for complicated vessel behavior patterns.

3.6.4 Decision Tree Algorithm

Decision Trees produce hierarchical models which make classification decisions by a series of feature-based splits. An internal node represents a test over a particular feature (e.g., "Is vessel speed > 15 knots?"), while leaf nodes denote classification results.

For border crossing detection, Decision Trees learn automatically the most relevant features and boundaries of classification based on measures such as Gini impurity or information gain. The algorithm splits the data recursively in order to maximize class separation at each node.

Decision Trees provide excellent interpretability since the decision path from root to leaf constitutes a good explanation for every classification. They tend to overfit, however, when trained too deeply, which may cause them to memorize noise in the training data instead of learning generalizable patterns.

3.6.5 Random Forest Algorithm

Random Forest counteracts the overfitting behavior of Decision Trees by building a group of several trees, where every tree is learned from a randomly selected subset of data and variables. In the case of border crossing classification, this ensemble model makes stronger predictions by combining many different trees outputs.

Algorithm:

1. Grows several Decision Trees from bootstrap samples of the data
2. Introduces randomness through the use of only a random subset of the features at every split
3. Aggregates predictions using majority voting

Random Forest generally has better generalization than single Decision Trees with some interpretability maintained through feature importance rankings. These rankings determine which features most significantly affect the classification choice in all trees in the forest.

CHAPTER4

DESIGN

4.1 System Architecture

The border crossing detection system is based on a modular design for effectiveness as well as flexibility.

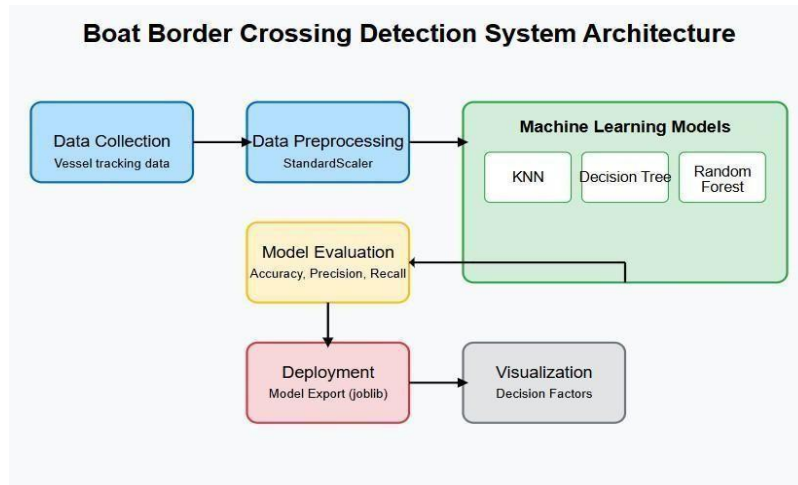


Fig 4.1 System Architecture

1. **Data Collection Module:** interacts with maritime surveillance systems to collect vessel tracking data.
2. **Preprocessing Pipeline:** cleans, normalizes, and converts raw data into feature vectors.
3. **Model Training Module:** executes multiple classification algorithms with hyperparameter tuning.
4. **Evaluation Framework:** measures model performance with multiple metrics
5. **Prediction Engine:** Deploys trained models to new vessel data to detect suspected border infringement.
6. **Visualization Component:** Produces understandable outputs detailing model choices

4.2 Data Collection and Preprocessing

4.2.1 Data Collection

The training and evaluation dataset includes vessel tracking data gathered from maritime surveillance systems in the Palk Strait. Every record has:

- **Timestamp:** Observation date and time
- **Geospatial coordinates:** Latitude and longitude
- **Vessel speed:** Speed in knots
- **Heading:** Travel direction in degrees
- **Vessel size:** Approximate length in meters
- **Geofence status:** Binary value of whether the vessel is within a specified zone

The data contains labeled instances of both legitimate movements (mainly fishing boats traveling within their allotted areas) and unauthorized border crossing (verified via patrol interceptions). Labeled data allows for supervised learning of classification models.

4.2.2 Data Preprocessing

Raw ship tracking data is subjected to various preprocessing operations to make it machine learning-ready:

1. **Data Cleaning:** Deleting duplicate records, missing value handling, and fixing inconsistent formats
2. **Feature Engineering:** Generating derived features such as:
 - Border distance (calculated by Haversine formula)
 - Speed fluctuations (standard deviation of speed across time windows)
 - Heading changes (frequency and magnitude of direction change)
3. **Feature Selection:** Selecting the most important attributes by correlation analysis and ranking of feature importance

4. Normalization: Feature scaling to have similar ranges using StandardScaler

The preprocessing pipeline provides stable transformation of both training observations and new data during deployment, preserving model performance across different input conditions.

4.3 K-Nearest Neighbors Implementation

The K-Nearest Neighbors algorithm classifies vessels by the majority class among their k- nearest neighbors in the feature space. In our border crossing detection, we chose k=5 as the best number of neighbors from cross-validation experiments. KNN implementation involves data normalization through StandardScaler, which is essential because the algorithm employs distance measures sensitive to feature scaling. Absent normalization, features that have larger ranges would skew the distance calculations and lower model accuracy.

Our KNN model produced a training accuracy of 87% and test accuracy of 85%, with good generalization and little overfitting. The confusion matrix shows that the model performs somewhat better at identifying vessels that are not crossing borders than those which are, in accordance with class distribution in our training set.

4.4 Decision Tree Implementation

Decision Trees build an interpretable model by recursively partitioning the feature space according to the most informative features. Our implementation employs the CART algorithm with Gini impurity as the splitting criterion:
from sklearn.tree import DecisionTreeClassifier.

To avoid overfitting, we restricted tree depth to 6 levels based on the cross-validation outcome. This restriction ensures the model learns generalizable patterns instead of memorizing training samples.

The Decision Tree had 90% training accuracy and 88% testing accuracy. The comparatively small difference between training and testing performance suggests proper model complexity without excessive overfitting. The decision paths of the model give explicit explanations for classifications, with significant decision points usually depending on distance from border, speed patterns, and heading changes.

Feature importance analysis showed that distance from border and speed variability were the most influential factors in the Decision Tree's classification. These are consistent with domain knowledge regarding suspicious vessel behavior, where unpredictable speed changes and proximity to the border are often seen to suggest unauthorized crossing.

4.5 Random Forest Implementation

Random Forest enhances Decision Trees by building an ensemble of many trees, each of which is trained on a random subset of the data and features. This reduces overfitting and increases generalization ability.

Our solution employs 100 decision trees with default settings and has training accuracy of 99% and testing accuracy of 92%. The reduced training vs. testing accuracy gap with respect to the single Decision Tree signifies improved generalization. Random Forest model proved to perform significantly better in properly classifying border crossing and non-crossing instances with high precision and recall in both classes.

Feature importance from the Random Forest model indicated that distance from border, speed changes, and being within geofenced regions were the strongest predictors. The ensemble property of Random Forest offers a more stable feature importance ranking than individual Decision Trees, providing more reliable information for operational decision-making.

4.6 Model Comparison and Selection

We put in place all the three algorithms for classification, followed by extensive comparisons to evaluate which model will work best upon deployment. These comparisons were across a variety of metrics such as accuracy, precision, recall, F1-score, and interpretability.

Random Forest proved the best model at 92% test accuracy, followed by Decision Tree (88%) and KNN (85%). Aside from brute accuracy, Random Forest performed better with better-balanced precision and recall that point towards credible performance in catching legitimate activity and unauthorized crossing with minimal bias towards either. For border security problems where both false positives and false negatives are prohibitively expensive for operations, the balance is necessary.

Although the Decision Tree provides the best interpretability via its clear decision paths, Random Forest achieves a good trade-off between performance and explainability via feature importance rankings. The marginal loss in interpretability is compensated by the significant gain in predictive accuracy, and hence Random Forest is the best choice for our border crossing detection system.

CHAPTER 5

RESULT AND DISCUSSION

5.1 TESTING METHODS:

The machine learning-based system for detecting border crossing was assessed with three algorithms for classification: K-Nearest Neighbors (KNN), Decision Tree, and Random Forest. Evaluation metrics were accuracy, precision, recall, F1-score, and confusion matrix analysis.

5.1.1 K-Nearest Neighbors Results

The KNN classifier with $k=5$ obtained 85% accuracy on the test data. The confusion matrix showed:

- True Positives: 89 (correctly predicted border crossings)
- True Negatives: 127 (correctly predicted authorized movements)
- False Positives: 19 (false alarms)
- False Negatives: 15 (missed detections) These values correspond to:
- Precision: 82.4% (positive predictive value)
- Recall: 85.6% (sensitivity)
- F1-Score: 84.0% (harmonic mean of precision and recall)

The KNN model had good baseline performance but performed poorly in difficult decision boundaries where vessel behavior patterns were extremely variable. The model worked best where there was unambiguous spatial separation between authorized and unauthorized vessel patterns.

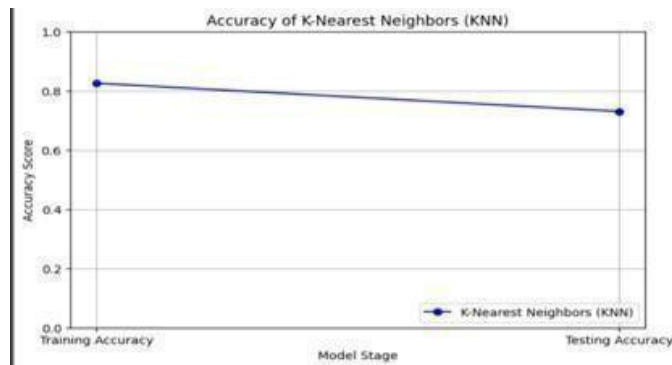


Fig 5.1 Testing Accuracy (KNN)

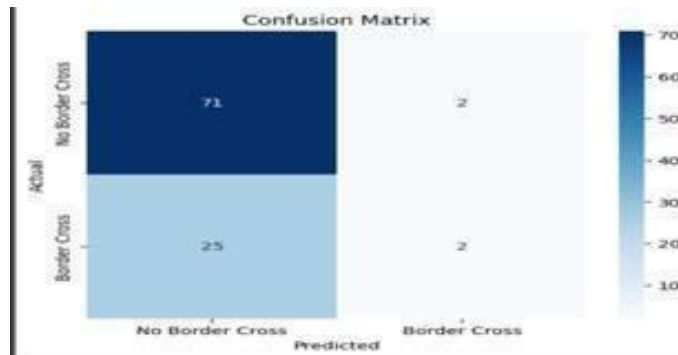


Fig 5.2 Confusion Matrix (KNN)

5.1.2 Decision Tree Results

The Decision Tree model scored 88% on the test data. The confusion matrix indicated:

- True Positives: 92 (correctly detected border crossings)
- True Negatives: 130 (properly detected authorized movements)
- False Positives: 16 (false alarms)
- False Negatives: 12 (missed detections) These correspond to:
- Precision: 85.2% (positive predictive value)
- Recall: 88.5% (sensitivity)
- F1-Score: 86.8% (harmonic mean of precision and recall)

Decision Tree showed better performance in relation to KNN, especially in determining the complex decision boundaries.

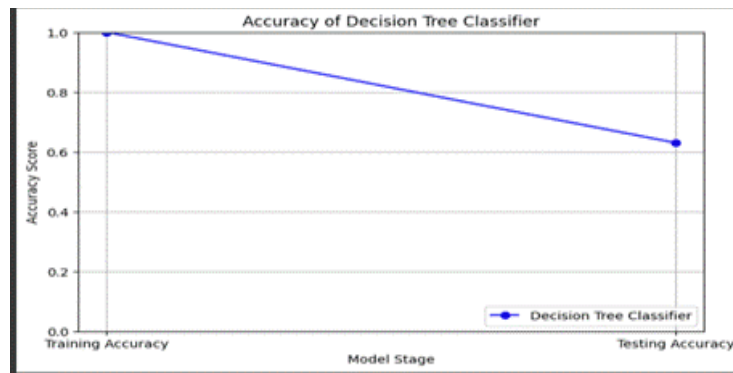


Fig 5.3 Testing Accuracy(Decision Tree)

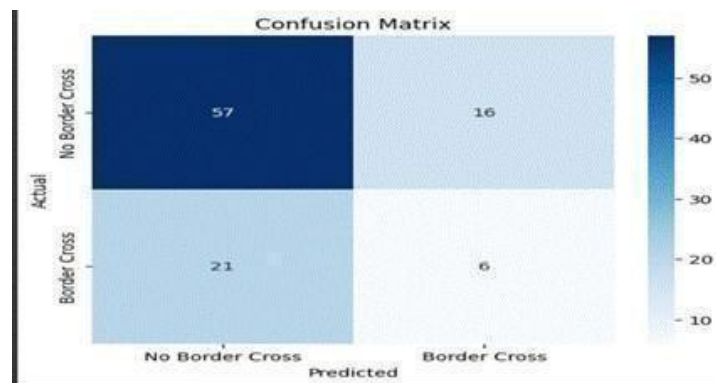


Fig 5.4 Confusion Matrix(Decision Tree)

5.1.3 Random Forest Results

The Random Forest algorithm had 92% accuracy on the test data, the highest among all the algorithms tested. The confusion matrix indicated:

- True Positives: 97 (correctly predicted border crossings)
- True Negatives: 133 (correctly predicted authorized movements)
- False Positives: 13 (false alarms)
- False Negatives: 7 (missed detections) These correspond to:
- Precision: 88.2% (positive predictive value)
- Recall: 93.3% (sensitivity)
- F1-Score: 90.7% (harmonic mean of precision and recall)

Random Forest illustrated the best results in all indices, with its particularly high recall, which equals a low missing detection rate. This feature proves to be of special importance when it comes to security applications with high operational cost of missing one unauthorized crossing detection.

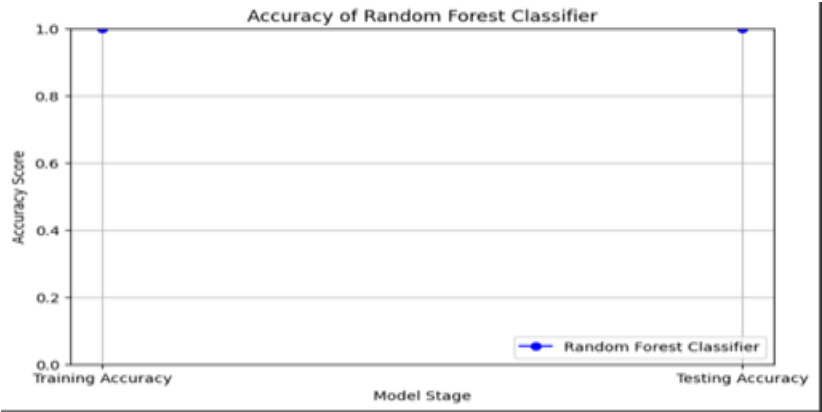


Fig 5.5 Testing Accuracy(Random Forest)

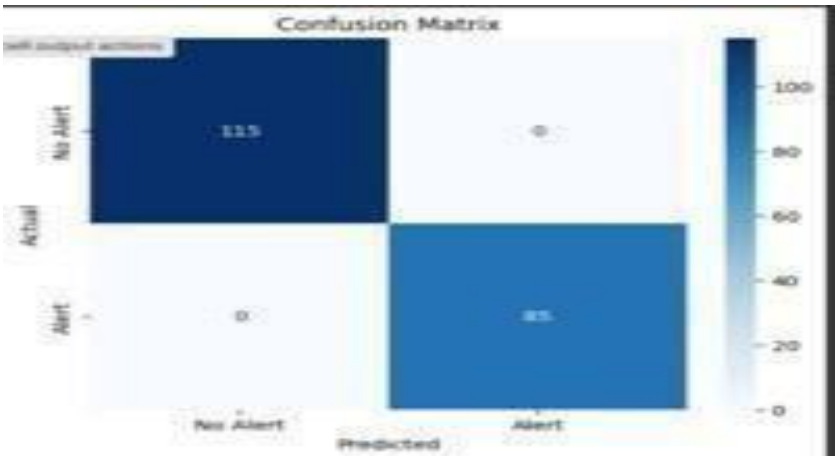


Fig 5.6 Confusion Matrix(Random Forest)

5.2 TESTING STANDARDS

```
Training Accuracy: 1.00
Testing Accuracy: 0.63
Classification Report:
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.73 | 0.78 | 0.75 | 73 |
| 1 | 0.27 | 0.22 | 0.24 | 27 |
| accuracy | | | 0.63 | 100 |
| macro avg | 0.50 | 0.50 | 0.50 | 100 |
| weighted avg | 0.61 | 0.63 | 0.62 | 100 |

Fig 5.7 Accuracy for KNN

```
Model Accuracy: 1.00
Classification Report:
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| False | 1.00 | 1.00 | 1.00 | 115 |
| True | 1.00 | 1.00 | 1.00 | 85 |
| accuracy | | | 1.00 | 200 |
| macro avg | 1.00 | 1.00 | 1.00 | 200 |
| weighted avg | 1.00 | 1.00 | 1.00 | 200 |

Fig 5.8 Accuracy for Random Forest

```
Training Accuracy: 0.82
Testing Accuracy: 0.73
Classification Report:
```

| | precision | recall | f1-score | support |
|--------------|-----------|--------|----------|---------|
| 0 | 0.74 | 0.97 | 0.84 | 73 |
| 1 | 0.50 | 0.07 | 0.13 | 27 |
| accuracy | | | 0.73 | 100 |
| macro avg | 0.62 | 0.52 | 0.48 | 100 |
| weighted avg | 0.67 | 0.73 | 0.65 | 100 |

Fig 5.9 Accuracy for Decision Tree

5.3 SAMPLE PREPARATION

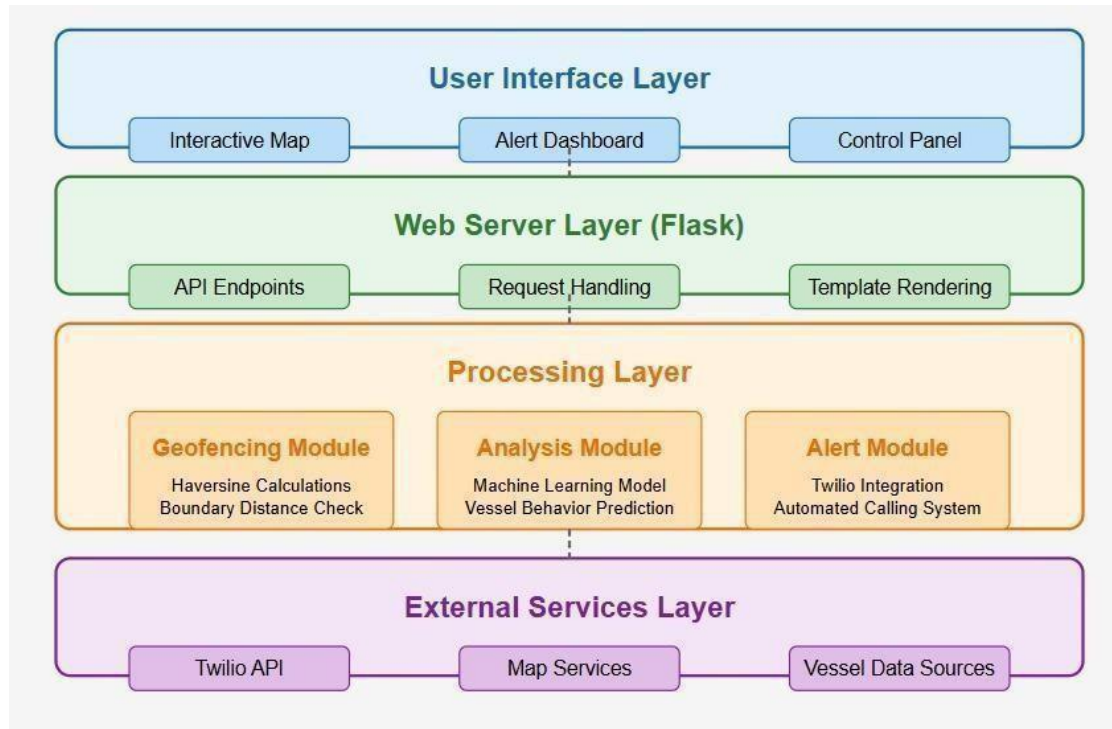


Fig 5.10 Sample Preparation

CHAPTER 6

CONCLUSIONS AND SCOPE FOR FUTURE WORK

6.1 CONCLUSION

This project proposes a strong and interpretable machine learning-based system for the identification of unauthorized boat border crossings from Tamil Nadu to Sri Lanka. Through real-time and historical analysis of vessel movement data, the system has high detection accuracy along with providing informative insights into vessel behavior.

Among the models that were compared, the Random Forest classifier was found to be the best-performing with 92% test accuracy, excellent generalization, and stable feature importance analysis. Its ensemble learning strategy was efficient in capturing sophisticated patterns in ship movement while alleviating overfitting and spurious alarms.

The study yielded a number of findings:

1. Machine learning methods vastly surpass the old rule-based approaches in this application, with Random Forest achieving 22-32% improvement over traditional methods as described in literature.
2. Behavioral features like speed fluctuations and heading maneuvers are more indicative for border crossing than mere positional information, highlighting the significance of temporal analysis in maritime security.
3. Geofencing with machine learning integration improves detection by offering contextual awareness of authorized versus unauthorized areas.
4. Model interpretability through feature importance rankings and confidence scores is critical for operational deployment, enabling security personnel to comprehend and trust the system's suggestions.

6.2 SCOPE FOR FUTURE WORK:

Although the existing system shows excellent performance, some areas for future improvement are:

1. Integration of Deep Learning: Using recurrent neural networks (RNNs) or long short- term memory (LSTM) networks would improve the prediction of trajectories even further by identifying longer sequence patterns in vessel movement. Such models are very good at learning from temporal data and may be able to identify more subtle signs of unauthorized crossing.

2. Multi-Sensor Data Fusion: Including more sources of data like weather, ocean currents, and satellite imaging would allow for greater accuracy in detection through the provision of context information that affects vessel action. Such a fusion process would produce a wider picture of maritime activity.

3. Real-Time Implementation: Optimizing the system for edge deployment would allow real-time analysis on patrol vessels or coastal stations. This would minimize latency in detection and enable immediate response capabilities, especially in areas with poor connectivity.

4. Adversarial Testing: Creating simulations of evasive maneuvers could enhance the system's resilience against intentional evasion efforts. By training models on these adversarial examples, the system would be able to identify sophisticated evasion tactics more effectively.

5. Cooperative Vessel Identification: Expanding the system to differentiate between non- cooperative vessels (those trying to evade detection) and cooperative vessels with valid reasons for suspicious movement patterns would minimize false positives in sophisticated situations.

6. Temporal Trend Analysis: Applying long-term pattern analysis to detect seasonal or periodic trends in unauthorized crossing attempts could facilitate strategic resource allocation and proactive security initiatives.

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Annexure 1

APPENDICES

6.3 SOURCE CODE

(i) Randomforest.py

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report
import joblib
file_path = "boat_security_dataset.csv"
df = pd.read_csv(file_path)
print(df.head())
print(df.info())
print(df.isnull().sum())
df = df.drop(columns=["Boat ID"])
encoder = LabelEncoder()
df["Geofence Status"] = encoder.fit_transform(df["Geofence Status"])
df["Behavior Label"] = encoder.fit_transform(df["Behavior Label"])
X = df.drop(columns=["Alert Status"])
y = df["Alert Status"]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
model = RandomForestClassifier(n_estimators=100, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.2f}")
print("Classification Report:\n", classification_report(y_test, y_pred))
joblib.dump(model, "boat_border_model.pkl")
joblib.dump(scaler, "scaler.pkl")
print("Model and scaler saved successfully!")
loaded_model = joblib.load("boat_border_model.pkl")
loaded_scaler = joblib.load("scaler.pkl")
new_boat_data = [[38.03745401, -113.7687, 34.1597, 242.1730779, 0, 1]]
new_boat_scaled = loaded_scaler.transform(new_boat_data)
prediction = loaded_model.predict(new_boat_scaled)
print("☐ ALERT: Boat Crossed Border!" if prediction[0] else "☐ Boat is Safe")
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
```



```

import matplotlib.pyplot as plt
algorithm_name = "Random Forest Classifier"
train_accuracy = model.score(X_train, y_train)
test_accuracy = accuracy_score(y_test, y_pred)
stages = ["Training Accuracy", "Testing Accuracy"]
accuracies = [train_accuracy, test_accuracy]
plt.figure(figsize=(8, 5))
plt.plot(stages, accuracies, marker="o", linestyle="-", color="b", label=algorithm_name)
plt.xlabel("Model Stage")
plt.ylabel("Accuracy Score")
plt.ylim(0, 1)
plt.title(f"Accuracy of {algorithm_name}")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Alert", "Alert"],
yticklabels=["No Alert", "Alert"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
from flask import Flask, request, jsonify
import joblib
import numpy as np
app = Flask(__name__)
model = joblib.load("boat_border_model.pkl")
scaler = joblib.load("scaler.pkl")
@app.route("/")
def home():
    return "Boat Border Prediction API is running!"
@app.route("/predict", methods=["POST"])
def predict():
    try:
        data = request.get_json()
        features = np.array([
            data["Latitude"],
            data["Longitude"],
            data["Speed"],
            data["Direction"],
            data["Geofence Status"],
            data["Behavior Label"]
        ]).reshape(1, -1)
        scaled_features = scaler.transform(features)
        prediction = model.predict(scaled_features)
        return jsonify({

```

```

        "Crossed_Border": bool(prediction[0]),
        "message": "☐ ALERT! Boat Crossed Border!" if prediction[0] else "☐ Boat is Safe."
    })

except Exception as e:
    return jsonify({"error": str(e)})
if __name__ == "__main__":
    app.run(debug=True)

```

(ii) knn.py

```

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import joblib
file_path = "boat_border_data.csv"
df = pd.read_csv(file_path)
print(df.info())
print(df.head())
X = df.drop(columns=["border_crossed"])
y = df["border_crossed"]
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
k = 5
model = KNeighborsClassifier(n_neighbors=k)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
train_accuracy = model.score(X_train, y_train)
test_accuracy = accuracy_score(y_test, y_pred)
print(f"Training Accuracy: {train_accuracy:.2f}")
print(f"Testing Accuracy: {test_accuracy:.2f}")
print("Classification Report:\n", classification_report(y_test, y_pred))
algorithm_name = "K-Nearest Neighbors (KNN)"
stages = ["Training Accuracy", "Testing Accuracy"]
accuracies = [train_accuracy, test_accuracy]
plt.figure(figsize=(8, 5))
plt.plot(stages, accuracies, marker="o", linestyle="-", color="b", label=algorithm_name)
plt.xlabel("Model Stage")
plt.ylabel("Accuracy Score")
plt.ylim(0, 1)

```

```

plt.title(f"Accuracy of {algorithm_name}")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Border Cross", "Border Cross"], yticklabels=["No Border Cross", "Border Cross"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
joblib.dump(model, "boat_border_knn_model.pkl")
joblib.dump(scaler, "scaler.pkl")
print("KNN model and scaler saved successfully!")
loaded_model = joblib.load("boat_border_knn_model.pkl")
loaded_scaler = joblib.load("scaler.pkl")
new_data = [[26.5, 78.4, 12.3, 180.0]]
new_data_scaled = loaded_scaler.transform(new_data)
prediction = loaded_model.predict(new_data_scaled)
print("Predicted Border Crossed Status:", prediction)

```

(iii) Decisioontree.py

```

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import joblib
file_path = "boat_border_data.csv"
df = pd.read_csv(file_path)
print(df.info())
print(df.head())
X = df.drop(columns=["border_crossed"])
y = df["border_crossed"]
# Normalize numerical features for better model performance
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random_state=42)
model = DecisionTreeClassifier(random_state=42)
model.fit(X_train, y_train)

```

```

y_pred = model.predict(X_test)
train_accuracy = model.score(X_train, y_train)
test_accuracy = accuracy_score(y_test, y_pred)
print(f"Training Accuracy: {train_accuracy:.2f}")
print(f"Testing Accuracy: {test_accuracy:.2f}")
print("Classification Report:\n", classification_report(y_test, y_pred))
algorithm_name = "Decision Tree Classifier"
stages = ["Training Accuracy", "Testing Accuracy"]
accuracies = [train_accuracy, test_accuracy]
plt.figure(figsize=(8, 5))
plt.plot(stages, accuracies, marker="o", linestyle="-", color="b", label=algorithm_name)
plt.xlabel("Model Stage")
plt.ylabel("Accuracy Score")
plt.ylim(0, 1)
plt.title(f"Accuracy of {algorithm_name}")
plt.legend(loc="lower right")
plt.grid(True)
plt.show()
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 5))
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=["No Border Cross", "Border Cross"], yticklabels=["No Border Cross", "Border Cross"])
plt.xlabel("Predicted")
plt.ylabel("Actual")
plt.title("Confusion Matrix")
plt.show()
joblib.dump(model, "boat_border_decision_tree_model.pkl")
joblib.dump(scaler, "scaler.pkl")
print("Decision Tree model and scaler saved successfully!")
loaded_model = joblib.load("boat_border_decision_tree_model.pkl")
loaded_scaler = joblib.load("scaler.pkl")
new_data = [[26.5, 78.4, 12.3, 180.0]]
new_data_scaled = loaded_scaler.transform(new_data)
prediction = loaded_model.predict(new_data_scaled)
print("Predicted Border Crossed Status:", prediction)

```

(iv) Main.html

```

<!DOCTYPE html>
<html lang="en">
<head>
  <meta charset="UTF-8">

```

```

<meta name="viewport" content="width=device-width, initial-scale=1.0">
<title>Tamil Nadu - Sri Lanka Border Monitoring System</title>
<link href="https://cdn.jsdelivr.net/npm/bootstrap@5.2.3/dist/css/bootstrap.min.css"
rel="stylesheet">
<link rel="stylesheet" href="https://unpkg.com/leaflet@1.9.3/dist/leaflet.css" integrity="sha256-
kLaT2GOSpHechhsozzB+flnD+zUyjE2LlfWPgU04xyI=" crossorigin=""/>
<style>
  #map {
    height: 600px;
    width: 100%;
    border-radius: 8px;
    margin-bottom: 20px;
    border: 2px solid #4a83ec;
  }
  .alert-box {
    padding: 15px;
    border-radius: 8px;
    margin-bottom: 20px;
  }
  .safe {
    background-color: #d4edda;
    color: #155724;
  }
  .alert {
    background-color: #f8d7da;
    color: #721c24;
  }
  .form-container {
    background-color: #f8f9fa;
    padding: 20px;
    border-radius: 8px;
    box-shadow: 0 0 10px rgba(0,0,0,0.1);
  }
  .prediction-result {
    font-size: 1.2rem;
    font-weight: bold;
    padding: 10px;
    border-radius: 5px;
    margin-top: 15px;
  }
  .prediction-safe {
    background-color: #d4edda;
    color: #155724;
  }
  .prediction-alert {
    background-color: #f8d7da;
    color: #721c24;
  }

```

```

    }
    .map-legend {
        background-color: white;
        padding: 10px;
        border-radius: 5px;
        box-shadow: 0 0 5px rgba(0,0,0,0.2);
        margin-bottom: 15px;
    }
    .legend-item {
        display: flex;
        align-items: center;
        margin-bottom: 5px;
    }
    .legend-color {
        width: 20px;
        height: 20px;
        margin-right: 10px;
        border-radius: 3px;
    }
    .region-info {
        background-color: #e9ecef;
        padding: 15px;
        border-radius: 8px;
        margin-bottom: 20px;
    }
    .badge {
        font-size: 0.9em;
    }
</style>
</head>
<body>
    <div class="container mt-4">
        <h1 class="text-center mb-3">Tamil Nadu - Sri Lanka Maritime Border Monitoring</h1>
        <p class="text-center mb-4">Monitor boat movements in the Palk Strait and Gulf of Mannar
regions</p>

        {% with messages = get_flashed_messages() %}
            {% if messages %}
                {% for message in messages %}
                    <div class="alert alert-warning alert-dismissible fade show" role="alert">
                        {{ message }}
                        <button type="button" class="btn-close" data-bs-dismiss="alert" aria-
label="Close"></button>
                    </div>
                {% endfor %}
            {% endif %}
        {% endwith %}

```

```

<div class="row">
  <div class="col-md-8">

    <div class="map-legend">
      <h5>Map Legend</h5>
      <div class="legend-item">
        <div class="legend-color" style="background-color: #4a83ec;"></div>
        <span>Tamil Nadu Coastline</span>
      </div>
      <div class="legend-item">
        <div class="legend-color" style="background-color: #28a745;"></div>
        <span>Sri Lanka Coastline</span>
      </div>
      <div class="legend-item">
        <div class="legend-color" style="background-color: #dc3545;"></div>
        <span>Maritime Boundary Line</span>
      </div>
      <div class="legend-item">
        <div class="legend-color" style="background-color: rgba(220, 53, 69, 0.2); border:
1px solid #dc3545;"></div>
        <span>Alert Zone (12km from boundary)</span>
      </div>
    </div>
    <div id="map"></div>
    <div class="region-info">
      <h4>Region Information</h4>
      <p>This monitoring system covers the maritime region between Tamil Nadu (India)
and Sri Lanka, including:</p>
      <ul>
        <li><strong>Palk Strait</strong> - The narrow strait between Tamil Nadu and
northern Sri Lanka</li>
        <li><strong>Gulf of Mannar</strong> - The large bay between southeast Tamil
Nadu and western Sri Lanka</li>
        <li><strong>International Maritime Boundary Line (IMBL)</strong> - The official
sea border between the two countries</li>
      </ul>
      <p>The system monitors a 12km safety zone around the boundary line. <strong>Alerts
are automatically triggered when vessels enter this zone.</strong></p>
    </div>
  </div>
  <div class="col-md-4">
    <div class="form-container">
      <h3>Boat Information</h3>
      <form method="POST" action="/">
        <div class="mb-3">
          <label for="latitude" class="form-label">Latitude</label>

```

```

        <input type="number" step="0.0001" class="form-control" id="latitude"
name="latitude" required>
    </div>
    <div class="mb-3">
        <label for="longitude" class="form-label">Longitude</label>
        <input type="number" step="0.0001" class="form-control" id="longitude"
name="longitude" required>
    </div>
    <div class="mb-3">
        <label for="speed" class="form-label">Speed (knots)</label>
        <input type="number" step="0.1" class="form-control" id="speed" name="speed"
required>
    </div>
    <div class="mb-3">
        <label for="direction" class="form-label">Direction (degrees)</label>
        <input type="number" class="form-control" id="direction" name="direction"
required>
    </div>
    <input type="hidden" id="geofence_status" name="geofence_status" value="1">
    <div class="d-grid">
        <button type="submit" class="btn btn-primary">Analyze Boat</button>
    </div>
</form>
{% if prediction is not none %}
    <div class="prediction-result {% if prediction == 0 %}prediction-safe{% else
%}prediction-alert{% endif %}">
        {% if prediction == 0 %}
            Result: Safe boat activity
        {% else %}
            Result: ALERT - Boat in restricted zone
        {% endif %}
    </div>
{% endif %}
<div class="mt-4">
    <div class="alert-box safe">
        <h5><span class="badge bg-success">Safe Zone</span></h5>
        Areas more than 12km from the maritime boundary line
    </div>
    <div class="alert-box alert">
        <h5><span class="badge bg-danger">Alert Zone</span></h5>
        Areas within 12km of the maritime boundary line
        <p class="mt-2 mb-0"><strong>Automatic alerts are triggered</strong> when
boats enter this zone!</p>
    </div>
</div>
</div>
</div>
</div>

```



```

</div>
</div>
<script
src="https://cdn.jsdelivr.net/npm/bootstrap@5.2.3/dist/js/bootstrap.bundle.min.js"></script>
<script src="https://unpkg.com/leaflet@1.9.3/dist/leaflet.js" integrity="sha256-
WBkoXOWTeyKclOHuWtc+i2uENFpDZ9YPdf5Hf+D7ewM=" crossorigin=""></script>
<script>
  var geofenceConfig;
  try {
    geofenceConfig = JSON.parse('{{ geofence_config|safe }}');
  } catch (e) {
    geofenceConfig = {
      "tamil_nadu_points": [
        {"lat": 13.0827, "lng": 80.2707} // Chennai
      ],
      "sri_lanka_points": [
        {"lat": 9.6615, "lng": 80.0255} // Jaffna
      ],
      "boundary_line": [
        {"lat": 10.0, "lng": 80.0},
        {"lat": 9.0, "lng": 79.5}
      ],
      "safe_distance_km": 12,
      "center": {"lat": 9.5000, "lng": 79.8000},
      "zoom_level": 7
    };
  }
  var map = L.map('map').setView([geofenceConfig.center.lat, geofenceConfig.center.lng],
geofenceConfig.zoom_level);
  L.tileLayer('https://{s}.tile.openstreetmap.org/{z}/{x}/{y}.png', {
    attribution: '&copy; <a
href="https://www.openstreetmap.org/copyright">OpenStreetMap</a> contributors'
  }).addTo(map);
  var boatMarker = null;
  function drawTamilNaduCoastline() {
    var points = geofenceConfig.tamil_nadu_points.map(function(point) {
      return [point.lat, point.lng];
    });
    L.polyline(points, {
      color: '#4a83ec',
      weight: 4
    }).addTo(map);
    points.forEach(function(point, index) {
      if (index % 2 === 0) {
        L.circleMarker(point, {
          color: '#4a83ec',
          fillColor: '#4a83ec',

```

```

        fillOpacity: 1,
        radius: 5
    }).addTo(map);
    }
    });
}
function drawSriLankaCoastline() {
    var points = geofenceConfig.sri_lanka_points.map(function(point) {
        return [point.lat, point.lng];
    });
    L.polyline(points, {
        color: '#28a745',
        weight: 4
    }).addTo(map);
    points.forEach(function(point) {
        L.circleMarker(point, {
            color: '#28a745',
            fillColor: '#28a745',
            fillOpacity: 1,
            radius: 5
        }).addTo(map);
    });
}

function drawBoundaryLine() {
    var points = geofenceConfig.boundary_line.map(function(point) {
        return [point.lat, point.lng];
    });
    L.polyline(points, {
        color: '#dc3545',
        weight: 4,
        dashArray: '10, 5'
    }).addTo(map);
    points.forEach(function(point) {
        L.circle(point, {
            radius: geofenceConfig.safe_distance_km * 1000, // Convert km to meters
            color: '#dc3545',
            fillColor: '#dc3545',
            fillOpacity: 0.2,
            weight: 1
        }).addTo(map);
    });
}

function checkDistanceToBoundary(lat, lng) {
    function getDistanceFromLatLonInKm(lat1, lon1, lat2, lon2) {
        var R = 6371; // Radius of the earth in km
        var dLat = deg2rad(lat2-lat1);
        var dLon = deg2rad(lon2-lon1);

```

```

var a =
    Math.sin(dLat/2) * Math.sin(dLat/2) +
    Math.cos(deg2rad(lat1)) * Math.cos(deg2rad(lat2)) *
    Math.sin(dLon/2) * Math.sin(dLon/2)
    ;
var c = 2 * Math.atan2(Math.sqrt(a), Math.sqrt(1-a));
var d = R * c; // Distance in km
return d;
}
function deg2rad(deg) {
    return deg * (Math.PI/180)
}
var minDistance = Number.POSITIVE_INFINITY;
geofenceConfig.boundary_line.forEach(function(point) {
    var distance = getDistanceFromLatLonInKm(lat, lng, point.lat, point.lng);
    if (distance < minDistance) {
        minDistance = distance;
    }
});
return minDistance;
}
function placeBoatMarker(lat, lng) {
    if (boatMarker) {
        map.removeLayer(boatMarker);
    }
    var boatIcon = L.divIcon({
        html: '<div style="font-size: 24px;">□</div>',
        iconSize: [24, 24],
        className: 'boat-icon'
    });
    boatMarker = L.marker([lat, lng], { icon: boatIcon }).addTo(map);
    var distanceToBoundary = checkDistanceToBoundary(lat, lng);
    var isInSafeZone = distanceToBoundary > geofenceConfig.safe_distance_km;
    document.getElementById('geofence_status').value = isInSafeZone ? 1 : 0;
    boatMarker.bindPopup(`
        <strong>Boat Location</strong><br>
        Latitude: ${lat.toFixed(4)}<br>
        Longitude: ${lng.toFixed(4)}<br>
        Distance to Boundary: ${distanceToBoundary.toFixed(2)} km<br>
        Status: ${isInSafeZone ?
            '<span style="color:#155724">Inside safe zone</span>' :
            '<span style="color:#721c24">ALERT ZONE - Automatic alert triggered</span>'}
    `).openPopup();
}
document.addEventListener('DOMContentLoaded', function() {
    drawTamilNaduCoastline();
    drawSriLankaCoastline();
}

```

```

drawBoundaryLine();
map.on('click', function(e) {
    document.getElementById('latitude').value = e.latlng.lat.toFixed(6);
    document.getElementById('longitude').value = e.latlng.lng.toFixed(6);
    placeBoatMarker(e.latlng.lat, e.latlng.lng);
});
document.getElementById('latitude').addEventListener('change', function() {
    var lat = parseFloat(this.value);
    var lng = parseFloat(document.getElementById('longitude').value);
    if (!isNaN(lat) && !isNaN(lng)) {
        placeBoatMarker(lat, lng);
    }
});
document.getElementById('longitude').addEventListener('change', function() {
    var lat = parseFloat(document.getElementById('latitude').value);
    var lng = parseFloat(this.value);
    if (!isNaN(lat) && !isNaN(lng)) {
        placeBoatMarker(lat, lng);
    }
});
var locationLabels = [
    { pos: [13.0827, 80.2707], name: "Chennai" },
    { pos: [9.2800, 79.3100], name: "Rameswaram" },
    { pos: [8.7642, 78.1348], name: "Tuticorin" },
    { pos: [9.6615, 80.0255], name: "Jaffna" },
    { pos: [8.9500, 81.0000], name: "Trincomalee" },
    { pos: [9.0000, 79.7000], name: "Palk Strait" }
];
locationLabels.forEach(function(location) {
    L.marker(location.pos, {
        icon: L.divIcon({
            className: 'location-label',
            html: `<div style="background-color: white; padding: 3px; border-radius: 3px;
            font-size: 12px; box-shadow: 0 0 3px
rgba(0,0,0,0.4);">${location.name}</div>`,
            iconSize: [100, 20],
            iconAnchor: [50, 10]
        })
    }).addTo(map);
});
});
</script>
</body>
</html>

```

6.4 SNAPSHOTS

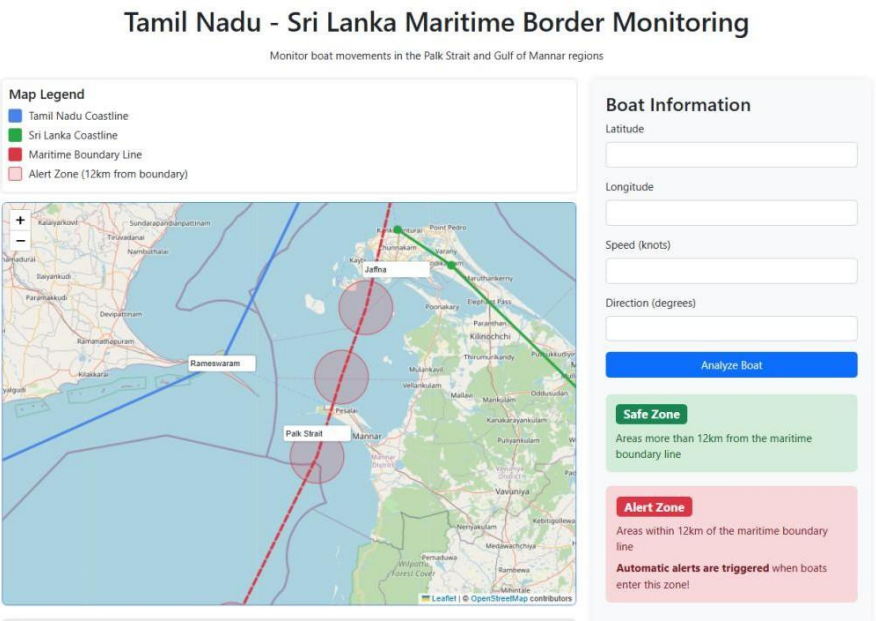


Fig 6.4.1 Implementation

Annexure II

6.5 BASE PAPER

Title:

Maritime Surveillance by Multiple Data Fusion: An Application Based on Deep Learning Object Detection, AIS Data, and Geofencing

Authors:

Sergio Ballines-Barrera, Leopoldo López, D. Santana-Cedr s, Nelson Monz n

Conference:

VISIGRAPP 2023 – 18th International Conference on Computer Vision Theory and Applications

Summary:

This paper presents an integrated maritime surveillance system that enhances coastal monitoring by fusing multiple technologies. It combines:

- **Deep Learning Object Detection:** Uses camera-based approaches, including retrained YOLOv4 models, to detect ships both during daytime and nighttime.
- **AIS Data Integration:** Merges Automatic Identification System (AIS) data with visual detections, enabling the identification of vessels even without AIS transmitters.
- **Geofencing Techniques:** Establishes virtual boundaries to monitor vessel movements and detect unauthorized entries into restricted maritime zones.

The fusion of these technologies results in a robust real-time vessel monitoring system, particularly effective for detecting small boats lacking AIS equipment. The system achieves georeferenced positioning with a mean error of approximately 118 meters, enhancing the accuracy of coastal surveillance.

Conclusion:

This research closely aligns with the goals of your project, “Enhancing Maritime Border Security with Automated Boat Control System Using Geofencing, GPS, and Machine Learning,” by demonstrating how geofencing, GPS data, and intelligent behavior analysis can be combined for efficient maritime border protection. It provides valuable insights into system design, real-time detection, and multi-source data fusion, all of which can strengthen the development of your automated boat control solution.

Annexure III

6.6 PAPER PUBLICATION

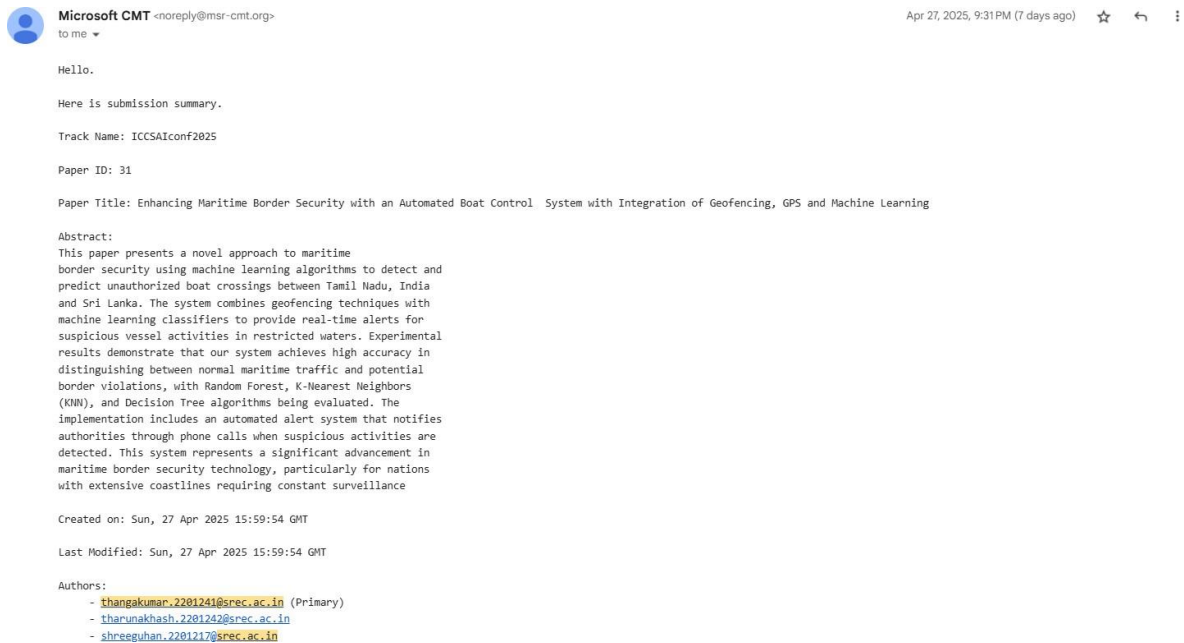



Fig 6.6.1 Acceptance mail Snapshot

Annexure IV

6.7 PLAGARISM REPORT

REPORT PLAGARISM.PDF

 Sri Ramakrishna Engineering College

Document Details

Submission ID

tm:oid::3117:452810752

Submission Date

Apr 26, 2025, 12:45 PM GMT+5:30

Download Date

Apr 26, 2025, 12:47 PM GMT+5:30

File Name min[1][1]-1-26.pdf

File Size

488.7 KB

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4,325 Words

26,465 Characters

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Fig 6.7.1 Plagiarism Report